INTRODUCTION

Recent advances in Intelligent Transportation Systems have been stimulated in order to adapt emerging threats and increasing volumes of disseminated information between vehicles and infrastructure.

In the literature, an epidemic (SEIR) model is used to analytically estimate the number of infected vehicles in a Connected Vehicle (CV) environment. Table 1 below illustrates the variables in the epidemic model and its corresponding updates in traffic:

- SEIR model: S (susceptible), E (exposed), I (infected), R (recovered)
- SEIR updates: S(i), E(i), I(i), R(i)
- Population: P
- Rate of exposure: λ
- Rate of infection: ρ
- Rate of recovery: β

The SEIR model can be mathematically represented as:

\[
\begin{align*}
\frac{dS}{dt} &= -\lambda E S - \beta I S + \mu R \\
\frac{dE}{dt} &= \lambda E S + \beta I S - \mu E \\
\frac{dI}{dt} &= \lambda E S + \beta I S - \mu I - \mu I \\
\frac{dR}{dt} &= \lambda E S + \beta I S + \mu I - \mu R \\
\end{align*}
\]

where \( \mu \) is the recovery rate of infected individuals, \( \lambda \) is the effective per capita contact rate, and \( \beta \) is the incidence rate that makes susceptible vehicles infected by one infected vehicle.

In the SEIR model, the population size is constant, and there is no heterogeneity. This approach fails to explain the variance in traffic flow as well as the interactions between vehicles on different density levels.

The study provides an analytical model to estimate a density-based contact rate \( \lambda = \lambda_0 \rho \) by utilizing the traffic dynamics to improve macroscopic models for dense urban scenarios.

STUDY APPROACH

Previous studies in the literature showed that the rate of infection and node speed depend on the local density of an infected node. The rate of infection has a non-linear dependence on the crowd concentration.

\[
\lambda = \rho \lambda_0
\]

In this method, each infected vehicle can only reach other vehicles within a predefined radius. Therefore, the local density of traffic needs to be estimated. The estimated density is valid only to the roadway stretch that the infected vehicle traverses.

- According to the two-fluid theory, the average speed of vehicles depends on the fraction of the stopping vehicles at high vehicular concentrations.

\[
\nu = \nu_0 \left( 1 - e^{-\frac{t}{\tau}} \right)
\]

Using the two-fluid theory, the literature suggested that the normalized local density on a roadway section can be estimated by:

\[
\rho = \frac{\nu_0}{\nu_0 \left( 1 - e^{-\frac{t}{\tau}} \right)}
\]

With this equation, it is now possible to estimate the local density when the values of \( \nu_0, \tau, \) and \( \nu \) are known for the section. The traffic simulation runs showed that in urban scenarios, the distribution of the fraction of stopped vehicles follows a Gaussian distribution with mean 0.36 and variance 0.15. Random \( \lambda \) values will be generated to find the average local density for given time and location using:

\[
\rho = \frac{\nu_0}{\nu_0 \left( 1 - e^{-\frac{t}{\tau}} \right)}
\]

SIMULATION MODEL

- 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 18.35 miles of roadway.

- 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 previous, it sends it out to the nearest reachable vehicle in downstream and all the other vehicles within the communication radius.

- Figure 3 below shows the number of runs and cumulative average information propagation time with cumulative standard deviation at each point. The form of the requested simulation runs is calculated using:

\[
\text{SEM} = \frac{\text{Standard Deviation}}{\sqrt{n}}
\]

- For the study, we used 20 runs to make sure the real mean is achieved with 95% confidence interval.

CONCLUSIONS

- 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 dissemination.
- Having a reliable estimate 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.