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Performance Modeling of Epidemic Routing with Heterogeneous Node Types

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***Abstract*—The delay performance of delay tolerant networks (DTN) can be improved by adding or replacing mobile nodes with higher mobility or transmit power. In this paper, we examine the design trade-offs in heterogeneous DTNs with two types of mobile relay nodes: normal and super. First we present the range of parameters in the Random Direction (RD) mobility model in which we have validated the Markovian assumption on the node inter-encounter intervals. Next, we describe the two-dimensional continuous time Markov chain (CTMC) model with absorption state, used for evaluating the performance of the heterogeneous DTNs. We demonstrate that the performance improvement of adding super nodes is not linear. For example, replacing 10% of the normal nodes with super nodes ones can achieve 40% of the delay reduction versus replacing all of them. Finally, Fluid Flow Approximation (FFA) and Moment Closure Methods for solving the CTMC with various error rates (about 10%) were developed to allow faster analysis of networks with large number of nodes.**

I. Introduction

To cope with intermittent connectivity in DTN, a number of multiple-copy routing strategies have been suggested [1], [2], [3], [4], [5], [6], [7] to improve the delay performance. Under these schemes, each message is allowed to copy itself to different relay nodes for message delivery. However they also introduce very large overhead which greatly limits the delay improvement. Under limited bandwidth and buffer constraints, we [8] show that delay performance can be contrarily degraded because of excessive replications.

In addition to multiple-copy routing, earlier work has proposed using motor buses [9] as auxiliary network nodes to form a DTN with heterogeneous node types. These nodes move in a faster speed which gives them the superior message relaying capability to improve delivery delay. However, the superior relaying capability also requires higher operating cost for node motorization. This kind of superior nodes is referred as *super nodes*. They are commonly constituted as a subset of relay nodes in DTNs with heterogeneous node types. Adopting higher cost super nodes in a DTN introduces a novel way to improve delivery delay. The trade-offs between them is illustrated in Fig. 1. A super node can be a motor bus which needs higher energy than a pedestrian for its physical movement. However, its higher mobility makes it a superior node that can better improve the delivery delay.

We are going to study the trade-offs between super node penetrating rate and delivery delay in heterogeneous DTNs. A DTN model with two heterogeneous node types of different speeds is considered. The two node types are named as *super node* and *normal node*. The former one refers to the high speed superior node type and the later one refers to the low speed ordinary node type. In this paper, we first reviewed the Random Direction (RD) mobility model for the inter-encounter interval. Then a two-dimensional continuous time Markov chain (CTMC) model with absorption state has been formulated for evaluating the delivery delay of heterogeneous DTNs. The results illustrate the marginal gain on delivery delay for successively added super node is diminishing. For example, we observe that having 10% super nodes in a DTN can already reduce the delay up to 40% versus the case of having 100% super nodes. Finally, we develop Fluid Flow Approximation (FFA) and Moment Closure Methods as alternative methods to solve the CTMC model with certain degree of accuracy (about 10%) to avoid the computational burden under large network settings. Further examination on their modeling error shows that they give lower error for the DTNs with more number of nodes or more homogeneous population.

This paper is organized as follow: Section II discusses some related work on homogeneous DTN model. Section III presents the system model of DTN with two heterogeneous node types. Then Section IV reviews the Random Direction (RD) mobility model with two heterogeneous node types. Performance modeling by continuous time Markov chain (CTMC) model, Fluid Flow Approximation (FFA) and Moment Closure Methods is shown in Section V-A and Section V-B. Finally, Section VI concludes this paper with some possible future work.

II. Related Work

The previous work [10], [11], [12] has used the Pure-Birth CTMC model with absorption state to evaluate Epidemic Routing (ER), Source Spraying (SS) and Binary Spraying (BS). Closed-form solutions on relating the delay to network setting parameters have been derived for both of them. In addition, the Fluid Flow Approximation (FFA), which is adopted from infectious disease spreading model, has also been proposed to model the performance of ER and its variations [13], [14]. FFA provides an asymptotic mean value solution on the number of infections for a spreading infectious disease which has

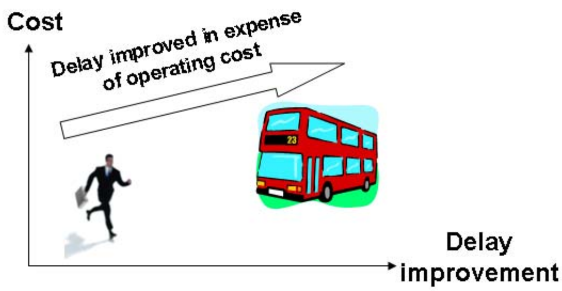

Fig. 1. Higher cost superior node for better delay improvement

been used to model ER to derive the performance metrics of different multiple-copy routing strategies [13].

However, these earlier work assumes all nodes behave homogeneously. It is not accurate enough to represent many real world scenarios such as a DTN operates in a city area comprises both vehicular nodes and pedestrian nodes. Thus we are going to investigate the performance modeling for DTNs with heterogeneously mixed nodes population.

III. System Model

We consider the case where only one message is under delivery by Epidemic Routing (ER) strategy. The model only considers the time span before the message is delivered. Both bandwidth and buffer constraints are assumed not exist and therefore the yielding delay result should be rather optimistic.

We first define the DTN model with two heterogeneous node types. A list of system model parameters is shown in Table I. Total number of nodes excluding the source node and the destination node is denoted by N. Then α portion of N nodes are super nodes and the remaining $\beta = 1 - \alpha$ portion of N nodes are normal nodes. The source and the destination are assumed to be normal nodes. We denote *inter-encounter interval* as the time between the start time of two consecutive meetings of any two nodes. Then *encounter rate* is reciprocal of the mean inter-encounter interval. Since there are two node types, we divide the encounter rate into three types: λ_{ss} denotes the super node to super node encounter rate, λ_{ns} denotes the normal node to super node encounter rate and λ_{nn} denotes the normal node to normal node encounter rate. The number of infected super nodes and infected normal nodes at time t is denoted by $I(t)$ and $J(t)$ respectively. Inter-encounter intervals are assumed independent and identically distributed with exponential distribution. We will validate the exponentially distributed inter-encounter interval property in the RD mobility model in Section IV.

IV. Random Direction (RD) Mobility Model with Two Heterogeneous Node Types

Author in [11] shows that inter-encounter interval is approximately exponential distribution in a RD mobility model when the node communication range is relatively small compared to the network area and the node movement speed is high. This property can be found useful in justifying the Markovian assumption in the CTMC model. Thus RD mobility model

TABLE I
System Model Parameters for Epidemic Routing (ER) evaluation

Parameter	Meaning
N	total number of nodes except source and destination
α	portion of super nodes
β	portion of normal nodes
λ_{ss}	encounter rate between super nodes and super nodes
λ_{ns}	encounter rate between normal nodes and super nodes
λ_{nn}	encounter rate between normal nodes and normal nodes

TABLE II
Parameters for Random Direction mobility model with two heterogeneous node types

Parameter	values
Network area (M)	1000x1000 m^2
Radio range (K)	50 m
Super node max. speed (V_{s-max})	60 ms^{-1}
Super node min. speed (V_{s-min})	15 ms^{-1}
Normal node max. speed (V_{n-max})	15 ms^{-1}
Normal node min. speed (V_{n-min})	10 ms^{-1}
Max. pause (P_{max})	5 s
Min. pause (P_{min})	2 s
Mean epoch length (L)	50 100 150 200 250 300 m

has been adopted in some earlier work [10], [11], [1] as the assumed mobility model for performance modeling. However, previous work has only considered the homogeneous model. We reviewed, via simulation, the inter-encounter interval distribution of RD mobility model under the two heterogeneous node types model. The epoch length parameter is especially considered because we found that it is important for the exponential distribution of inter-encounter interval in the RD mobility model.

Table II lists the parameters under our investigation. A super node has a higher average speed than normal node while other settings are equal. We computed the Mean Absolute Error (MAE) between the simulation's empirical distribution and the exponential distribution over different mean epoch lengths ($\bar{L}$). The means of inter-encounter interval $1/\lambda_{ss}$, $1/\lambda_{ns}$ and $1/\lambda_{nn}$ for the exponential distribution are estimated by the simulation as well as the analytical expressions (1) and (2). For the analytical result, the means of homogeneous case $1/\lambda_{ss}$ and $1/\lambda_{nn}$ are directly known from Section 3.1 of [15] while the mean of heterogeneous case $1/\lambda_{ns}$ can be derived from the homogeneous case result with some modifications [16]. The two expressions for homogeneous case and heterogeneous case are shown in (1) and (2) respectively.

$$EM_{homo} = M/[2K(p_m^2 \hat{v} + 2p_m(1-p_m)\bar{v})] \quad (1)$$

$$EM_{heter} = M/[2K(p_{m-s}p_{m-n}\hat{v} + p_{m-s}(1 - p_{m-n})\bar{v}_s + p_{m-n}(1-p_{m-s})\bar{v}_n)] \quad (2)$$

$\bar{v}_s$ and $\bar{v}_n$ are the average speed of a super node and a normal node respectively while $\bar{v}$ is the average speed of the node for homogeneous model. They both equal to the mean of maximum speed limit and minimum speed limit. $\hat{v}$ is the average relative speed between a node pair. It equals to $E[||\vec{A} - \vec{B}||]$ for any two nodes moving with velocities

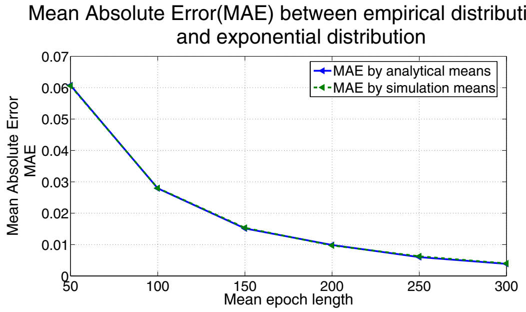

Fig. 2. Mean Absolute Error(MAE) between empirical distribution and exponential distribution

$\vec{A}$ and $\vec{B}$. Then p_{m-s} and p_{m-n} are the average moving probability for a super node and a normal node respectively while p_m is the average moving probability for homogeneous model. The three terms of moving probability both equal to $\bar{T}_{move}/(\bar{T}_{move}+\bar{T}_{stop})$. Then $\bar{T}_{stop}=(P_{max}+P_{min})/2$ and $\bar{T}_{move}=\bar{L}/\bar{v}$.

With the reference exponential distribution functions taking the means estimated by the simulation as well as the expressions (1) and (2), MAE results between empirical distribution and exponential distribution are shown in Fig. 2 under the settings in Table II. The results by analytical mean and simulation mean are closely matched with each other which validated the mean inter-encounter interval computed by (1) and (2). The result shows that inter-encounter interval is very close to exponential distributed if epoch length is long enough. By this validation result, we found that mean epoch length ($\bar{L}$) is an additional factor affecting the exponential distribution of inter-encounter interval of RD mobility model with two heterogeneous node types. In particular, the mobility pattern with long epoch length is expected to be more commonly found in city area where node movement is constrained by long straight streets and roads. The result of RD mobility model with long epoch length setting justifies the adopted assumption of exponential distribution of inter-encounter interval for the later continuous time Markov chain (CTMC) model.

Throughout all the results in this paper, we assume all nodes follow the RD mobility model such that the three encounter rate parameters λ_{ss}, λ_{ns} and λ_{nn} are assigned by the reciprocal of the numerical results computed by (1) and (2).

V. Performance Modeling of Epidemic Routing in DTN with Two Heterogeneous Node Types

A. Continuous Time Markov Chain (CTMC) Model

Multiple-copy routing allows a message to copy itself to multiple relay nodes, then all nodes received the copy will carry it to the destination. It is modeled by the Pure-Birth CTMC model with absorption state. The set of states comprises a range of integer which denotes the number of nodes carrying a copy. When a message copies itself to an additional node, it corresponds to a jumping into a higher value state in the CTMC model. The absorption state represents that the message has been successfully delivered. In this section, the previous CTMC model is extended for the two heterogeneous node types model. Then the mean delay results are presented under different settings.

ER [2] strategy is considered which floods the network for message delivery. Therefore a message in a relay node is always allowed to copy itself to any other encountering nodes. The process of spreading message copies is analog to the spreading of an infectious disease. For convenience, we adopt the terminology from Epidemiology to denote a node carrying a message copy as an *infected* node.

In contrast to homogeneous case, the CTMC model formulation requires additional tracing on the type of nodes carrying the copy. We adopt a two dimensional state space CTMC model, which is shown in Fig. 3, for tracing the number of infected nodes of each type. At a particular state (i,j), i and j represent the population of infected super nodes and infected normal nodes respectively. The value of i is ranging from 0 to $N\alpha$ while the value of j is ranging from 1 to $N\beta+1$. The later one has an offset of plus one because the source node is not counted in the total population size N.

When it is in state (i,j), i super nodes and j normal nodes are carrying the message copies. Transition from (i,j) to $(i+1,j)$ is triggered when one of these infected nodes from either type encounters a super node that is uninfected. Each infected super node and infected normal node encounters an uninfected super node with a rate equals to λ_{ss} and λ_{ns} respectively. So the aggregated encounter rate between an uninfected super node to any one of the currently infected nodes equals to $i\lambda_{ss}+j\lambda_{ns}$. In addition, the remaining population size of uninfected super nodes equals to $N\alpha-i$, and infecting any one of them leads to the transition from (i,j) to $(i+1,j)$. Therefore the total rate for super node population increment at state (i,j), which is denoted as $R_x(i,j)$, equals to $(i\lambda_{ss}+j\lambda_{ns})(N\alpha-i)$. Similarly the total rate for normal node population increment at (i,j), which is denoted as $R_y(i,j)$, equals to $(i\lambda_{ns}+j\lambda_{nn})(N\beta-j+1)$.

The message is successfully delivered if any one of the infected nodes encounter the destination. Since the destination node is assumed to be a normal node, the transition rate toward absorption state D at state (i,j) equals to $R_{dest}(i,j)=i\lambda_{ns}+j\lambda_{nn}$. To sum up, the transition rates $R_x(i,j)$ and $R_y(i,j)$ for traversing among the transient states as well as the transition rate $R_{dest}(i,j)$ toward absorption state D are:

- $R_x(i,j)=(i\lambda_{ss}+j\lambda_{ns})(N\alpha-i)$
- $R_y(i,j)=(i\lambda_{ns}+j\lambda_{nn})(N\beta-j+1)$
- $R_{dest}(i,j)=i\lambda_{ns}+j\lambda_{nn}$

Mean Delay Result by CTMC Model: The mean delay is computed by transient analysis in the appendixes of [17] and a set of numerical results is shown in Fig. 4. RD mobility model is assumed for the encounter rate parameters under the settings in Table II but V_{s-max} is varying among the values 30, 60, 90 and 120 while $\bar{L}$ is fixed at 300. Total number of nodes N equals to 50.

Fig. 4 shows the results of mean delay across different percentages of super node. Delay is decreasing with a diminishing rate when the percentage of super nodes increases. This shows

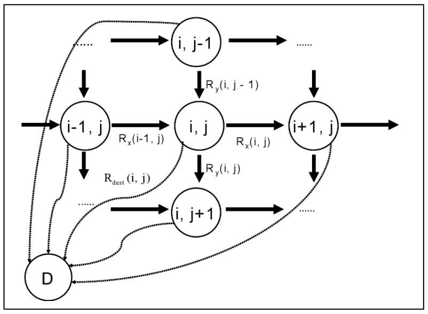

Fig. 3. CTMC model of Epidemic Routing (ER) with two heterogeneous node types

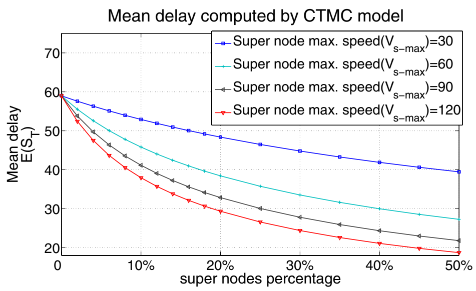

Fig. 4. Mean delay by CTMC model

that using small amount of super nodes is sufficient for large delay improvement. The result of $V_{s-max} = 120$ particularly illustrates that replacing 10% of the normal nodes with super nodes ones can achieve 40% of the delay reduction versus replacing all of them. At last, we observe that higher maximum speed of super node also leads to lower delay which is quite obvious.

B. Fluid Flow Approximation (FFA)

Continuous time Markov chain (CTMC) model provides an exact solution for evaluating some performance metrics of multiple-copy routing. However, the size of state space quickly becomes intractable when total number of nodes N becomes large. Some previous work has considered an alternative Fluid Flow Approximation (FFA) [13], [14] to resolve the performance metrics of interest. Fluid Flow Approximation (FFA) has been widely used in Epidemiology and has been introduced to model ER in [13]. It provides mean value solution for performance metrics with computational complexity that is independent of total number of nodes N. For homogeneous case, a set of ordinary differential equations (ODEs) describing the number of infected nodes has been derived for ER and its variants [14]. In this section, we extend the ODE solution in [14] for the two heterogeneous node types model.

1) Ordinary Differential Equations (ODE) for FFA: We first show a system of ordinary differential equations (ODE) by following [14] to describe the ER under the two heterogeneous node types model. The derivation can be found in [16]. The resulting expressions for mean number of infected super nodes and infected normal nodes are:

$$\bar{I}'(t) = (N\alpha - \bar{I}(t))\bar{I}(t)\lambda_{ss} + (N\alpha - \bar{I}(t))\bar{J}(t)\lambda_{ns} \quad (3)$$

$$\bar{J}'(t) = (N\beta - \bar{J}(t) + \bar{J}(0))\bar{I}(t)\lambda_{ns} + (N\beta - \bar{J}(t) + \bar{J}(0))\bar{J}(0)\lambda_{nn} \quad (4)$$

The result is known as the fluid limit solution of the CTMC model in Fig. 3 as $N \to \infty$. They provide an asymptotic mean value solution on the number of infected nodes at time t. Then we further add one more ODE for the cumulative distribution function (CDF) of delay $P(t)$. The derivation of $P(t)$ can be found in [14]. We apply directly their result with the replacement of encounter rate parameter which gives:

$$P'(t) = (\lambda_{ns}\bar{I}(t) + \lambda_{nn}\bar{J}(t))(1 - P(t)) \quad (5)$$

2) Moment Closure Methods: Fluid Flow Approximation (FFA) provides an asymptotic mean value solution which acts as only an approximation for small size network. In this section, we show an alternative way to derive the ODEs by considering the Kolmogorov Forward Equation. Then we adopt the Moment Closure Methods [14] to improve the accuracy of FFA. Finally the effectiveness of Moment Closure Methods on improving the accuracies is examined by the numerical results.

We follow a similar approach as the one shown in the appendix C of [14] to derive the cumulant generating function for the state variables of the CTMC model corresponding to the number of infected nodes. The resulting cumulant generating function is derived in Chapter 4 of [16] which yields the following system of differential equations for the first order cumulant (mean) :

$$\bar{I}'(t) = \bar{I}(t)\lambda_{ss}\alpha N + \bar{J}(t)\lambda_{ns}\alpha N - \lambda_{ns}Cov(I,J) - \lambda_{ns}\bar{I}(t)\bar{J}(t) - \lambda_{ss}Var(I) - \lambda_{ss}(\bar{I}(t)^2) \quad (6)$$

$$\bar{J}'(t) = \bar{I}(t)\lambda_{ns}(\beta N + 1) + \bar{J}(t)\lambda_{nn}(\beta N + 1) - \lambda_{ns} Cov(I,J) - \lambda_{ns}\bar{I}(t)\bar{J}(t) - \lambda_{nn}Var(J) - \lambda_{nn} (\bar{J}(t)^2) \quad (7)$$

where $\bar{I}(t)$, $\bar{J}(t)$, $Var(I)$, $Var(J)$ and $Cov(I,J)$ denote the mean number of infected super nodes, the mean number of infected normal nodes, the variance on the number of infected super nodes, the variance on the number of infected normal nodes and the covariance between number of infected super nodes and number of infected normal nodes respectively. The later three terms are corresponding to the second order cumulants with t being omitted for notational simplicity. These three second order cumulants can be derived by taking higher order derivative on the cumulant generating function. We see that they are further depending on the third order cumulants. In contrast, setting the three terms to zero yields the ODEs of FFA in (3) and (4).

From the cumulant generating function in Chapter 4 of [16], we see that the lower order moments are depending on the higher order moments. Thus the system of moment differential equations is in infinite size and is not solvable. The system of equations is approximated by Moment Closure Methods which truncate the system at some moment orders. In Section V-B1, the simplest Moment Closure Method FFA, which ignores all the stochastic variability, has been derived to estimate the delay performance.

We adopted the set of Moment Closure Methods in [14] to improve the FFA by estimating the ignored second order cumulants $Var(I)$, $Var(J)$ and $Cov(I,J)$. The techniques employed by the Moment Closure Methods in the previous literatures [18], [19], [20] are based on the assumption that the state variables $I(t)$ and $J(t)$ at a particular time $t \geq 0$ follow some distributions and use their special properties to close the system of moment differential equations. For example, Multi-variate Normal (MVN) assumes the state variables follow multi-variate normal distribution which gives zero value for the third order cumulants to close the moment differential equations at second order. In particular, we consider two additional Moment Closure Methods:

- Lognormal method: It assumes the logarithm of state variables $I(t)$ and $J(t)$ follow a multi-variate normal distribution. Then the third order cumulants can be expressed in terms of lower order cumulants.
- Third order method: It is suggested in [14], which simply set the third order cumulants to zero.

3) Numerical Solutions of Moment Closure Methods: We are going to examine the three Moment Closure Methods described above: FFA, Lognormal method and Third order method. The three investigating methods close the moment differential equations at first, second and third order moments respectively. According to their characteristics on the closing order, we denote the labels "1st order moment" for the FFA, "2rd order moment" for the Lognormal method and "3rd order moment" for the Third order method.

We illustrate some numerical results of covariance $Cov(I,J)$, delay CDF $P(t)$, mean delay $\bar{D}$ and relative modeling errors Err_{rel} for all Moment Closure Methods. They are shown in a series of graphs from Fig. 5 to Fig. 8.

We similarly assume the encounter rate parameters are assigned by (1) and (2). The settings are following Table II but only the case $\bar{L}$ equals to 300 is considered. In Fig. 5 and Fig. 6, total number of nodes N is fixed at 50 and only the delay results for the settings of 8% super nodes and 60% super nodes are shown for time spanning from 0 to 100 seconds. On the other hand, Fig. 7 and Fig. 8 adopt the same setting but they also consider the 150 nodes setting. Their presenting results are mean delay $\bar{D}$ and relative error Err_{rel} against different node heterogeneity settings from 0% to 100% super nodes.

In addition to the numerical results of the three Moment Closure Methods, CTMC model numerical results are also shown to compare against the approximation methods. The corresponding covariance, delay distribution and delay mean are computed numerically in Chapter 4 of [16]. Fig. 5 shows the covariance $Cov(I,J)$ against time. The result by FFA is not shown among the labeled curves because it always equals to zero which is corresponding to the x-axis. The result by CTMC model shows that $Cov(I,J)$ is always positive across

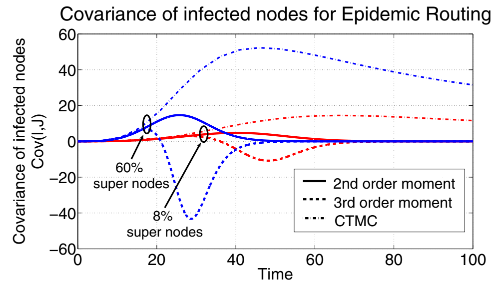

Fig. 5. Covariance of infected nodes by Moment Closure Methods and CTMC model

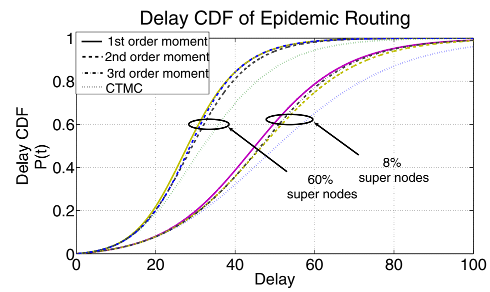

Fig. 6. Delay CDF by Moment Closure Methods and CTMC model

the time spanned and the results of $Cov(I,J)$ by different Moment Closure Methods are always smaller than the CTMC result. It reflects that the covariance is underestimated by the Moment Closure Methods. Similar observations can be found for the variance terms [16]. They lead to the underestimation of delay as shown in the delay CDF $P(t)$ in Fig. 6.

In Fig. 7, mean delay $\bar{D}$ of different Moment Closure Methods and CTMC are plotted against different percentages of super nodes with total number of nodes equals to 50 and 150 respectively. The mean delay results by Moment Closure Methods are always lower than CTMC result because of the underestimated variances and covariance. The results at 0% super nodes correspond to the homogeneous setting where all nodes are normal nodes. These results are same as those computed from the ODEs in [14] where the authors in [14] have derived the ODEs for one-dimensional CTMC model.

The corresponding relative error Err_{rel} result for the settings in Fig. 7 is shown in Fig. 8. It shows that the second order moment closure method gives the best estimation among the three methods. In addition, DTN with more nodes can improve the accuracy for the three Moment Closure Methods. It is because when number of network nodes N is large, the variability of infected population at particular time t become smaller. Thus ignoring the variability causes less impact on the error. Moreover, we also observe that the relative error are higher when the population is heterogeneous rather than homogeneous which can be a possible future work for further investigation.

VI. Conclusion and Future Work

Under a heterogeneously mixed population with two node types, we reviewed the RD mobility model and investigated

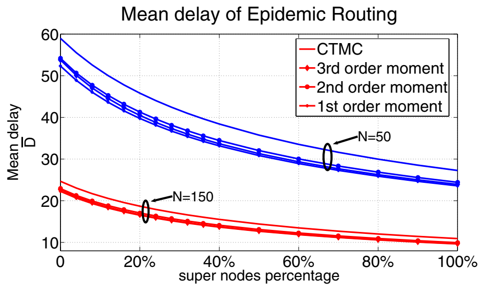

Fig. 7. Mean delay by Moment Closure Method and CTMC model for different number of nodes N

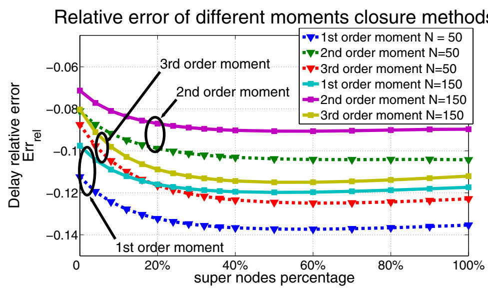

Fig. 8. Relative error on mean delay of Moment Closure Methods for different number of nodes N

the performance modeling of ER. The exponential distribution of inter-encounter interval of RD mobility model with two heterogeneous node types was validated. Some exceptional cases were also revealed which are corresponding to short epoch length settings.

For the performance modeling, we extended the previous models in homogeneous case for the heterogeneous case. A two-dimensional CTMC model has been formulated which extended the one-dimensional model for Epidemic Routing. Through the extended models, we found the diminishing gain of delay performance for successively added super node. It suggests that a small amount of super nodes is already sufficient for delay improvement. Moreover, we also show the use of Fluid Flow Approximation (FFA) [14], [13] and Moment Closure Methods [14] to alleviate the computational burden when N is large with reasonable error (about 10%). The results show that second order Moment Closure Method gives the best estimation while the modeling error can also be smaller for DTN with more number of nodes or less heterogeneous setting.

Our model on node heterogeneity has been set up by two heterogeneous node types with different speeds. However, model on node heterogeneity can also be established by alternative parameters such as radio range, epoch length and pause length. There are also more possible extensions on performance modeling, including increasing the number of node types, modeling other multiple-copy routing strategies and considering the resource constraints. The Moment Closure Methods can also be further improved by devising a more close estimation on state variables distribution to close the moment differential equations.

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