Analytical Modeling of Information Dissipation in Urban Arterials with Connected Vehicles

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ANALYTICAL MODELING OF INFORMATION DISSIPATION IN URBAN ARTERIALS WITH CONNECTED VEHICLES

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ABSTRACT

In this study, we developed a macroscopic analytical model for modeling the vehicle-to-vehicle (V2V) communication process. The proposed information propagation methodology is based on the Susceptible-Infected-Removed (SIR) model that is used to represent the spread of epidemics in a fixed region analytically. The enhanced version of this epidemic model with the addition of exposed class is used to replicate the information dissemination in connected vehicle (CV) environments. The proposed analytical model predicts the time it takes to inform all vehicles present on the given roadway. The model is developed in a way that it can adapt to a variety of connected vehicle market penetration levels. Finally, it is validated using simulation results obtained from a calibrated model coded using PARAMICS, traffic micro-simulation software. The results showed that the analytical model could accurately predict the contact rate of infected nodes which explains how fast the information will dissipate in dense urban conditions.

Connected Vehicles, Epidemic Models, SIR, SEIR, Micro-simulation, V2V, Wireless Communication, DSRC

INTRODUCTION

Information dissemination is a powerful and fundamental social process in modern societies. The most of the technological infrastructures have been developed to provide a platform to communicate various types of information in the last couple of decades. Recent advances in Intelligent Transportation Systems have been stimulated in order to adapt emerging trends and increasing volumes of disseminated information between vehicles and infrastructure. Vehicle-to-vehicle (V2V) communications technologies in a Connected Vehicle (CV) environment can deliver a data-rich platform for travelers based on information anonymously transmitted from vehicles without any infrastructure requirements. The dynamics of traffic flow, inter-vehicle communication protocol, and dissemination of information are the three underlying factors of the V2V based communication. Various analytical and simulation models have been developed for the propagation of information in recent years (*1; 2*). Although such models are very well defined, they require significant effort for the development and calibration and also are computationally very expensive. Thus, it is a real challenge to use them for multiple scenario evaluation studies especially if these studies require quick response times. As an alternative, few studies attempted to model the spread of information from the vehicle to vehicle using an approach analogous to spread of infection in an epidemic (*3-6*). The primary objective of these studies was to use an epidemic model to analytically capture the dynamics of information flow in CV environments. The idea of the basic Susceptible-Infected-Removed (SIR) model is first introduced by Kermack and McKendrick (*7)*. In this macroscopic model, a population is composed of three groups of individuals: susceptible (S), infectious (I) and recovered (R). In the literature, this epidemic model is used to analytically estimate the number of informed vehicles in a CV environment. The SIR model is enhanced by incorporating an exposed class E (*8*). TABLE 1 below illustrates the variables in the epidemic model and its corresponding variables in traffic.

TABLE 1 Epidemic Model Variables and its Corresponding Variables in Traffic

Description	**Epidemic Model Variables**	**Corresponding Traffic Variables**
Total Population	N	Total number of CVs
Susceptible Population	S	CVs that can potentially receive information from other vehicles in traffic
Exposed Population	E	CVs that receive the information but cannot transmit it to other vehicles until the next time step
Infected Population	I	CVs with information to be transferred
Recovered	R	CVs that receive the critical information and that are removed from the network

The exposed class corresponds to the vehicles which received the information, but they are not immediately ready to transmit it to the other vehicles until the next time step. The SEIR model can be mathematically represented as:

$$\frac{\partial S}{\partial t} = -\lambda IS / N$$
$$\frac{\partial E}{\partial t} = \lambda IS / N - gE$$
$$\frac{\partial I}{\partial t} = gE - mI \qquad (1)$$
$$\frac{\partial R}{\partial t} = mI$$

where m is the recovery rate of infected individuals, λ is the effective per capita contact rate and the incidence rate that makes susceptible vehicles infectious is $\lambda IS / N$, and g is the rate at which the exposed nodes become infected (Thus, the mean infectious period is 1/g). To generalize the model for various population sizes, it is normalized according to s = S/N, e = E/N, i = I/N, and r = R/N (*8*):

$$s' = -\lambda is$$
$$e' = \lambda is - ge$$
$$i' = ge - mi \qquad (2)$$
$$r' = mi$$

In the SEIR model, the population size is constant, and there is no heterogeneity. This approach fails to explain the vehicle dynamics in traffic flow as well as the interactions between vehicles on different density levels. The market penetration level of CVs plays a crucial role in CV applications and information propagation. Therefore, the SEIR model can be improved by introducing a new density based per capita contact rate. This rate relies on the vehicle density and traffic speed. This study aims to model the effects of the market penetration on information propagation in CV environments by fusing microscopic traffic behavior with macroscopic analytical models. The proposed approach provides an analytical model to estimate a density-based contact rate ($\lambda^{density-dependent}$) by utilizing the traffic dynamics to improve macroscopic models for dense urban scenarios.

Current simulation-based approaches not only require longer time intervals to execute and instantaneous information collected from vehicles at every time step but also coding of the target network to run simulations. To address these limitations and provide a faster estimation of information flow in urban scenarios, this study proposes an analytical model to investigate information propagation by integrating a density base contact rate to the epidemic model. This addition results in better understanding of the relationship between traffic density and information dissemination and the analytical model enables a faster analysis of information flow in CV applications. The rest of this paper is organized as follows. In section 2, the existing literature about epidemic models in information dissemination is explained, while in Section 3, an analytical approach for describing density-dependent epidemic information dissemination model is presented. The proposed model is evaluated and analyzed in Section 4. Finally, the last section summarizes the contribution of the paper and discusses the future work.

LITERATURE REVIEW

One of the most demanding problems in wireless networks is the capability to discern network behavior and evaluate their performance in large-scale scenarios in which a large a number of nodes need to interact with each other. In these cases, simulations and emulations of actual systems become useful since the deployment of real systems is costly and not practical. However, even using the calibrated simulation models may be computationally expensive due to the high system complexity in such scenarios. Therefore, analytical models can fill the gap of the tools that are required to understand the network behavior and conduct performance assessments. Information propagation modeling in wireless networks has attracted the considerable attention from the researchers in recent years (*3; 4; 9; 10*).

In the transportation domain, information dissemination models can be used to understand the information flow in CV environments. Indrakanti, Ozbay and Mudigonda (*6)* are one of the first to propose a macroscopic analytical approach to model the V2V communication process using a spread of infection models. The proposed model was based on the SIR model, and it predicted the number of infected (informed) vehicles on the roadway at any time for a combination of the number of lanes, speed limits, flows and market penetrations. The comparison of the numerical model and the simulation model was executed using PARAMICS microsimulation tool. The results showed that the number of infected and uninfected vehicles fluctuated over time and the fluctuation oscillates between an absolute maximum and a minimum value. Wu, Fujimoto and Riley (*2)* presented an analytical model to understand the spatial propagation of information in V2V networks. They investigated the average delay in transferring a message from one location to the other with one-way vehicle traffic. Two different models were proposed to explain message propagation under sparse and dense network conditions. The validation of the models was done through two simulations. The first one considered undisturbed vehicle traffic model and the second one was controlled by a microscopic traffic simulator CORSIM (*11*). The results from simulations illustrated that the speed of the propagation was faster than what models predicted. The relative errors of the predicted propagation speed were between 10% and 20%.

Islam et al. (*12)* proposed analytical models to explain data dissemination in the wireless mobile network. They considered both the single and multiple object diffusion processes in wireless networks and presented analytical models explaining each approach. Epidemic-based data propagation system was used as a Markov process to model the behavior of the scheme. Their model contained a contention rate among the communicating nodes when multiple ones try to broadcast data simultaneously. The model results were compared against simulated results with a discrete event simulator written in C++. For single and multiple object diffusion, the results showed that analytical results and simulated results match with close proximity. They concluded that message propagation rate experienced a phase transition as a function of node density, radio range, and speed in a wireless network.

Kim, Peeta and He (*13)* suggested a macroscopic model to take traffic flow dynamics and communication constraints into consideration when determining the information flow propagation wave speed. The solution obtained by the proposed model was its closed-form solution of wave speed which relies on the density, communication frequency, and shape of the communication kernel that describes the success rate of communications. The results were validated against simulated results using a Cell Transmission Model (CTM). The experiment simulation network was 30 km with homogeneous section characteristics. The time interval for the simulation was 0.5 seconds. The results showed that the wave speeds increase as the density of traffic flow increases and analytical results fit the speeds generated by the simulated experiments. As the following study, Kim, Peeta and He (*14)* integrated an epidemic model to a CTM based traffic flow model to understand single hop dynamic information flow propagation. To model the success rate of vehicle communication, a simulation-based approach was used.

They again compared model results with simulated results obtained from a network consisting of 200 cells that were equivalent to 22 miles of highway. The assumptions about traffic flow remained the same. However, they investigated uni and bi-directional highways under different market penetration rates in this study. A roadway incident was also simulated to understand the effects of a non-uniform traffic stream. The results pointed out that the analytical formulation overestimated of the propagation of wave speed only under sparse density conditions.

Although using simulation the realistic vehicular traffic pattern can be captured, most papers in the literature fail to report how many runs were actually executed to obtain simulated results. Jin and Recker (*1)* presented an analytical model for multi-hop connectivity of vehicle communication systems. The model assumed that the vehicles' positions were all known through observations. Their model also replicated the stochastic nature of traffic and did not require repeating traffic simulations. A scenario with only one way traffic and a higher market penetration level was analyzed without any effect of merging and diverging vehicles in the study. The results showed that the arbitrary distribution of vehicles dramatically affects the performance of communication. Knowing the exact locations of all vehicles, the model was able to estimate multi-hop connectivity at any time point between nodes.

Goscé, Barton and Johansson (*5)* showed an approach that analytically improves current disease spreading models. The spread of disease rely on the crowd behavior, and the contact rate is a fundamental parameter in their study. Therefore, they proposed a method that analytically calculates the contact rate using the local crowd density within a corridor and compared the model's outcomes with an agent-based simulation. The results of the study showed that such contact rate varies significantly depending on the crowd density in the studied environment and current models may give significant over or underestimations of the spread of disease in particular density conditions. The second part of the book written by Chiasserini, Gribaudo and Manini (*15)* talks about broadcasting safety messages in a CV environment. It explains a stochastic analytical model for message dissemination and channel access mechanisms for multi-hop broadcasting in depth. A similar dissemination methodology where the information is first sent to the furthest available vehicle is adopted in this study. Their approach also considers the message block probability and transient system behavior which assures the viable information exchange of the networks. The next section will explain the proposed analytical model to calculate a density-dependent contact rate in detail. This contact rate is analogous to the one suggested by (*5*), however, the local density is calculated using an approach derived from the two-fluid theory (*16*).

STUDY APPROACH

Analytical Model for Urban Arterials

As Goscé, Barton and Johansson suggested in their paper where they analytically modeled the spread of disease in confined and crowded spaces (*5*), this study attempts to take traffic density and dynamics into account while calculating the contact rate based on the variables of an epidemic model. This section explains the proposed analytical method to calculate an improved density based contact rate. Two-fluid theorem (*17*) is utilized to calculate the spatiotemporal distribution of the local density which is required to find the number of vehicles in the infection radius in an urban scenario. Two-fluid theorem suggests that the average speed relies on the faction of the cars that are stopped. The theory uses the ratio of the total time that probe vehicle was stopped to its travel time to find the average fraction of vehicles stopped. The average speed can be predicted using this fraction. Given the fundamental relationship proposed by Pipes (*18*), traffic density can also be estimated. More details about this estimation approach can be found in

(*16*). The proposed contact rate can be introduced to the SEIR model to more accurately estimate the number of infected (informed) vehicles in a network. Goscé, Barton and Johansson (*5)* showed that the rate of infection and node speed depend on the local density of an infected node for pedestrians. They illustrated that the rate of infection has a non-linear dependence on the crowd concentration. Using a similar terminology, the rate of infection for an individual vehicle can be calculated as follows:

$$\lambda = Area \times \rho_{local} \tag{3}$$

where ρ_{local} is the local density. Therefore, the local density of traffic needs to be estimated to construct an approach in order to estimate density-dependent infection rate. In this method, each infected vehicle can only reach n other vehicles within a predefined radius. The number of vehicles that can be reached is actually time dependent $n(t) = Area \times \rho(t)$ (*5*). However, a probability-based spatiotemporal estimation of the local density derived from the two-fluid flow theory (*17*) is used in this paper. The two-fluid theory is shown to be specially suitable for urban scenarios with interrupted traffic flows (*17*). Since vehicles can send the information within a predefined radius, the value of R=480 ft. used as the distance that can be reached by the infected vehicle. The estimated density is valid only for the roadway stretch (vehicles/mile) that the infected vehicle traverses. The radius is relatively small because we are only interested in the backward propagation. FIGURE 1 shows the representation of the information flow and the effective radius.

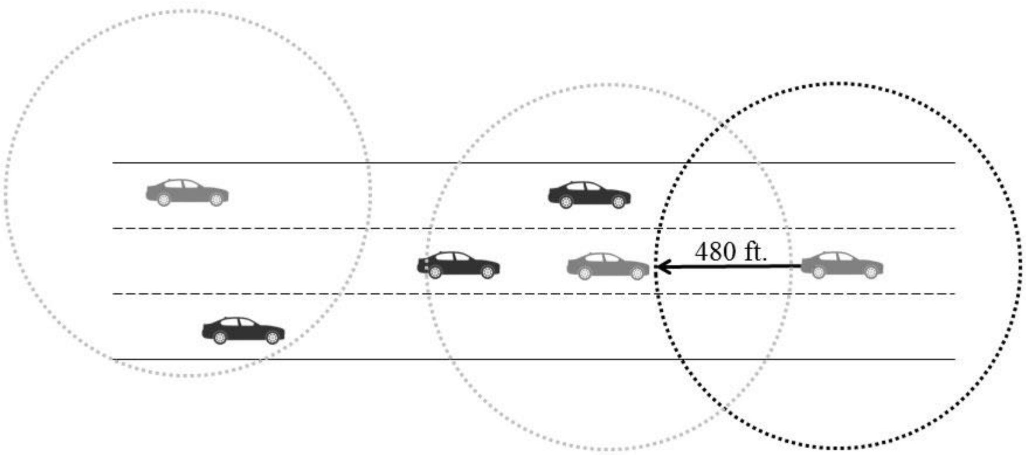

FIGURE 1 Representation of the information flow and the effective radius

According to the two-fluid theory (*17*), the average speed of vehicles depends on the fraction of the stopping vehicles f_s at high vehicular concentrations. The two-fluid theory states that the average speed of moving cars u_r relies on the fraction of cars that are moving.

$$u_r = u_{\mathrm{m}}(1 - f_s)^{\eta+1} \tag{4}$$

where u_m is the average maximum speed and η is a transportation network's level of service parameter. Although the exact number of stopped vehicles may not be determined in lower CV penetration levels, the fraction of the stopped vehicles can be reasonably estimated only using the data coming from the equipped vehicles. Using the two-fluid theory, Artimy (*16)* suggested that the normalized local density on a roadway section can be estimated using the equation:

$$\rho' = \frac{\rho}{\rho_j} = \left[\frac{(1 - T_s / T_t)^{\eta+1}}{\lambda'} + 1 \right]^{-1} \quad (5)$$

where T_s / T_t is the ratio of the stopping time to total trip time which equals to the fraction of stopped vehicles, λ' is the normalized sensitivity of the vehicle interaction given by

$$\lambda' = \frac{\lambda}{u_m \rho_j} \quad (6)$$

where ρ_j is the maximum vehicle density. With **Eq. 5**, it is now possible to estimate the local density when the values of f_s , u_m , and k_j are known for the section. Our traffic micro-simulations showed that in urban scenarios, the Gaussian distribution fits f_s data fairly well with parameters $\mu = 0.36$ and $\rho = 0.13$ according to **Eq. 7**

$$f(f_s | \mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(f_s - \mu)^2}{2\sigma^2}} \quad (7)$$

Random $f_s = T_s / T_t$ values will be generated to find the average local density for given time and location. The probability density function of the fraction of stopped vehicles is illustrated in FIGURE 2.

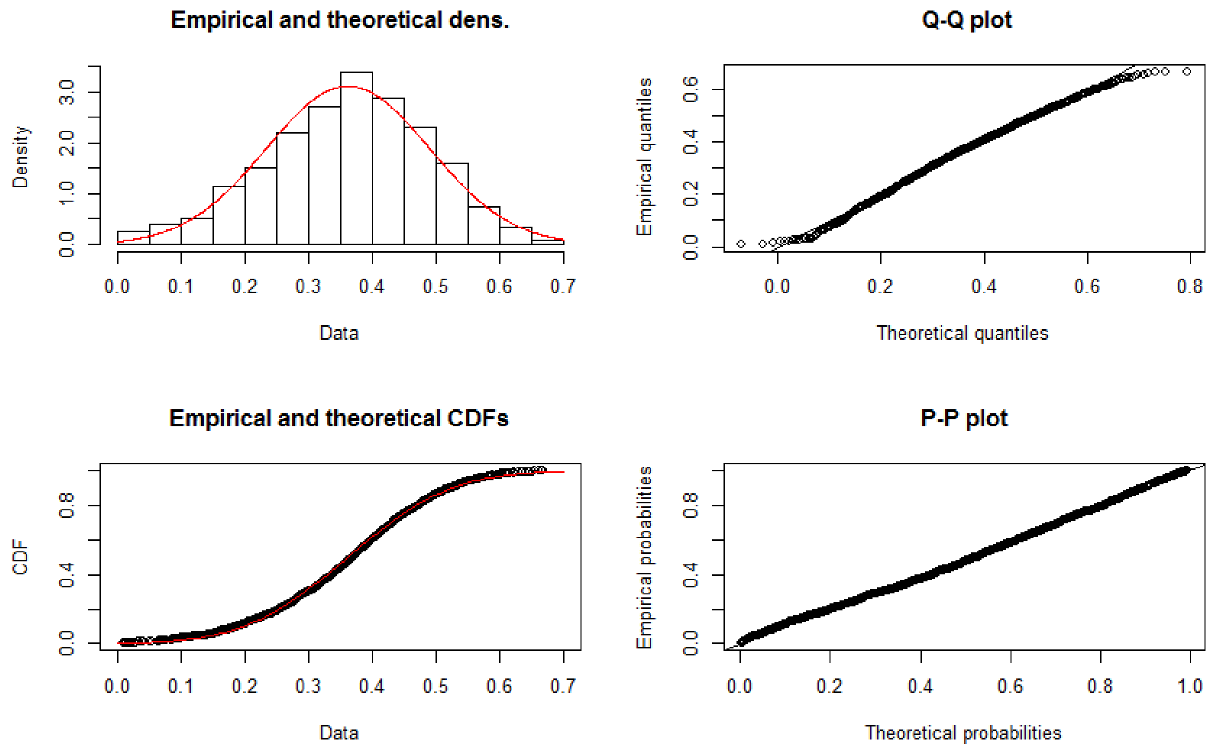

FIGURE 2 Fitted probability density function of stopped vehicles

The fraction of stopped vehicles can be used as a proxy to estimate local density around the infected vehicle. Therefore, from an individual infected vehicle's perspective, the value of the local density can be calculated as:

$$\rho_{local} = \rho_j \times \theta \times \rho' = \rho_j \times \theta \times \left[\frac{(1-T_s/T_t)^{\eta+1}}{\lambda'} + 1 \right]^{-1} \quad (8)$$

where θ is the market penetration level of CVs. Substituting 8 into equation 3 we obtain:

$$\lambda^{density-dependent} = c \times R \times \rho_{local} = c \times R \times \rho_j \times \theta \times \left[\frac{(1-T_s/T_t)^{\eta+1}}{\lambda'} + 1 \right]^{-1} \quad (9)$$

where c is the penetration level specific correction factor for successful transmissions. The factor can be calculated with the assumption that there is only one vehicle $R \times \rho_j \times \left[\frac{(1-T_s/T_t)^{\eta+1}}{\lambda'} + 1 \right]^{-1} = 1$ in the transmission area. Assuming that the transmission rate is constant up to 0.1 vehicles/per second (5) and there is a random crossover between constant transmission rate and density-dependent transmission rate after such value, c will be calculated as = $0.1/\theta$.

The Description of the Microscopic Traffic Simulation Model Used for Model Validation

To validate the analytical model, the microscopic traffic simulation software PARAMICS is used to model urban traffic in the downtown Brooklyn area of New York City. The traffic simulation model contains 36 intersections, 22 traffic signals, 19 traffic zones, and 16.35 miles of roadway. While creating the network, the actual properties of roadway links such as the signal timing, length, lane width, number of lanes, and speed limit are also considered. The microscopic traffic simulation model is calibrated for the AM peak period (7-10AM) using the volume data collected at most of the intersections on the selected route. The model is also calibrated for travel time between Tillary Street and Grand Army Plaza (Southbound). FIGURE 3 below illustrates the study location and the generated traffic simulation model in PARAMICS.

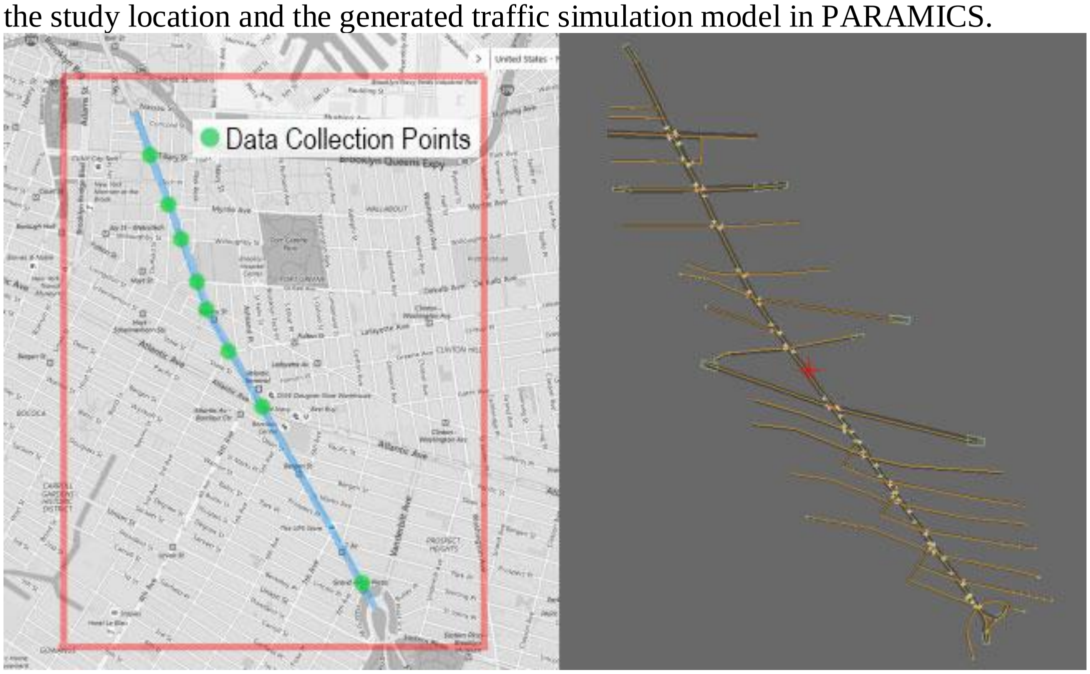

FIGURE 3 Study location

After calibrating the simulation network, back-ward information propagation is simulated using vehicle trajectories generated by the micro-simulation software. The assumption in information dissemination is that at every time step (0.1 seconds), the vehicle can either receive or send a message. Once the vehicle receives the message from its precedent, it sends it out to the furthest reachable vehicle in downstream and all the other vehicles within the communication radius. The first message is generated by a random vehicle traveling on Southbound on Atlantic Avenue and Flatbush Avenue intersection at a random time step in the simulation. The information propagates to the first intersection which can be seen in the upper left corner of the figure. Coupling traffic simulation models with network communication models remains a time-consuming and challenging task. Lack of knowledge in what wireless technology that will be used, field data, and the parameters that are required to be calibrated for each wireless communication model make this task particularly complicated. Thus, parameters such as the message latency and drop rate are assumed to be "0" for simplicity, and these can later be incorporated into the calculations once reliable results can be retrieved from field tests. A python code is developed to emulate the information dissemination in the network. It reads the trajectory file and checks the surrounding vehicles of the informed node downstream and transfers the information to the furthest vehicle. The next section will show the results obtained from both the analytical and simulation model.

Determining the Number of Runs

FIGURE 4 shows the number of runs and the cumulative average information propagation time with cumulative standard deviation at each point. It shows the importance of the number of simulation runs in determining the actual average.

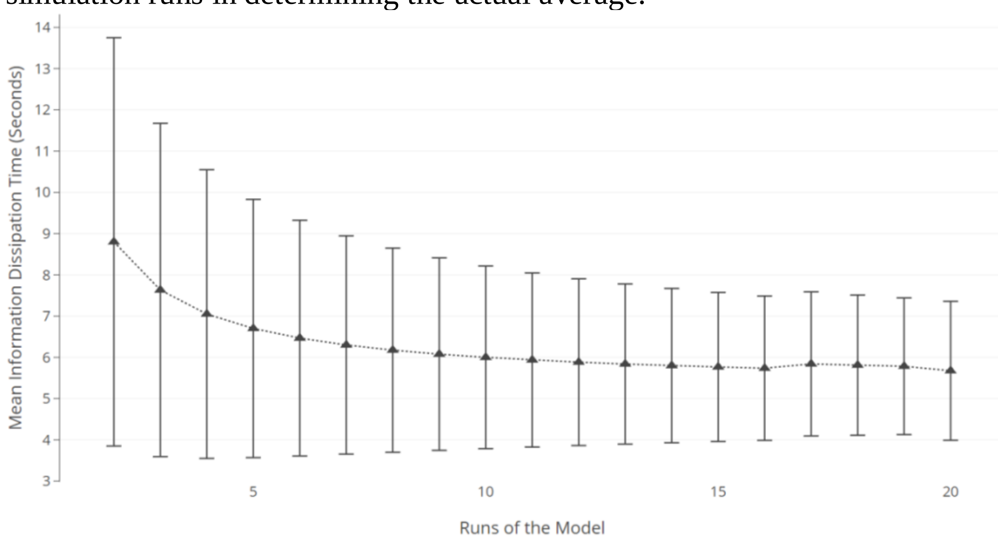

FIGURE 4 Average information dissipation time vs. runs of the model

The number of required simulation runs is determined by using the standard error of the mean (SEM) in this study. Eq. 10. shows the relationship between the SEM, the variance, and size of the sample

$$SEM = \sqrt{Variance / N} = S\tan dard\ \ deviation / \sqrt{N} \qquad (10)$$

Assuming that the values are independent and identically distributed, the number of simulation runs ±1second variation with 95% confidence based on Eq. 10 would be SEM = 1/1.96 = 0.51. Estimating the standard deviation from FIGURE 4 as being 2 seconds then the number of runs can be calculated as 2/sqrt(N) = 0.51. Solving this for N, we can obtain N = 15 runs. For this study, we used 20 runs to make sure the real mean is achieved with 95% confidence interval.

FIGURE 5 demonstrates the change in standard deviation between run N and N-1 across 20 runs. It can be seen that after around 15 runs, the change in standard deviation fluctuates around 0.

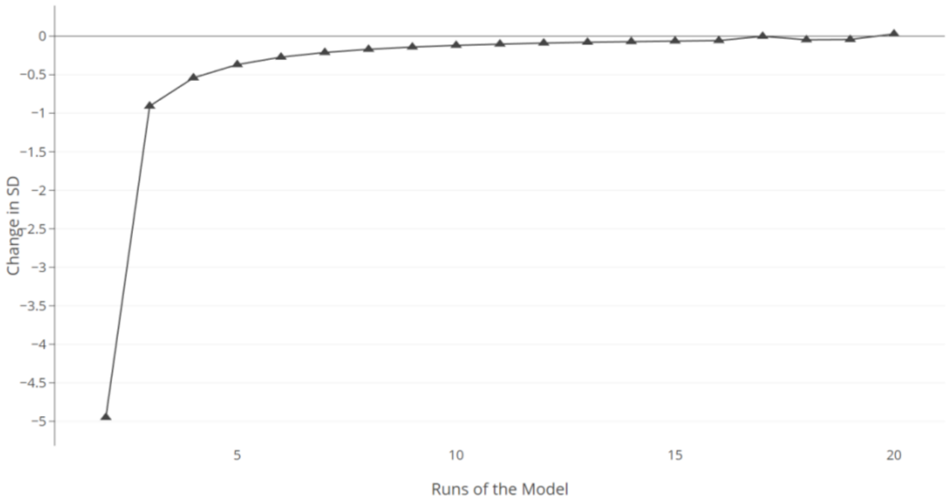

FIGURE 5 Standard deviation between run N and N-1

NUMERICAL RESULTS

The proposed analytical model's contact rate estimation results are compared to the results retrieved from the traffic simulation model in this section. The microscopic traffic simulation model is run 20 times for each CV market penetration with different seeds totaling up to 280 runs in order to capture the stochastic nature of traffic. It has been observed after 20 runs, the amount of change in the average value of information dissemination time is less than 5%. The free flow speed of 30 miles/hour, level of service of 0.72 as suggested for urban scenarios by (*19*), and the jam density of 150 vehicles/mile/lane are used in the analytical model to compute the contact rate. Various market penetration levels from 1 to 100% with 7.1% increments are used to investigate the effects of CV density on the information dissipation speed. FIGURE 6 shows both of the results obtained from the analytical and simulation model. The average contact rate value calculated from 20 simulation runs and 20 replications of the analytical model are used to generate the plot. The average number of vehicles present in the section is taken as 60. Y-axis shows the time it takes for all vehicles to retrieve information released by the initial vehicle and X-axis illustrates different market penetration levels. Although the model under or overestimates the information propagation time for specific market penetration values, the errors lie within a reasonable range with a mean of 9.6 seconds for higher penetration levels than 20%. Furthermore, it is worth mentioning that running the microscopic traffic simulation model, storing trajectories, and calculating contact rates for only one market penetration level takes more than 5 hours. On the other hand, the analytical model can execute the same task in less than a second by incorporating the market penetration level as an input. Therefore, using an analytical model is particularly convenient and computationally fast to analyze various market penetration levels, and it is possible to conduct a more granular analysis to evaluate the effects of market penetration on the contact rate.

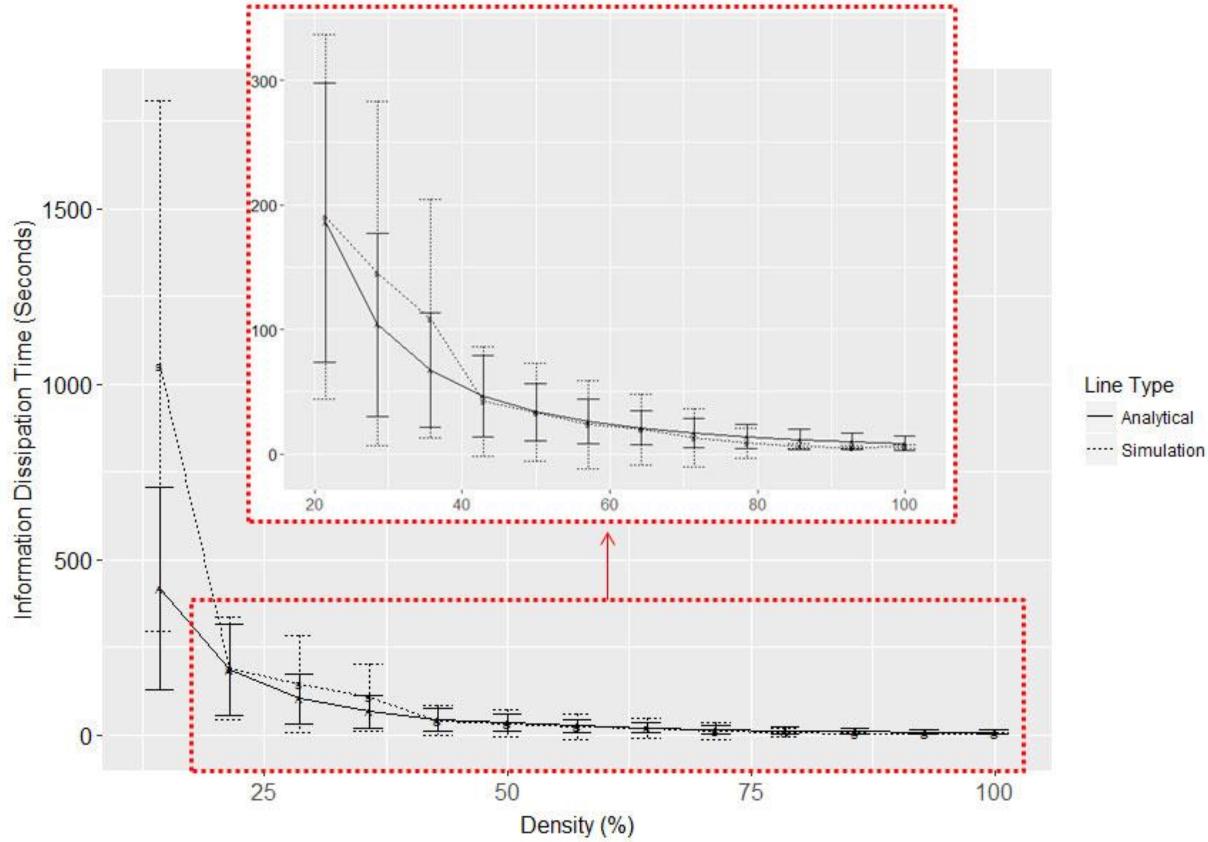

FIGURE 6 Analytical vs. Simulation Results

FIGURE 7 shows the evolution of the susceptible population over time with a constant contact rate and a density-based contact rate for commonly used market penetrations for CV applications particularly 20, 50 and 100%. The susceptible vehicles are the proportion of all vehicles in traffic that can receive and send information. In other words, the susceptible vehicles are connected. Once the vehicle receives the information, it is transferred from the susceptible population to exposed population, and later on to the infected population in the next time step. To show the relationship in FIGURE 7, it is assumed 100% of the vehicles are susceptible meaning that the CV market penetration rate is 100%. When the susceptible population becomes “0”, it means that all the vehicles in the network received the information sent by the initial vehicle. It can be seen that susceptible population reaches to “0” after 250 seconds for the most of the density based and the constant contact rates. However, the difference between the curves shows that the constant contact rate may critically under or over-estimate the speed of the information dissipation in CV environments. The susceptible population converges to “0” after 1000 seconds in the 20% market penetration contact rate scenario.

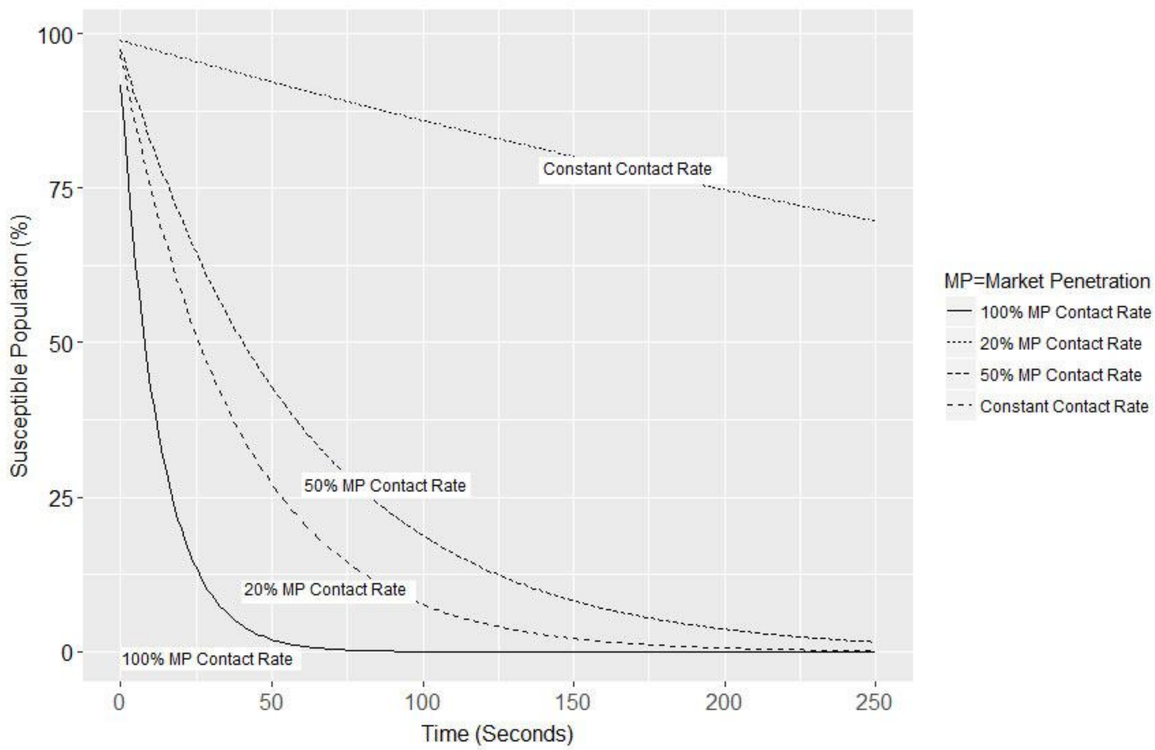

FIGURE 7 Evolution of susceptible population

It should be noted that for the scenarios with less than 10% CV penetration levels, the information never reaches the targeted intersection. It is safe to assume that with higher levels of penetration, there will always be a vehicle within a 480-foot radius that can be reached. The longest distance between two intersections is 489 feet in the simulation network. It is highly probable for CVs to send the information to another CV that is located at an intersection downstream when the traffic signal turns to red.

CONCLUSIONS

Information dissemination is critical for safety, mobility and environmental smart city and CV applications. This study proposes an analytical model to predict the time it takes to transfer information from an infected node to all the other nodes in a network using an enhanced SIR model. The existing simulation-based approaches not only require a longer time to execute but also coding of the target network to run simulations. The analytical approach utilizes a density-based contact rate. This addition results in better understanding of the relationship between traffic density and information dissemination and the analytical model enables a faster analysis of information flow in CV applications without the need of creating a simulation network. The proposed model's accuracy is tested against the results obtained from a calibrated micro-simulation model. The microscopic traffic simulation software PARAMICS is used to model urban traffic in the downtown Brooklyn area of New York City. The traffic simulation model is run for 20 times per market penetration level to reflect the stochastic nature of traffic the best. The comparative results indicate that the model can predict the information dissemination time reasonably well for higher market penetration levels than 20%. The results validated that the approach is efficient for dense urban scenarios with higher traffic densities. It also has been observed that the density of CVs plays a crucial role in the speed of information dissipation. Having a reliable estimation of the information propagation speed could be especially useful for officials to implement adaptive traffic control strategies and estimate the network effects of the intended changes over time. As a future work, the traffic generation and removal rate generation rate will be modeled in a more complex urban network and freeway scenarios.

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