Evaluation of Cluster Effect in Mobile Opportunistic Networks

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***Abstract*—This paper analyses how data dissemination occurs in mobile Opportunistic Networks by evaluating the impact of different parameters such as density of neighbors, communication range, and speed. There exist several analytical models to evaluate the data dissemination time in *OppNets*. These models were developed based on a very strong assumption of uniform distribution of infected nodes. We prove that this assumption does not work for the whole spectrum of mobile *OppNets*. This paper shows our simulation results validated with our analytical model and discusses the impact of different parameters on data dissemination.**

I. Introduction

Opportunistic networks (*OppNets*) are a type of networks where data is forwarded based on communication opportunities between nodes by using different communication technologies e.g. Bluetooth, WiFi-Direct, LoRa [1]. Data can get a chance to be disseminated to different nodes when two nodes get in contact, so that a receiver can be opportunistically the next hop to forward the data throughout the network. A communication opportunity may occur by means of mobility, especially in sparse network areas where a node might not have any neighbor in some point of time but may have a neighbor with the movement of another node or moving to another location with any kind of transportation. In contrast to Mobile Ad Hoc Networks (MANETs), *OppNets* do not aim a synchronous communication between nodes, so that routing in real time is not a requirement. MANETs are mainly for multi hop communications and assume that each node keeps a route to any other node in order to contribute to the traffic in the network. By contrast, *OppNets* do not rely on any route and are based on one hop communications since the data is forwarded only in case two nodes are within the communication range of each other. Moreover, comparing to Delay Tolerant Networks (DTNs), there is no end-to-end path and usually there is no specific destination for the data to be disseminated finally.

OppNets consider how dissemination occurs throughout the network and aim to have as many as possible nodes infected with the data at the end. Data dissemination follows store-carry-forward paradigm. If currently no communication opportunity exists for a node, the data is stored in the local cache until encountering a neighbor. Therefore, nodes do not rely on any network infrastructure, instead each node acts individually in case of having data available in its cache. *OppNets* usually describe a network with the nodes having heterogeneous mobility models, communication technologies, caching policies and forwarding algorithms. Since, this type of networks is applicable to any kind of situation whether it is a disaster area or city/village area with either low or high density of nodes, any kind of data can be disseminated. For instance, a location specific emergency message, a city announcement by the city hall, an advertisement, an event notification or a good joke among students in a campus area [2] or even collection of specific data in a remote location. In any case, data dissemination time plays an important role to identify which percentage of the network received the data in a particular point of time and how long it took for everyone to receive.

This paper focuses on modeling of data dissemination time in *OppNets* for destination oriented communication. Our contribution is twofold: firstly, the success probability of infecting a new node is analytically modeled based on *Absorbing Markov Chain*. The probability distribution of data dissemination time is derived to have an understanding of data spread modeled which is applicable to any scenario in *OppNets*. Secondly, the proposed model is verified using a network simulator, focusing on mobile *OppNets* scenarios with different communication ranges, speeds, and time interval between communication of the node pairs. The selected set of scenarios covers a different level of distributions of infected nodes from uniform to clustered. When the limited communication range does not let nodes to reach any part of the network, it will result in having infected nodes transmitting the data to only nearby nodes which are in a relatively small area compared to the network which will result in a cluster of the infected nodes. Having new neighbors leads to a dissemination of the data, but this will be either not possible in case of static nodes or will not be happening often if the nodes are moving with a very low speed. To the best of our knowledge, cluster effect is not studied in the literature. This gives us a bridge to consider cluster effect to see what parameters may effect and its relation with the data dissemination. Therefore, in this work we mainly focus on the parameter study. The extensive investigation and the impact on parameters is analysed and discussed for mobile *OppNets* applications in this paper.

II. Related work

A. *Modeling of Data Dissemination in* OppNets

Modeling of data dissemination in *OppNets* has been widely studied in last decade [3]–[17]. Most papers proposed an

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average delay calculation rather than a probability distribution [13] [14] [15] [3] [5] [8] [9] [11]. However, giving the whole spectrum of delay considering of all probabilities helps to have a clear understanding of data spread over a network. Success probability is a key factor for the calculation of data dissemination time as it represents the probability that data dissemination can take place and it will continue until each node receives the data in the network.

This paper derives the Probability Distribution Function (PDF) of dissemination time based on the calculation of success probabilities. We derive the success probability analytically in contrast to previous work of [10] and [12], in which the success probability is directly taken from the real life traces. Further, the success probability in our earlier work [16] considers only the case, where an infected node can meet a non-infected one. We have extended [16] to include the other possibility of that a non-infected node may also encounter an infected neighbor (see Figure 1).

Regarding the evaluation of our proposed model, a network simulator is used to compare scenarios with different communication ranges, node speeds and inter contact times to the analytical model. In most of *OppNets* studies, Monte Carlo simulators are preferred [3], [5]–[10], [14], [17].

Our selected scenarios cover all possible cases of different distributions of infected nodes that can occur from uniform to clusters. Compared to our previous work [16], mobile scenarios are taken into account and analysing the parameters that how they affect the data dissemination is the focus of this work. We do not propose a completely new analytical model, but as a lot of papers do not consider cluster effect, we justify this is not true and show what parameters impact. Though the authors of [10] validate a mobile *OppNets* scenario, their analytical model was not validated for scenarios which do not have a uniform distribution of infected nodes, as experienced at low speed and low communication range. Table I shows a comparison of research papers based on the analytical model proposed and features considered. The main performance metric evaluated in this work is data dissemination time. We do not focus on throughput as it is in general not an interesting metric for *OppNets* since *OppNets* are based on store-carry-forward paradigm.

B. *Routing Protocols in* OppNets

There are various types of routing protocols in *OppNets* such as flooding based, destination oriented, destination-less, reinforcement based, deterministic, stochastic etc. Some of the forwarding algorithms let nodes exchange data based on unicast communication for instance HiBOp [18], Epidemic [19], Randomized Rumor Spreading (RRS) [20], PRoPHET [21], Adaptive Routing [22], SimBet [23] while some others use broadcast or multicast type of communication e.g. Spray and Wait [24], BUBBLE Rap [25], Keetchi [26]. In this paper, modeling of data dissemination time in mobile scenarios is studied for unicast transmission between node pairs and RRS is used for the evaluation of the proposed analytical model with simulation since RRS is a forwarding algorithm for disseminating recent updates which are called as *rumors* to all nodes by using randomized communication in a distributed environment and takes the approach of *rumor mongering*. Rumor mongering is a concept that whenever a node has a *hot rumor*, it chooses a node within its communication range and just disseminates the *hot rumor*. In our paper, *hot rumor* is considered as a new data item. The size of the rumor is not limited in a contact event and each rumor exchange is considered as a single transmission.

III. Modeling of Data Dissemination Time in OppNets

Data is stored, carried and forwarded when an infected node encounters a non-infected neighbor node. Contact opportunity between two nodes are called as events and we assume that they occur based on a Poisson process. The intensity of the Poisson process which is denoted as λ defines the contact rate of any particular node in the network.

Data dissemination is modeled based on an Absorbing Markov Chain and the number of infected nodes in the network denotes the states [16]. Transition from state α to α+1 occurs when a non-infected node receives the data from one of its infected neighbors. The ultimate goal is having all nodes in the network infected. Therefore, dissemination starts from the originator node (state α=1) and continues until the Markov Chain reaches the absorbing state *N*. As data dissemination time is the time it takes for all nodes in the network to receive the data, this also includes the transmission time at each sender and that the data is in the buffer until it finds another communication opportunity to be disseminated.

A. *Success Probability*

Success probability is the probability of two nodes being in contact and resulting a data dissemination. Hence, the node pair should consist of one infected and one non-infected node to have a successful event.

Success probability of state transition from α to α+1 can be depicted as p_α. Having all nodes randomly distributed over the network, to have a successful event, two cases are investigated in mobile *OppNets* which is a communication from an infected node to a non-infected neighbor (p_α^1) or vice versa (p_α^2). At the end, success probability to go to the state α+1 from α is the summation of these two probabilities as in equation (2). From practical point of view, usually infected nodes are triggered to start a communication with their neighbors. In fact, considering of a realistic scenario, non-infected nodes are also able to start a communication with their neighbor and if this neighbor is an infected one, there will be a data dissemination. Hence, compared to our work in [16], in this work, any possibility that can lead to a successful dissemination is considered in the success proability. In [16], only infected nodes are able to start a communication. Therefore success probability is only depending on the case that an infected node selects a non-infected neighbor. In this work, we extend the assumption by letting non-infected nodes also start a communication with their neighbors. In this case, success proability includes also

TABLE I: Comparison of The Papers

	Analytical Evaluation		Results Validation		Features Considered		
References	Analytical Model	Performance Indicators	Simulator	Traces/Testbed	Mobility Model	Routing Protocol	Cluster Effect Considered
[3]	Markov Chain	Drop Ratio	Matlab	–	TVCM and SLAW	Epidemic, Two-hop, Spray and Wait	No
[5]	Markov Chain	Average Message Delay, Energy Consumption	✓(Not mentioned)	–	Random Walk	Epidemic, Spray and Wait	No
[6]	Markov Chain	Flooding Time	✓ (Not mentioned)	MIT Cell, MIT BT, Infocom06, Vehicular, UCSD, Cambridge	SWIM	Basic forwarding approach	No
[7]	Markov Chain	Delay	C++	Cambridge	Ideal Mobility Model	Social-aware Forwarding Protocols	No
[8]	–	Delivery Delay	✓ (Not mentioned)	Cabspotting, Infocom06, Sigcomm	Synthetic Mobility with Gamma Distribution	Random Routing Protocol	No
[9]	–	Expected Delay	✓ (Not mentioned)	Cambridge, Infocom05, RollerNet	Synthetic Mobility with Pareto Distribution	Social-aware and Social-oblivious Strategies	No
[10]	Bounding Markov chain	Delay PMF	✓ (Not mentioned)	Reality Mining trace and Infocom 2005 trace	HCMM and SLAW	Epidemic Routing	No
[11]	Data Grid Model	Average Data Dissemination Time	OMNeT++	–	Random Way Point and Random Direction	No routing	No
Proposed Model	Absorbing Markov Chain	PDF of Dissemination Time	OPS	–	Random Way Point	Randomized Rumor Spreading	Yes

the situation where a non-infected node selects an infected neighbor (p_α^2) which will lead to a sucessful dissemination. The comparison of these two approaches can be seen in Figure 1.

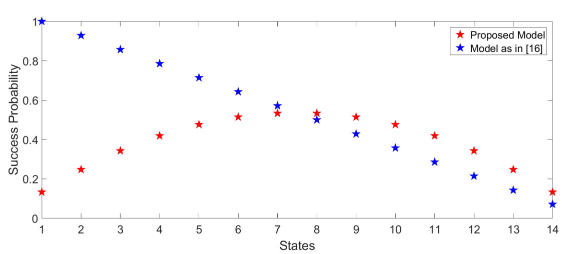

Fig. 1: Comparison of Success Probabilities

$$p_\alpha^1 = \frac{\alpha}{N}\frac{N-\alpha}{N-1} \quad \text{and} \quad p_\alpha^2 = \frac{N-\alpha}{N}\frac{\alpha}{N-1} \tag{1}$$

$$p_\alpha = p_\alpha^1 + p_\alpha^2 = 2\frac{\alpha}{N}\frac{N-\alpha}{N-1} \tag{2}$$

B. Data Dissemination Time

According to the assumption that arrival of the events (contacts) is based on a Poisson process with rate λ, time between two contacts can be expressed by the Probability Density Function (PDF) $\lambda e^{-\lambda x}$. Given that number of contacts going from state α to α+1 is k and inter-arrival times are independent and identically exponentially distributed random variables, time taken between two consecutive states would be then the summation of these random variables which results actually in an Erlang distribution for the corresponding PDF as expressed in equation (3).

$$P(x|K=k) = \frac{\lambda^k}{(k-1)!}x^{k-1}e^{-\lambda x} \tag{3}$$

Given that kth trial is the first success to go to the next state, probability of having k number of contacts between two states can be computed with the PDF of geometric distribution as in equation (4). Finally, time of staying in state α can be expressed as equation (9) and as it can be seen that the time staying in one state is actually exponentially distributed with the rate λp_α.

$$P(K=k) = p_\alpha(1-p_\alpha)^{k-1} \tag{4}$$

$$P(x) = \sum_{k=1}^{\infty} P(K=k)P(x|K=k) \tag{5}$$

$$P(x) = \sum_{k=1}^{\infty} \frac{p_\alpha \lambda^k (1-p_\alpha)^{k-1} x^{k-1} e^{-\lambda x}}{(k-1)!} \quad (6)$$

$$P(x) = p_\alpha e^{-\lambda x} \lambda \sum_{n=0}^{\infty} \frac{(\lambda(1-p_\alpha)x)^n}{n!} \quad (7)$$

$$P(x) = p_\alpha e^{-\lambda x} \lambda e^{\lambda(1-p_\alpha)x} \quad (8)$$

$$P(x) = \lambda p_\alpha e^{-\lambda p_\alpha x} \quad (9)$$

To have the probability distribution of data dissemination time, we may refer to the PDF of the dissemination time that is the summation of non-identical exponentially distributed random variables with rates λp_α which is given by equations (10) and (11). Two equations are necessary because the corresponding theorem requires that all probabilities (p_α) are different. Therefore, as success probabilities actually have a symmetry for the first half of the network and second half, we derive the equations for both half of the network first. The data dissemination time is then calculated as the sum of two times covering the dissemination times to a first half of the nodes and a second half of the nodes, respectively. The corresponding PDFs are $f_1(x)$ and $f_2(x)$. The PDF of data dissemination time to infect all nodes in the network will be obtained by the convolution of $f_1(x)$ and $f_2(x)$ as shown in equation (12).

$$\begin{aligned} P(x_{1\to\lfloor\frac{N}{2}\rfloor}) &= f_1(x) \\ &= \left(\prod_{\alpha=1}^{\lfloor\frac{N}{2}\rfloor} \lambda p_\alpha\right) \sum_{i=1}^{\lfloor\frac{N}{2}\rfloor} \frac{e^{-\lambda p_i x}}{\prod_{j=1, j\neq i}^{\lfloor\frac{N}{2}\rfloor}(p_j - p_i)\lambda} \end{aligned} \quad (10)$$

$$\begin{aligned} P(x_{\lfloor\frac{N+1}{2}\rfloor\to N-1}) &= f_2(x) \\ &= \left(\prod_{\alpha=\lfloor\frac{N+1}{2}\rfloor}^{N-1} \lambda p_\alpha\right) \sum_{i=\lfloor\frac{N+1}{2}\rfloor}^{N-1} \frac{e^{-\lambda p_i x}}{\prod_{j=\lfloor\frac{N+1}{2}\rfloor, j\neq i}^{N-1}(p_j - p_i)\lambda} \end{aligned} \quad (11)$$

$$(f_1 * f_2)(x) = \int_0^x f_1(y) f_2(x-y) dy \quad (12)$$

IV. Analysis of Results

A. Methods, Tools and Scenarios

The Opportunistic Protocol Simulator (OPS) [27] is an OMNeT++ [28] based simulator, developed by the University of Bremen for simulating *OppNets*. The node architecture of OPS provides application, routing, link adaption and link layers together with the mobility. A message is generated in the application layer and after generating the message, the routing layer forwards it depending on the routing protocol used. The OPS offers three routing protocols that are Epidemic, Keetchi and RRS. Mobility in OPS architecture is from the INET framework [29] and therefore any mobility model provided by INET can be used. In this paper, simulation results are obtained by using the OPS simulator.

For the mobility purpose in the simulation, Random Waypoint (RWP) [30] is used to let the nodes move around in the network. RWP is a mostly used synthetic mobility model where nodes move straight to the next location with a certain velocity. When a node arrives in the waypoint, it waits there for a random time and decides the next waypoint randomly from a uniform distribution. The velocity for the next location is also drawn randomly from a velocity distribution.

Our scenario with 15 nodes, reflects that drones flying above a remote agricultural field or people cycling or driving in a remote village, disseminating a data item which consists of a piece of local information such as an emergency occurred in the neighboring environment or an interesting piece of gossip. The nodes are deployed in an $1km^2$ area. We evaluated this scenario with speeds (denoted as s) of $8.3\,\mathrm{m/s}$, $16\,\mathrm{m/s}$, $20\,\mathrm{m/s}$ and $32\,\mathrm{m/s}$, by varying the communication range, r_{CR}, to $150\,\mathrm{m}$, $200\,\mathrm{m}$ and $400\,\mathrm{m}$. The meeting opportunity of node pairs, t is configured with a negative exponential distribution with the mean $1\,\mathrm{sec}$, $3\,\mathrm{sec}$, $5\,\mathrm{sec}$, $10\,\mathrm{sec}$, $15\,\mathrm{sec}$, $20\,\mathrm{sec}$, $30\,\mathrm{sec}$ and $40\,\mathrm{sec}$ for each set up. The meeting opportunity represents when a routing strategy selects a node pair to exchange data. The time between the selection of node pairs in RRS is negative exponentially distributed. This is not same with the distribution of the nodes in the network or in other words position of the nodes. Nodes are uniformly distributed in the network at the beginning of each simulation run. Then, they start moving based on the mobility model RWP. The mobility model is helpful for RRS routing protocol. Because RRS selects which node pairs will communicate and it can have a chance to select different node pairs in each time as the position of each node changes with the movement.

B. Simulation Results Analysis

Each of the above mentioned simulated scenario was run for 1000 runs and the mean of the success probability of each state, $p_{\alpha(Sim)}$ is compared with the analytical success probability of each state, $p_{\alpha(AM)}$. The empirical CDF of the dissemination time is shown for 1000 simulation runs, and compared with the analytical CDF derived from (12).

In this paper, we have selected only two sub scenarios to visualise the comparison of the simulation and the analytical results.

- *Scenario-1*: t = $30\,\mathrm{sec}$, r_{CR} = $400\,\mathrm{m}$, and s = $16\,\mathrm{m/s}$
- *Scenario-2*: t = $10\,\mathrm{sec}$, r_{CR} = $150\,\mathrm{m}$, and s = $8.3\,\mathrm{m/s}$

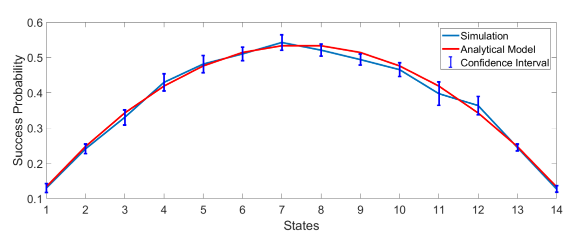

Fig. 2: Scenario-1 Success Probability vs States

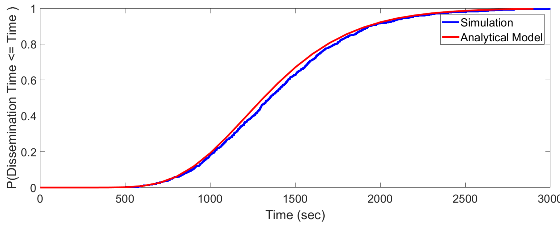

Fig. 3: Scenario-1 CDF of Dissemination Time

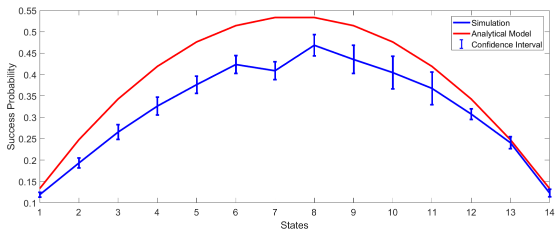

Fig. 4: Scenario-2 Success Probability vs States

Both the success probability (Figure 4) and the CDF of the dissemination time (Figure 5) of the *Scenario-2* are deviated from the proposed analytical model, while the *Scenario-1* (Figure 2 and Figure 3) shows the perfect match. Further *Scenario-1* takes longer time to disseminate the message to all the nodes, while the *Scenario-2* shows the faster dissemination time. This is due to the fact that the communication opportunity among two node pairs occurs more frequently in *Scenario-2*.

Our model is valid under the assumption that the infected nodes are distributed in the network uniformly. The uniform distribution of the infected nodes in mobile *OppNets* depends on the following factors in our simulated scenarios:

- *Speed* (s) - The higher the speed, the faster the infected nodes move to have them distributed uniformly.
- *Time between two communication opportunities* ($t = 1/\lambda$) - A higher frequency of meetings may result in meeting nodes from the neighborhood more frequently and thereby creating clusters of infected nodes.
- *Average number of nodes in the vicinity* (n) - A higher number of neighbors makes data dissemination faster.
- *Communication Range* (r_{CR}) - A lower the communication range creates more clusters of infected nodes.

The interaction of the above factors determines decide the infected nodes are distributed uniformly or form clusters. As both possibilities can occur in real mobile *OppNets* applications, we further investigate how the above factors affect the proposed model.

V. Validation of the Model

The distance that a node travels till it meets another node, denoted as d, can be computed according to the equation (13) and shown as a fraction of r_{CR}. For a given scenario, the d depends on the speed, the communication range and how often two nodes meet. The later represents the mean of the exponential distribution which is configured in the simulator

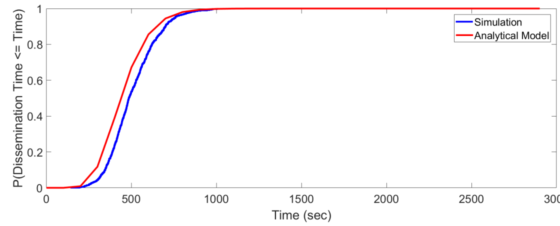

Fig. 5: Scenario-2 CDF of Dissemination Time

as the inter meeting times between two nodes, denoted as t. The communication range and the network size determine the average number of neighbors, denoted as n in a given scenario and the n is computed according to the equation (14).

$$d = \frac{t \cdot s}{r_{CR}} \tag{13}$$

$$n = N \cdot \frac{\pi r_{CR}^2}{A} \tag{14}$$

In order to analyse the deviation with regard to the analytical model for each simulated scenario, the difference between the analytical and simulated success probability of all the states is computed as in the equation (15), as denoted as $RMSD$ (Root Mean Square of the Differences). The lower the $RMSD$ indicates more matching of our simulation results with the proposed analytical model. Figure 6 shows that how the $RMSD$ changes with regard to all the factors discussed earlier, the speed, the communication range, number of neighbors and the average time of meeting two nodes. The impact of all these factors are shown as $d \cdot n$. Figure 6 indicates that our analytical model matches with the simulation results with higher communication range and higher speed for a given node density.

A lower communication range does not let nodes to select a node from any part of the network and therefore, data dissemination forms a cluster of infected nodes. This violates our analytical assumption of the uniform distribution of infected nodes, showing the higher $RMSD$.

Figure 7 shows two extreme cases of our scenarios ("$r_{CR} = 150\,\mathrm{m}$ with $s = 8.3\,\mathrm{m/s}$" and "$r_{CR} = 400\,\mathrm{m}$ with $s = 32\,\mathrm{m/s}$") highlighting the impact of varying t under the same r_{CR} and s values. In the first case with lowest r_{CR} and the lowest s, t has an impact on $RMSD$, showing the deviation with our analytical model. In this case, with the higher t values, nodes can have an opportunity to go outside of their communication range until the next communication opportunity occurs. This results in meeting new neighbors and helping to create the uniform distribution of the infected nodes in the network. But, lower t creates clusters of infected nodes as they will meet mostly the same neighbors for several communication opportunities.

However, t will not have a noticeable impact on $RMSD$ when the nodes have higher r_{CR} and s in the second case. Because, with the higher communication range nodes have the opportunity of having many neighbors and the higher speed allows them to move faster within the network even if the t is really small. This results in meeting new neighbors irrespective of the t values, showing matching results with the proposed analytical model. In summary, the simulation results follow the analytical model for $d \cdot n > 2$.

$$RMSD = \sqrt{\frac{\sum_{\alpha=1}^{\alpha=N-1} \left(p_{\alpha(AM)} - p_{\alpha(Sim)}\right)^2}{N-1}} \tag{15}$$

VI. Conclusion and Future Work

The proposed analytical model computes the distribution of the data dissemination time to have much better understanding of *OppNets* scenarios. This was derived based on Absorbing Markov Chain which is applicable to any scenario in *OppNets*. We discussed the impact on the dissemination time of mobile *OPPNets* applications, considering the parameters such as the speed, the communication range, and the average number of neighbors. Our analysis is done using simulations and validated by the analytical model with the assumption that the infected nodes are uniformly distributed.

Our parameter study prove that the most common assumption of the uniform distribution of infected nodes in *OppNets* is not a realistic assumption for all scenarios. The uniform distribution of infected nodes is valid for mobile scenarios with higher communication range and higher speed. A limited communication range does not let nodes to select a node from any part of the network and therefore, data dissemination to nearby nodes forms a cluster of infected nodes. However, a higher speed of mobility helps to spread the infected nodes in the network reducing the effect of having infected clusters even with limited communication range. To the best of our knowledge, none of the previous work validated their analytical model for scenarios where cluster of infected nodes can occur.

As future work;

- Impact of caching policy is not considered in this work. Instead of assumption of having infinite cache, nodes should be considered as having a limited cache with a caching policy and its effect on data dissemination should be analysed.
- Results can be analysed with a different mobility model. Modeling the mobility was not the scope of this work, therefore RWP was selected just to have mobile nodes in the network and ease the cluster effect as RWP helps node being in any random position in the network. If another mobility model is used for instance SWIM [31], the results might be different. However, infected nodes can be still clustered as SWIM works with the decision of home location and how much of the time a node should remain in the home location.
- Our model should be enhanced to consider the cluster effect of infected nodes that can also occur in *OppNets* as it is not always possible to have the infected nodes uniformly distributed over the network.

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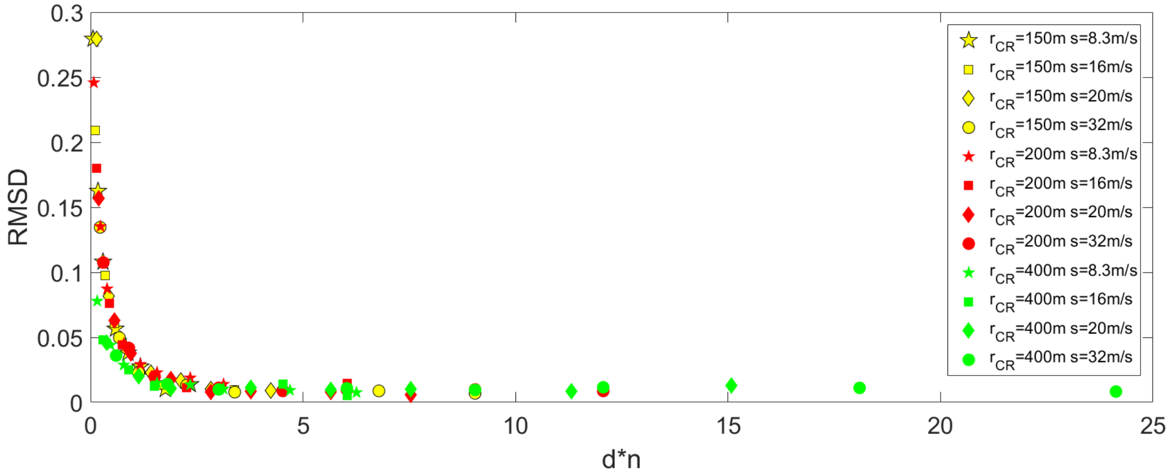

Fig. 6: $RMSD$ vs $d.n$

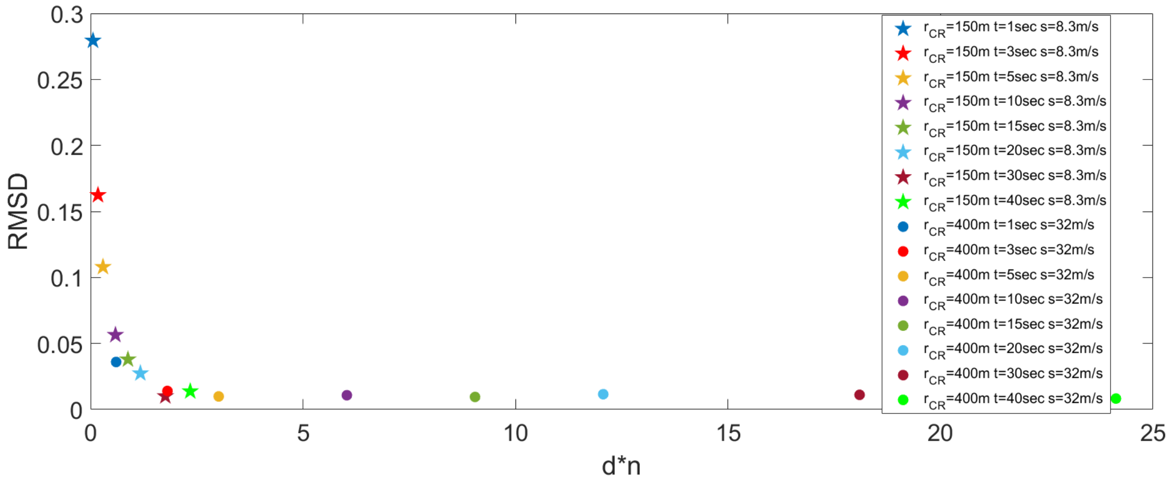

Fig. 7: $RMSD$ vs $d.n$ for $r_{CR} = 150\,\mathrm{m}$ and $r_{CR} = 400\,\mathrm{m}$ for different t values

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