Biologically Inspired Modeling of Vehicle to Vehicle Communication for Intelligent Transportation Systems Applications

by

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ABSTRACT OF THE THESIS

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In this study we developed a macroscopic model for simulating the vehicle to vehicle communication process. Real-time information propagation via vehicle-to-vehicle communication is part of the Vehicle Infrastructure Integration (VII) initiative, aimed at improving the traffic conditions on existing roadways. In VII, Vehicles communicate among themselves using wireless technology. Each vehicle broadcasts any available information regarding the roadway (which might include time taken to travel a small stretch, any hazardous conditions, incidents etc) and other vehicles upstream, which might not be aware of the conditions ahead, receive the information. In this thesis, a fraction of the vehicles traveling on the network are assumed to be equipped with the wireless technology and have the ability to communicate. These are called the "instrumented" vehicles. The proposed model is based on the Susceptible – Infected – Removed (SIR) model that is used to model the spread of epidemics in a region. We call

the vehicles that have received a signal from another vehicle as ‘infected vehicles’, and those instrumented vehicles that have not received a wireless message are called ‘susceptible vehicles’. The present model predicts the number of infected vehicles present on the roadway at every instant of time. The model is developed for a variety of traffic conditions including different volumes, speed limits and number of lanes. Finally, it is validated using simulation results obtained from Paramics, a microscopic traffic simulation software. Various observations related to the process of vehicle to vehicle communication were also made.

Table of Contents

List of Illustrations

List of Tables

CHAPTER 1: INTRODUCTION

In the present day world, the use of the wireless communication in the field of transportation is limited to the use of GPS in calculating routes. The information regarding the congestion on a particular route is available either while traveling on the route (electronic message signs), or by other means such as the radio, internet etc. While these provide necessary and important traffic information to the road users, they do not cover a complete network, and the information is available for a few sections that constitute a very small fraction of the network. There is a need for such information to be available on a greater scale to improve the efficiency of the networks and reduce congestion-related delays. The congestion problem resulted in 4.2 billion hours of travel delay, 2.9 billion gallons of wasted fuel, and a net urban congestion cost of nearly $80 billion, as given in one of the publications titled Transportation Vision 2030 by Research in Innovative Technology and Administration (RITA).

Ideally up-to-date traffic information should be available to the users on a real-time basis. Vehicle-to-vehicle communication finds a good application in these conditions and has a huge potential to bring down delays. In such a scenario, the vehicles traveling on the network act as nodes that receive and transmit information based on the conditions that they experience while traveling. This information is shared among all the vehicles present in the network. In this manner, vehicles become aware of the situations prevailing on every link of the network and make routing decisions. The delays could then be minimized effectively by alternate routing, which is possible by prior warnings to the users. This not only helps in reducing congestion on a specific road but also in utilizing the existing transportation network in an optimum manner. If delays are experienced in spite of optimally distributing the traffic over the entire network, it means the network has reached capacity and there would be a need for new alternatives such as constructing new roads or encouraging public transit. Vehicle-to-vehicle communication is not just limited to delay monitoring. It also finds application for other purposes as well. This could include lane closures, ramp metering and warnings for hazardous conditions on roads.

In fact, the information that can be captures and disseminated by vehicles is not limited to traffic conditions. Most of the vehicles have a wealth of sensors that can be used to capture roadways hazards such as potholes, bumps, ice, rain, and others. Clearly, it is impossible to deploy fixed sensors to monitor and detect such dynamic events over a very large transportation networks. Existing or easy to install in-vehicle can be a very viable alternative to capture this type of information. The key, however, is to be able to disseminate the exact location and type of the road hazards to incoming vehicles once it is detected. Vehicle-to-vehicle communication is an ideal medium to achieve this ambitious yet revolutionary goal.

The information about the travel times (or other road hazards) can alternatively be made available on every roadway using the electronic message boards and/or some other stationary devices installed alongside the roadway which can interact with the vehicles. But the installation of these devices on each roadway involves an enormous amount of investment, and is practically infeasible. However if there are devices installed in the vehicles, that interact among themselves (just like a GPS which is presently used by a large number of vehicle owners), the problem of installation of stationary detectors or other devices along the roadway could be avoided.

The recent years have seen the emergence of wireless technologies and this could be tapped for the application in the field of transportation. The Dedicated Short Range Communication (DSRC), a tool approved for licensing by the Federal Communications Commission (FCC) in 2003 and the revolution in the services of the ITS give rise to an increased interest in vehicle infrastructure integration (VII). This is an initiative where the departments of transportation and the vehicle manufacturing companies are working together to evaluate the feasibility of communication among the vehicles to improve the existing transportation system. Hence if such a system is feasible, where the vehicle is the information seeker and also acts as the information donor, it would be a great step towards congestion mitigation.

The present study is aimed at understanding the vehicle-to-vehicle communication process from the perspective of transportation engineering. We develop a model that predicts the number of vehicles that are traveling on a road network and have received the information by vehicle-to-vehicle communication regarding a particular roadway. This model is analogous to the Susceptible-Infected-Removed (S-I-R) model that models the spread of an epidemic in a region. Analytical modeling of this phenomenon is slightly tricky because of the inherent randomness involved with vehicle networks. The arrivals, human behavior, lane changing, speed limits and the relative speeds among vehicles – all of them have an important role to play. We tried to make mathematical models purely based on behavior of vehicles on road networks, which did not accurately predict actual behavior. However, we were able to draw some important conclusions out of those models, which are presented at a later part of this study.

The rest of the thesis is written as follows. Chapter 2 contains the problem definition, chapter 3 contains a review of studies that were conducted earlier in the related fields, chapter 4 explains the vehicle-to-vehicle communication algorithm we used to validate the model, chapter 5 explains some of the failed models and important observations made out of them, chapter 6 contains the methodology involved in developing the model and the final model. Chapter 7 contains some extensions made to the model, Chapter 8 compares the results with other studies and chapter 9 states the conclusions of the entire study.

CHAPTER 2: PROBLEM DEFINITION

Consider an origin-destination pair A and B, A being the origin and B the destination as shown in figure 2-1. Assume that A and B are connected by two routes. Route number 1 has an average speed of 65 MPH and is 20 miles long, which takes about 19 minutes to reach the destination. On the other hand, route number 2 is 17 miles long and has an average speed of 40 MPH. This makes it less attractive because it takes almost 26 minutes of travel time to reach B by this route. As a result of this difference, most of the commuters to B will make use of route 1. On a typical day route 2 remains uncongested as more commuters use route 1.

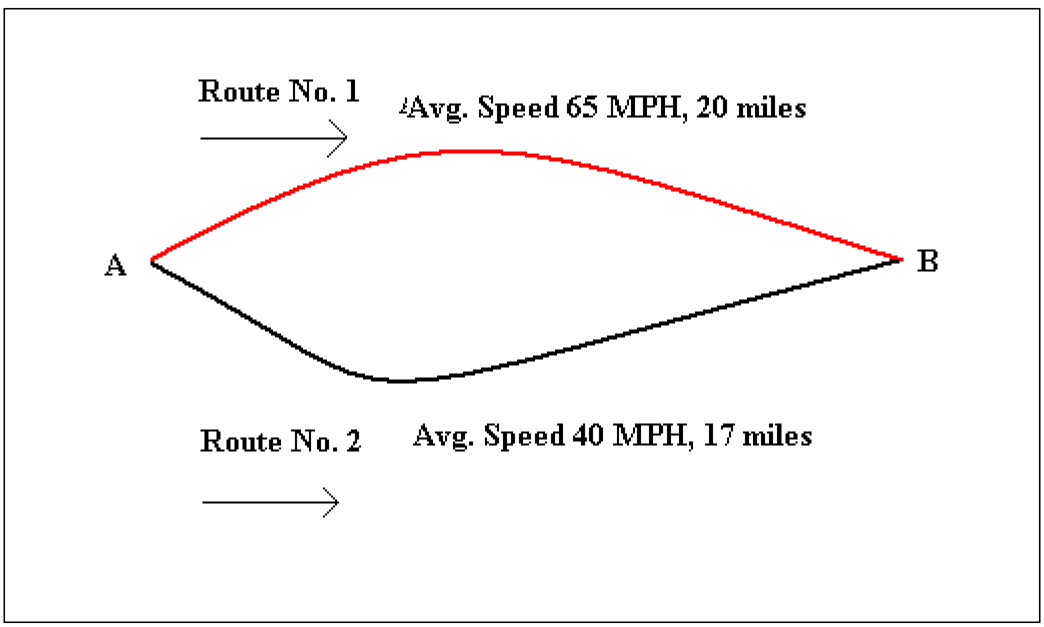


Figure 2-1: Two routes available to commute between A and B.

On a particular day, if there is an incident on route 1, it increases the travel time significantly. As the commuters are not aware of the incident they do not realize the congestion until they go into the route. As a result, route 1 remains to be congested and route 2 remains empty.

Now let's assume that vehicles have the ability to communicate among themselves and transmit traffic information between one another. Whenever there is congestion on route number 1 leading to substantial delays, the sensors in the vehicle make note of the abnormality in travel time and transmit the information related to the delay. The transmission is made by the built-in wireless system in the vehicle that is meant for transmission. These systems make use of the channels allocated for them, namely the DSRC systems(Wikipedia, 2009). They broadcast information to other vehicles as well as receive it from them. Based on the bandwidth and the frequency allocated to these systems and other inherent properties of these systems, they have a finite maximum range for transmitting information by broadcasting. If there is any other vehicle present in the broadcast radius of the broadcasting vehicle, communication would be possible and the second vehicle receives the information that was broadcast. After receiving the information, the vehicle broadcasts the information by itself so that the other vehicles in its neighborhood receive it. This thus forms a long communication chain of vehicles.

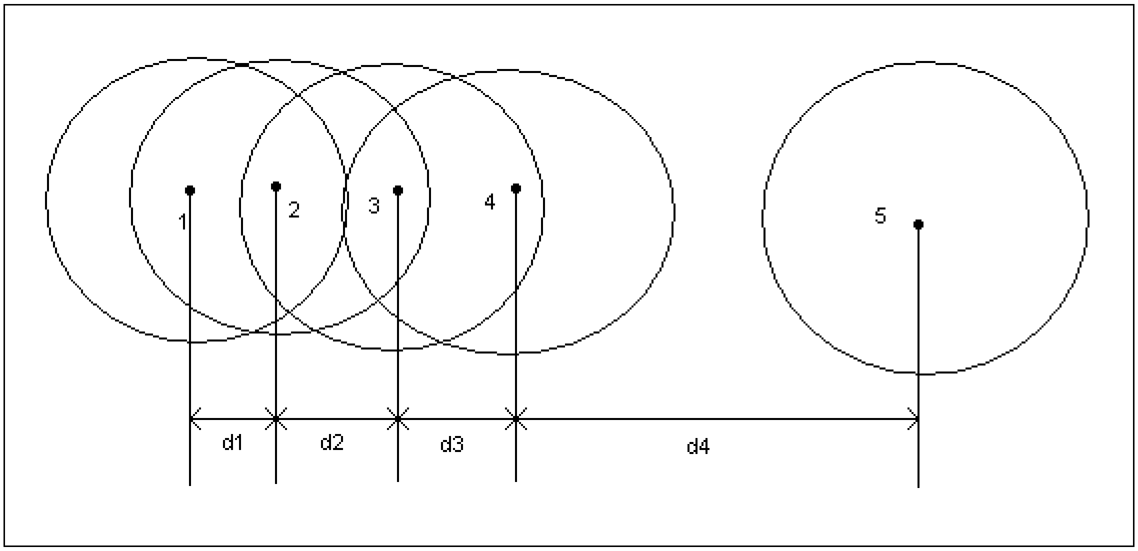


Figure 2-2: Communication chain of interacting vehicles

The figure 2-2 above shows a series of vehicles. The distances ‘d1’, ‘d2’, ‘d3’ and ‘d4’ are the distances between two consecutive interacting vehicles ‘1’, ‘2’, ‘3’ and ‘4’ respectively. The distances ‘d1’, ‘d2’ and ‘d3’ are smaller than the radius of communication for DSRC systems. This makes possible the communication between the vehicles ‘1’, ‘2’, ‘3’ and ‘4’. However, vehicle ‘5’, which is farther away from the communicating vehicles, cannot receive any information from vehicle ‘4’. As a result the vehicles beyond vehicle ‘5’ will not be able to receive any information from vehicle ‘5’. It is vital that the distances between interacting vehicles do not exceed the radius of communication for the DSRC systems. If the connectivity is maintained, wireless signal transmission takes place among vehicles and last for very long distances. Please make sure that spacing after paragraphs is consistent.

Looking back at figure 2-1, the delays are experienced on the route number 1, which are realized by the vehicles traveling on it. The corresponding information is broadcasted by them. If the aforementioned connectivity is maintained, the vehicles at A will have the valuable information regarding the non-recurrent delay (due to the accident) on the route and make use of the other route.

In some cases, the connection might not be complete at one point of time, but as a result of the relative speed between vehicles, two vehicles might get close enough to each other for interaction.

Another important point to be noted is that not all the vehicles using the road will be able to interact. It would be practically infeasible to install these systems on every existing vehicle. It is assumed in this study that a small percentage of vehicles that use the roadways use these systems and the communications take place between these vehicles. In the study, we call this small percentage of wireless equipped vehicles as 'market penetration'. Based on the connectivity, some of these vehicles will be informed and rest of them will not.

This forms the basis for the study. As a result of the connectivity issue, not all the vehicles will necessarily be informed. The spread of information depends on how close the instrumented vehicles are traveling. We model the number of informed and number of uninformed vehicles on the roadway for various traffic and geometric conditions.

CHAPTER 3: LITERATURE REVIEW

Vehicle-to-vehicle communication has been a popular topic among researchers in various fields. There have been a lot of studies by researchers in the field of wireless communication for developing the communication devices. Research has also been ongoing in the field of transportation regarding the spread of information. Various mathematical and simulation models were developed in the recent past. We present the highlights of some of the interesting research work here.

3.1 Vehicle Infrastructure Integration (VII)

Vehicle Infrastructure Integration (VII) is defined as an initiative fostering research and applications development for a series of technologies directly linking road vehicles to their physical surroundings, first and foremost in order to improve road safety (Wikipedia, 2009). A major component of ITS is the VII Initiative, a cooperative effort between Federal and State transportation departments and automobile manufacturers. Together they are evaluating the feasibility of deploying a communications system that will be used for improving the safety and efficiency of the Nation’s road transportation system (RITA, 2009).

Primary applications as given in the website include:

1. Warning drivers of unsafe conditions or imminent collisions.
2. Warning drivers if they are about to run off the road or speed around a curve too fast.
3. Informing system operators of real-time congestion, weather conditions and incidents.

4. Electronic payment capabilities.
5. Providing operators with information on corridor capacity for real-time management, planning and provision of corridor-wide advisories to drivers.

The California Partners for Advanced Transit and Highways (PATH) has been very active in exploring new methods to enhance safety and improve the efficiency of the transportation systems. Research is generally aimed at providing assistance to drivers, forward collision avoidance, intersection safety improvement by VII. In one of the studies (Sengupta et al., 2007), wireless based communication systems were used in unison with sensor based systems to develop a Cooperative Collision Warning (CCW) System. The PATH program in collaboration with Caltrans and MTA plans to deploy a test bed in the Northern California region (VII California, 2009). The objective of such a test bed would be to test the vehicles as probe vehicles, intelligent on-ramp metering, probe vehicles providing weather data, incident information to vehicles, collision warning and so on. In some studies, researchers (Chan and Bougler, 2005) designed and implemented a collision warning system at a traffic signal intersection. For this purpose they made use of vehicle-to-vehicle communication systems and vehicle-to-roadside communication systems that give warning messages to drivers in case of an imminent collision. Various issues involved in deploying VII related services were (Dong et al., 2006) explored and resolved in a realistic setting. Reviews were made on (Misener and Shladover, 2006) reviewing some of the research conducted at PATH in the field of VII and its applications to improve safety of roadways.

The research on vehicle-to-vehicle communication can be broadly classified into two different areas. One area consists of the research on design and development of the devices, their integration, functionality, application and testing. This research is performed primarily in the fields of wireless systems and electrical engineering. The other area consists of modeling the vehicle-to-vehicle communication behavior from a transportation engineering perspective. This involves mathematical, analytical or simulation modeling of traffic networks and the rate of communication among vehicles.

3.2 Dedicated Short Range Communication (DSRC) Systems

FCC allocated DSRC systems exclusively for vehicle to vehicle communication. It defines DSRC systems as a one-way or two-way short- to medium-range wireless communication channels specifically designed for automotive use and a corresponding set of protocols and standards. It uses a spectrum of 75MHZ in the 5.9GHZ band. The decision to use the spectrum in the 5GHz range is due to its spectral environment and propagation characteristics, which are suited for vehicular environments. Waves propagating in this spectrum can offer high data rate communications for long distances of up to 1000 meters with very little sensitivity to weather changes. There are other applications for DSRC systems in addition to vehicle-to-vehicle communication. These include: (RITA Website, 2009).

1. Emergency warning system for vehicles
2. Cooperative Adaptive Cruise Control
3. Cooperative Forward Collision Warning
4. Intersection collision avoidance

5. Approaching emergency vehicle warning (Blue Waves)
6. Vehicle safety inspection
7. Transit or emergency vehicle signal priority
8. Electronic parking payments
9. Commercial vehicle clearance and safety inspections
10. In-vehicle signing
11. Rollover warning
12. Probe data collection
13. Highway-rail intersection warning
14. Electronic toll collection

Another study (Singh et al., 2002) was based on the application of wireless systems in inter-vehicle communications provides a very good insight into the properties of wireless systems to be implanted in vehicles. They conducted a field study using two laptops built with Wireless Local Area Network Systems (WLAN. The two laptop computers were placed in two different cars) and monitored the transfer of data between the two. Testing was done on freeways, urban roads and suburban roads. Many important observations were made including the fact that communication by this method is possible up to a distance of one Kilometer. Reducing the throughput (that is, the rate of transfer of data in Kilobits per second) increased the distance or the radius of communication.

3.3 In-vehicle wireless systems

There are several other studies based on wireless research. These studies are aimed at developing protocols for vehicle-to-vehicle communication and vehicle-to-roadside communication.

A combination of vehicular ad-hoc networks and a central hub that communicates with vehicles and called it VGrid was proposed (Anda et al., 2002). This algorithm was simulated on two lanes that merge on to a single lane. By effective communication between vehicles and the central hub, the throughput at the merge was increased.

Number of studies were aimed at developing a MAC layer protocol simulation and discuss various modeling issues involved in the current vehicle communication channel (Zang et al., 2005, Daizo et al., 2004), which is the DSRC. Xu and Barth (2004) describe a simple methodology for inter-vehicle communication (IVC) process an energy efficient process by modulating power levels and transmission levels based on traffic and communication conditions. Korkmaz et al. (2004) designed a new protocol for IVC which is designed to be more efficient in urban areas that have tall buildings and hinder the signal propagation of DSRC systems by addressing some of the issues. Some protocols for IVC were also developed by Petit et al. (2006) where they estimate overall throughput for different levels of market penetrations. IVC was made more efficient by integrating it with GPS based systems(Sun et al., 2000). Al-Hanbali et al. (2006) study the concept of relay throughput, which is the maximum rate at which a node can relay data from a source to a destination. Another study (Choffenes and Bustamante, 2006) is based on vehicular networks but used a vehicular mobility model that was different from Al-Hanbali et al. (2006). In order to study the performance of a mobile wireless network, the mobility of the moving wireless nodes has to be modeled accurately. While all the studies mentioned here approximate the vehicular movement based on some existing models, Saha and Johnson (2004) propose a more realistic model for vehicle movement based on urban traffic movement. They compared this model with the movements of vehicles assumed by other approximated models. A similar study was conducted by Hartenstein et al (2001) by simulating vehicle movements, addressing the rationale behind selecting the specific radio broadcast and develop a vehicle based ad hoc network for inter-vehicle communication. Nekoui et al. (2008) study the implementation of Vehicular Ad Hoc Networks (VANETs) for improving the safety at intersections. For this purpose, the VANETs communicate with each other only when they are very close to each other.

Zhang et al. (2005) conducted another study on IVC. Their focus was on calculating the interference probability between packets that were disseminated. Probability of interference is a function of speed, arrival rate of equipped vehicles, packet size and maximum transmission rate. This algorithm was used in VISTA GIS software with two different routing algorithms.

Farver (2005) proposed a two-layered system for vehicle routing. One of them is a centralized system, that communicates with the vehicles and assigns routes based on volumes of traffic in different routes and the second layer consists of a decentralized system where the vehicles react to circumstances prevailing on their route and make minor modifications to the route.

Kosonen and Bargiela (2000) propose a different kind of a solution to urban traffic congestion. This idea is alternative to the present idea of installation of on-board systems. A well calibrated model for the whole urban network could be developed and simulated on a microscopic traffic simulation software, and based on the observations made in the simulation information regarding potential bottlenecks has to be supplied to the road users via the internet.

3.4 Research on spread of information by wireless communication in vehicular networks

Wang (2007) developed an analytical model to observe the transmission propagation by inter-vehicle communication. The equipped vehicles are assumed to follow a poisson distribution for spacing. For the purpose of communication, each signal transfer was assumed to be a Markov process, where the next relay is completely independent of the present relay. Based on these assumptions the distance of propagation of a wireless signal was estimated for different values of probability and transmission ranges. The propagation distance was based on the probability of presence of a neighboring vehicle. The total distance of propagation in such cases would be the distance between the beginning of the network and the first vehicle that cannot find a neighbor. There could be a scope for faster following vehicles to close this any gaps in the traffic stream and become a neighbor to the last vehicle, thereby completing a connection on the network. This area could probably be explored and we try to investigate it in this study.

Kim et al. (2007) make use of a microscopic traffic simulation study to estimate the minimum size of the data set required for making a reliable estimate of travel time information on a link. The simulation was based on the model of a real road network that is a part of the Baltimore-Washington Parkway, in the North-bound direction. When vehicles travel on the stretch, they take different times to travel and these times could vary significantly at times. They use a simple normal distribution based model that predicts the number of data points required for an assumed level of confidence. This study is not related to the design or functioning of IVC in any manner but is important because it emphasizes on the sample size.

Wu et al. (2004) study and analytical model for vehicle-to-vehicle communication and validate it by using a simulation model in Corsim. Conditions and assumptions were made for a straight sample network. Three different conditions of traffic- dense, medium and uncongested conditions were assumed. The analytical model assumed the starting point of vehicles as a Poisson process. Then a random speed is assigned for each vehicle and the speed was assumed to remain constant for the rest of the journey. Simulation was performed for different market penetrations for different traffic conditions. The measured quantity is the total distance of propagation in 100 seconds. Another important aspect in this study is that the total propagation distance was measured after 100 seconds of simulation. This time could be sufficient for the simulation to reach a steady state, but the information could spread to a greater distance with progress of time. The distance could have been measured after another period of time (may be after 100 more seconds of simulation) so that it gives an idea about the rate of spread of traffic information. We try to address this issue in our study.

Ukkusuri and Du (2006) studied the connectivity of vehicular networks using a probabilistic approach. They assumed an exponential distribution of vehicles that have the ability to communicate, and based on the distribution suggested an optimal radius for communication that would maximize connectivity. In addition, probability of finding two neighbors-one upstream and the other downstream was also estimated. This study gives an idea about how close are the neighbors and how possible is the communication. However, while validating the model, it did not match reality. This main reason for the difference was pointed out as the randomness involved in actual traffic. The vehicles do not necessarily follow exponential distribution for spacing and the varying speeds while traveling on the network also raises some more issues. A robustness factor was introduced into the model that makes it more accurate. This factor was obtained by performing simulations in a traffic simulation software and fitting the obtained results into the model by regression. In this study, just like other studies the connectivity aspect was the main aspect. The rate of spread of information was not described.

Wu et al. (2006) studied the vehicle-to-vehicle communication on the model of a real network. It consisted of a 6-mile stretch of roadway on I-75 in Florida. Simulation was performed in Corsim for the current day demands during A.M. peak, P.M. peak and the nighttime periods. The results indicated how relative speeds played a role in carrying the information from one end of the stretch to the other. The delay in reaching the other end of the network was also recorded as a function of market penetration for all the three periods of the day. In addition, the percentage of simulation time the network stayed connected was also obtained.

Yang et al. (2005) conducted a simulation study on a sample network to study the propagation distance as a function of market penetration, under a condition that the tolerance is only 60 seconds. This was done for a number of transmission ranges, and IVC success probability was also measured by conducting multiple simulations. In addition they created an incident and the thus formed shock wave was found to be moving slower than the data transmission, which proves that this is good to notify incidents.

Jin and Recker (2005) propose a cell-based analytical model where probabilities are assumed for each vehicle to be in a cell and another probability for successful transmission of wireless signals. The results are for minimum sample size, the transmission distance and other parameters. They estimated a maximum distance of propagation of traffic information, just like most of the other studies specified above.

Ozbay et al. (2007) perform a simulation study in Paramics to understand the spread of information by wireless systems in vehicular networks. A device called as *TrafficRep* is installed in some of the vehicles and is responsible for communication. It is connected to a GPS device, a static digital map database of the road network, a data acquisition device, and a WiFi link. The communication between vehicles is investigated on a well calibrated model of a traffic network in New Jersey, by creating an incident at a specific location and observing the rate of spread of this message among the vehicles present in the network. While the rest of the studies are performed on one dimensional networks, this was made on a two dimensional network.

From all the above studies that are related to communication on the road networks, the following observations could be drawn, leading to raise some questions that follow.

1. Almost all of the studies (Wang (2007), Wu et al. (2006), Zhang et al. (2005), Jin and Recker (2005)) specify a distance to which the communication signal can reach by multiple hops by relaying from a number of vehicles. Why is the distance such an important factor that it has been such a popular parameter?
2. Many studies gave a lot of importance to the connectivity (Wang (2007), Wu et al. (2006), Zhang et al. (2005)) which definitely plays a primal role in spreading the information. But if at some point where the connectivity fails, it was assumed that the communication stops. But there is always a non-zero relative speed between vehicles traveling on a road. Why can't an equipped vehicle that travels faster catch up with one of the leading vehicles and bring back the connectivity?
3. No other study except the one by Ozbay et al. (2007) discussed the rate of spread of information on a road network. Speed at which the traffic information propagates by wireless communication on the roadway is definitely good information to know. For example, if an incident occurs on a road in Manhattan, how long will it take for the information to reach New Brunswick? We explore the reasons for ignoring this aspect in other studies here. We presented the reasons at a later part of the thesis after we go into the details of our analysis.
4. Another point to be noted here is that some of the analytical models (Wang (2007), Wu et al. (2006) assumed mathematical distributions for spacing of the equipped vehicles. What spacing distribution is the best one that could be used to

model vehicular communication? There are well accepted headway distributions for the following for general traffic. But for equipped vehicles this becomes more problematic due to the issues such as market penetration and lack of any real-data.

5. Some of the studies (Wu et al. (2004), Zhang et al. (2005), (Yang and Recker, (2005), and Ozbay et al.,(2007)) are based on simulation and some of the studies are analytical models (Wang (2007), Wu et al. (2006), and Jin and Recker (2005)). But no model can comprehensively model the vehicle-to-vehicle communication phenomenon considering all the parameters involved in vehicles traveling on a roadway.

We try to address all of the above issues in the present study. We tried developing different kinds of models that predict the vehicle-to-vehicle communication phenomenon accurately but all the models, barring the current model, have failed owing to a variety of reasons. These failed models, however, give us an insight into the whole process and enable us to understand it in a better way. We also describe a couple of failed models in a later chapter because they are not only relevant to the study but also answer some of the questioned described above.

In the next chapter we describe the procedure we adopted for obtaining results from Paramics. We use these simulation results as the primary results and compare the models with these results in order to validate them.

CHAPTER 4: SIMULATING VEHICLE-TO-VEHICLE COMMUNICATION IN PARAMICS

A model that is developed to replicate vehicle-to-vehicle communication among traffic networks needs to be validated carefully. Otherwise the model does not make any sense as one would never know if that is the way the communication takes place.

In order to validate the model, we used the results generated from traffic simulations performed in Paramics. Paramics is Scottish software used for the study of traffic flow. It uses a simple node-link system that is used to build complicated networks. The software allows setting custom vehicles, traffic signals, ramps, and many more functionalities. In addition it has the Application Programmer Interface (API) feature which allows the user to override the existing car following and other rules and use user specified rules by programming in C++. Such an extendible facility provides an opportunity to study the communication process. Thus it was assumed that Paramics would be one of the best tools available to model the corridor. Figure 4-1 shows the model that was built in Paramics.

The network is ten miles long, with a fixed number of lanes and fixed speed limit all through its length. When the demands are set between origin and destinations zones and the simulation is started, vehicles travel according to the car following, lane changing and other rules that are used by Paramics. Paramics uses well calibrated models to represent the movement of traffic and we assumed that the results generated from such a traffic movement will represent reality very closely.

The whole analysis of by simulation is divided into two parts. The first part extracts the coordinates and other important information about the vehicles from the Paramics network. The data obtained here is imported to another Matlab program that processes this data and generates the results regarding the communication status of the wireless signal. It should be noted this study is aimed at understanding the vehicular communication from a transportation engineering perspective. We did not develop a complete wireless communication protocol. We however assumed that the signal transmission occurs in similar lines to the “smart scheme” described by Goel et al. (2004). That is, every vehicle carries travel time information on various links on a road network. Whenever the vehicle passes a link, it notes the travel time and compares it with the travel time available with it. If the present travel time is significantly higher than the time available in the database it releases a transmission signal in order for the other vehicles to be informed. Transmissions could also be initiated if there was an abrupt braking of the vehicle, bad roadway or any kind of hazards that the vehicles upstream should know. Questions arise about the how significant the difference travel times should be in order to initiate a signal transmission. We did not go into that type of analysis but were more concerned with the propagation of this resulting signal along the roadway. For the purpose of simulation in Paramics, we however have assumed that each vehicle broadcasts a signal two times every second, and the signal reaches the other vehicle in one-tenth of a second. Each vehicle keeps broadcasting the signal about a particular link if it is not more than 10 miles upstream of the link and stops the broadcast a mile after it has passed the location.

4.1. Extracting vehicle information

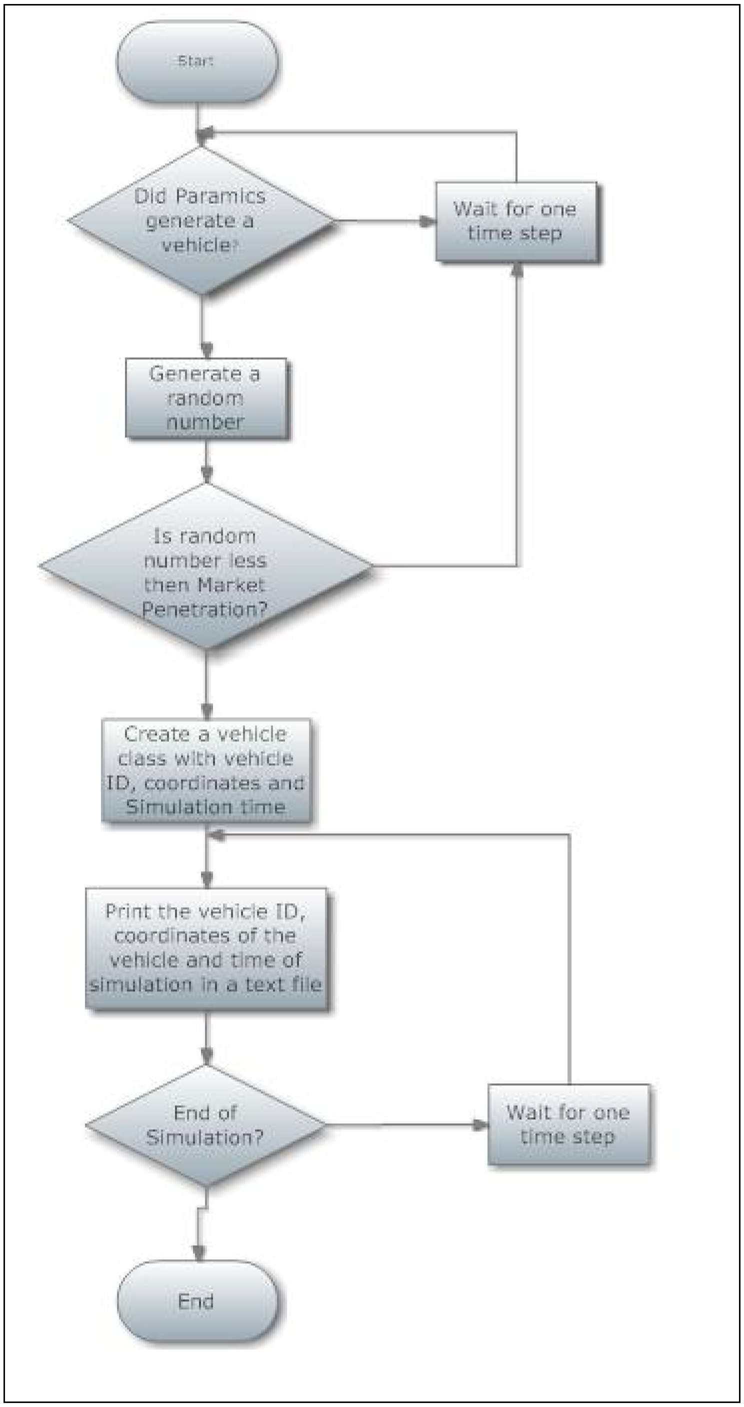


Figure 4-1: A flowchart showing the process involved in generating the coordinates of vehicles.

The API extracts coordinates for the specified vehicles after every second, and stores them in a text file. The data being stored in the file include the unique ID of the vehicle that was assigned by Paramics, the time of simulation and the coordinates.

Figure 4-1 shows the algorithm used to extract the positional coordinates of the instrumented vehicles and the time of simulation of every vehicle during which the vehicle was in that position.

Paramics generates vehicles randomly based on its inbuilt algorithm. Whenever a vehicle is released, we generate a random number between 0 and 1 and compare the value with the market penetration. If the value of the random number is less than market penetration, the vehicle is assumed to be instrumented.

Paramics assigns a unique identification number for this vehicle and makes it convenient for the users to refer to this vehicle by using the ID. As soon as this vehicle is generated, the API records the positional coordinates, the ID and the simulation time and records this information for every time step in a separate text file, as long as this vehicle exists in the network.

The text file therefore will contain the vehicle IDs, the coordinates and the simulation times in the order of increasing times. At the end of simulation, this file is secured and stored separately for further processing.

4.2 Processing the extracted information

We use a code developed in Matlab to process this extracted data. Based on the positional coordinates of vehicles at various simulation times, the vehicles may or may not be close enough to one another for communication. The algorithm is shown in the form of a flowchart in figure 4-2 below.

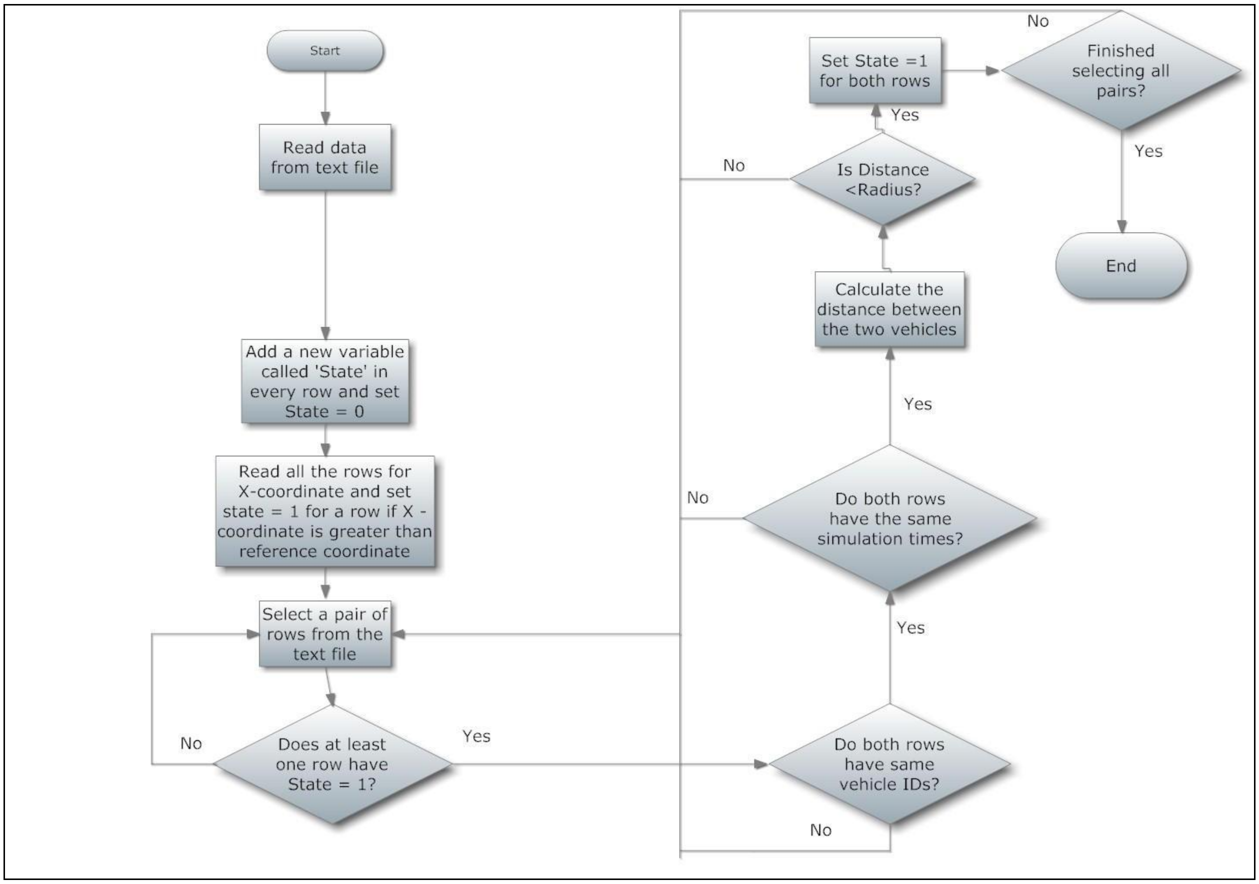


Figure 4-2: A flowchart explaining the procedure followed for processing the data obtained from the Paramics output file.

The Paramcs output file is imported into Matlab and is stored as an array of numbers. This array has three columns. The first column contains the vehicle IDs, second contains the X-coordinates third column consists of simulation times.

A number of operations are carried out in this algorithm. The first operation is to find out the largest X-coordinate and set the ninety fifth percentile value of this number as the reference line for the vehicles. This reference line, in reality means a point on the road where there is an incident or a place with prevailing hazardous conditions for driving (a bump or an oil slick for example may be considered as hazardous conditions). At this point all the instrumented vehicles obtain the information directly from the road. They are assumed to contain sensors that interact with the roadway and the hazards or messages are communicated by wireless systems (Ozbay et al., 2007). The instrumented vehicles may or may not possess the information about this point by wireless communication depending on the presence of a neighboring and informed instrumented vehicle, but will definitely get the information when they reach this particular point on the roadway.

A fourth column is introduced to the raw data. This is a binary variable and represents the state of the vehicle at that point of time. If state is one, it means that the vehicle is aware of the hazard ahead of it and if it is zero the vehicle is waiting to get informed. The state value is set at zero at this point of time. The raw data now consists of four columns – the vehicle IDs, X-coordinates, simulation times and the fourth is the information states.

The algorithm checks for all the X-coordinates that have passed the reference line and changes the state variable’s value in the corresponding row to one. Now, each row represents the condition of a vehicle by specifying its ID, its position, simulation time step and whether the vehicle is informed or not.

The main part of the algorithm starts from here. The algorithm selects a pair of vehicles at every time step, checks if at least one of them is informed, and if they are neighbors. If they are neighbors, the other vehicle that was uninformed will now become informed and the state variable in the fourth column changes to one. The algorithm checks for all the vehicle pairs in this manner.

The algorithm finally counts and stores the vehicle related information for each time step in three separate arrays. These arrays contain the number of informed vehicles, number of uninformed vehicles and the total number of instrumented vehicles at each time step.

CHAPTER 5: PRELIMINARY ANALYSIS AND RESULTS

5.1 Statistical Model Based on Normally Distributed Spacing.

Here is one simple model that will predict the minimum density of the instrumented vehicles that is required for a successful spread of infection all through the network:

We know that the spread of infection happens only when an uninformed vehicle is inside the radius of influence of an informed vehicle.

In regular traffic, the instrumented vehicles will be distributed randomly in a network. The main parameter in this model is the spacing distribution between the instrumented vehicles. The following scenario is assumed: (Figure 5-1)

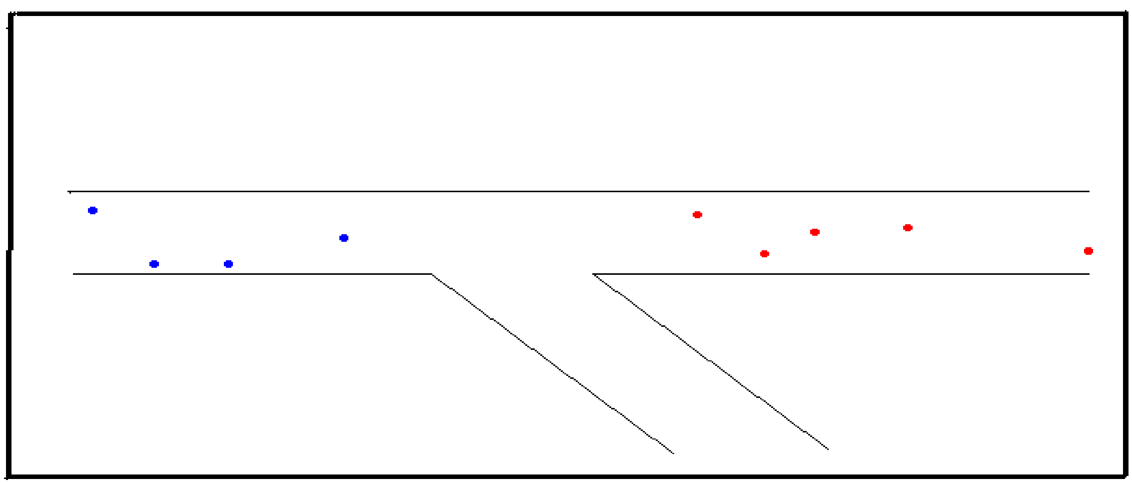


Figure 5-1: A random distribution of instrumented vehicles.

In the above figure, the positions of instrumented vehicles at a random time is shown. The red dots represent the vehicles that are informed and the blue dots are the instrumented vehicles that are not. It is further assumed that the time taken for the signal to get transmitted between vehicles is negligible and it takes place whenever two vehicles are close enough. In the current network, an instrumented vehicle obtains some information about the roadway either by communicating with other vehicles, or when it reaches the far right portion of the network. This information could be related to the travel time on the link after passing the junction, or a warning message indicating an incident that has occurred at the far right. The vehicles upstream to the junction have an opportunity to detour if they get the necessary information about the road ahead. On the other hand, the drivers of these vehicles should be given sufficient time make a detour. It is assumed that a driver will be able to make a smooth maneuver and make a detour if he gets the information when he is located at the extreme left of the roadway in the figure. So, it is imperative that all the instrumented vehicles in the road stretch shown in the figure will have to be informed. In the above figure, the vehicles in the second half of the figure are uninformed because the closest informed vehicle is farther than the radius of influence. The positions are always random and a single such “missing link” will make the whole chain of following vehicles unaware.

The current model is a very simple statistical model that predicts minimum traffic volume so that all the vehicles in the road strech are aware at a desired confidence level. The following variables are used in the model:

1. D is the distance between any two vehicles and is assumed to be normally distributed.

2. r is the communication radius of the wireless system installed in a vehicle.

3. k is a new random variable defined as the difference between D and r as follows:

$$k = D - r \tag{5.1}$$

4. μ_D, σ_D are the mean and standard deviations of the random varialble D.

5. μ_k, σ_k are the mean and standard deviations of the random variable k.

If $D < r$, The infection propagates, else it does not.

The assumption that the spacings are normally distributed makes the random variable k also normally distributed. Now, for the propagation to take place k < 0. The corresponding standard normal variable Z will be:

$$Z = (0 - \mu_k) / \sigma_k \tag{5.2}$$

Then a hypothesis test is conducted with the following hypothesis:

Null hypothesis: k < 0

Alternative hypoethsis: $k \geq 0$

If $\varphi(Z) > 0.95$ (or any desired level of confidence) the particular set of μ_k, σ_k will be acccepted.

The density of the instrumented vehicles is obtained from simulation in Paramics. This is done by running the simulation for multiple times, noting the densities at every instance of time and calculating mean and standard deviations from the data.

When these results were compared with the simulation results, it was observed that the model did not accurately represent the behavior that was observed in reality. One important conclusion would be the fact that the spacings are not normally distributed. In addition, a confidence of 95% means that the spacings are less than the radius of influence on 95% of occasions. However, for the rest of the 5% of the times, it is likely that the spacings will be greater than the radius. The communication system however fails to stay connected even if the spacing exceeds the radius on just one occasion. So even if the model predicts a connected and communicating network, it does not stay connected in reality. This model does not answer any of the questions that were raised earlier, except that the spacing is not in a normal distribution function. This model does not eliminate the use of simulation and is definitely not comprehensive. So we move on and make another mathematical model that makes use of the whole process of vehicle motion and communication, starting from scratch.

5.2 Average Speed Estimation Model

The most importance aspect in the information propagation process is the distance between instrumented vehicles. Communication is possible when the vehicles are close enough. However, when the inter-vehicle distance is large, the governing criterion for vehicle communication could become the relative speed. Consider the diagram shown in Figure 5-2. The red dots in Figure 5-2 are the positions of instrumented vehicles that have the information about the hazard. The blue dots are the positions at which the instrumented vehicles without any information are located. Whenever there is a void between vehicles, as a result of the limited ability of the communicating devices in the vehicles the information will not be transmitted to the vehicles upstream. However some of the faster vehicles try to catch up with the vehicles downstream and fill the "missing link" in the communication chain. When they come close enough, the signal is transmitted.

The green line intersecting the roadway at the right is the reference point. At the green line, there could be a damaged road, or an incident that has just occurred, which is causing the vehicles to slow down or stop. This is the point at which the instrumented vehicles inevitably receive the information. When the first instrumented vehicle reaches this point, it senses the hazard and tries to warn the other traffic by transmitting it as a wireless signal. The vehicles upstream to this reference point receive this information if they are close enough to the vehicle ahead. Otherwise, they are unaware of the hazard or the congested link until they reach this reference line.

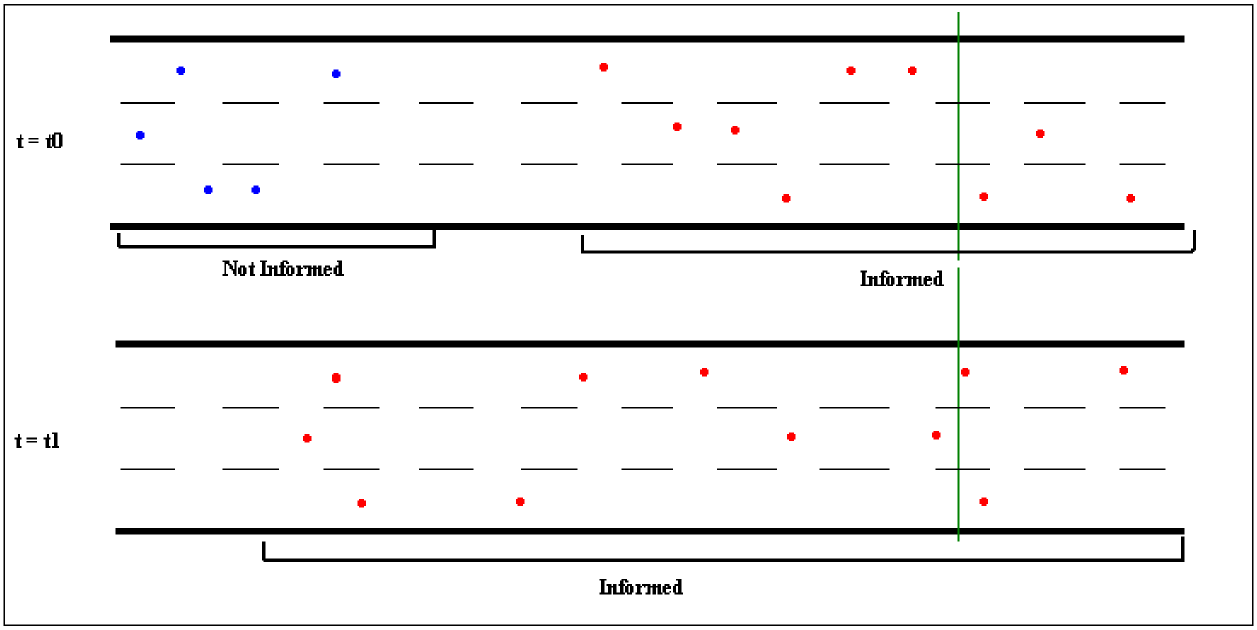


Figure 5-2: Positions and status of instrumented vehicles at two different instances.

We assume that the time taken for the wireless signal to propagate between vehicles is negligibly small when compared to the time taken for the vehicles to move by a finite distance. So, from the time two instrumented vehicles come close enough to the time the signal transfer takes place, the two vehicles will have hardly moved.

In the figure, at time $t = t_0$, as a result of the larger gap (larger than the radius of influence of the wireless system) between the instrumented vehicles, the vehicles upstream are unable to receive information. This large gap between one pair of vehicles makes the whole chain unaware and makes it the 'missing link'. However, some of these uninformed vehicles that are faster tend to close the gap with the vehicles ahead. In the case of these vehicles coming close to the informed vehicles, they get informed, which happens at $t = t_1$. The signal immediately is transmitted to the neighboring vehicles that are close, and this process continues all along the upstream direction. When one 'missing link' or a gap is filled, it immediately spreads the information further downstream, if there are any following vehicles. The relative speed between the vehicles is the governing factor for transmitting the warning signal backwards. When there is no such catching up by the following vehicles, the weak link cannot be taken care of, and in such cases the instrumented vehicles remain uninformed until they reach the reference line.

In the current study, we model the above processes mathematically and develop a mathematical equation that expresses the speed at which the information is propagating in the network. The following notations and assumptions are used to represent the parameters:

1. The density of the instrumented vehicles (in vehicles per mile) is denoted by ρ .
2. The speeds of all the vehicles in the network (in miles per hour) are distributed uniformly between $v_{\min}$ and $v_{\max}$.
3. v_{fr} is the free flow speed in the network in miles per hour.
4. The spacing between the vehicles is assumed to be exponentially distributed.
5. The radius of influence of the wireless system is 'R'miles.
6. The fraction of instrumented vehicles in the network is 'M'.
7. The length of the roadway that contains 'N' number of neighboring vehicles is 'L' miles.
8. The total time taken for gap to get covered and the signal to propagate is 'T' hours.
9. The spacing between two vehicles is 'h' miles.

10. The length of the whole stretch is 'D' miles.
11. When two vehicles are considered, the speed of the leading vehicle (both in miles per hour)is 'v_l' and the speed of the following vehicle is 'v_f'.
12. The position of a vehicle from the point of entry (which is considered as origin, in miles) is 'x'.
13. 'v' is the average speed of platoon of instrumented vehicles that is close enough to communicate, in miles per hour.
14. k_1 and k_2 are the constants that define the speed-density relationship for the traffic.
15. $S_{\min}$ is the minimum spacing required for the traffic to be in a free flow state in miles.

From here onwards, instrumented vehicles will be referred as vehicles unless otherwise specified. Two vehicles are positioned with a distance $r(r > R)$ between them. When the speed of the following vehicle is greater than the speed of the leading vehicle ($v_f > v_l$) the time taken for the following vehicle to come close to the leading vehicle will be governed by the relative speed between the two vehicles (by saying "close" we mean the distance between the two is less than or equal to the radius of influence 'R') and is given by the following equation.

$$t = (r - R) / (v_f - v_l) \tag{5.3}$$

On the other hand, slower following vehicles (slower than the slowest of the leading vehicles) will not receive the information until they reach the reference line. If the position of such a following vehicle is 'x', the time taken for following vehicle to travel the remaining distance (D – x) on the network will be:

$$t = (D - x) / (v_l) \tag{5.4}$$

The average time taken for the following vehicle to get informed about the hazard will be the average of the above two random variables averaged over the entire network.

$$T = \int_R^D (\frac{\rho}{2}) e^{-\rho r} \int_0^D \frac{D - x}{D + v_f} dx dr + \int_R^D (\frac{\rho}{2(v_f - v_l)})(r - R) e^{-\rho r} dr \tag{5.5}$$

Equation (5.5) is a sum of two terms. The first term represents the average time taken for the following vehicle to reach the reference line. The integration term inside the main integral is the total time vehicles take to reach the reference line from any point 'x'. The other part of the first term is the exponential probability density function associated with this time. The second term is the average time taken for the information to propagate when the following vehicle catches up. Here, the speed of the following vehicle will be more than the speed of the leading vehicle.

In the above time, the wireless communication signal will have travelled a distance 'R'. As soon as the signal transfer to the following vehicle occurs, the information is instantaneously transmitted to the neighboring vehicles. The presence of neighboring vehicles (if any) will further help in the propagation of the signal over a longer distance. Here, we estimate the average length over which the signal propagates by virtue of proximity of instrumented vehicles.

In a general case 'N' vehicles are close to each other in such a way that the transfer of signal to the first vehicle ensures the signal propagation to the rest of the vehicles. The probability for a pair of vehicles to be close to each other for an exponential distribution is $(1-e^{-\rho R})$. For (N+1) vehicles to be close, the probability becomes:

$$P = (1-e^{-\rho R})^N \tag{5.6}$$

The length of the roadway occupied by these vehicles will be the sum of spacing between each of the vehicle pairs. If $h_1, h_2 .....h_n$ are the spacing between N such pairs the total length of the platoon of neighboring vehicles will be

$$l = h_1 + h_2 + ... + h_n \tag{5.7}$$

To get the average length occupied by a platoon of such vehicles, the length of platoon is calculated when the number of vehicles in the platoon is N = 2, 3, 4…(N+1), and obtain the probability of occurrence of such a platoon. The product of the two quantities is then summed over number of vehicles.

$$L = \sum_{i=0}^{n} (1-e^{-\rho R})^i (\sum_{j=0}^{i} h_j) \tag{5.8}$$

The above equation is a discrete summation. Each term is the product of length of platoon of 'i' vehicles and the probability for them to be close. This cannot be calculated easily because the headways are random numbers. The above expression could be simplified by estimating an average headway and the whole equation could be modified by making it continuous as follows:

$$H = \int_0^R \rho r e^{-\rho r} dr \tag{5.9}$$

The average rate at which the signal propagates upstream will be the ratio of sum of the average length 'L' of the platoon and radius of influence 'R' over the average time 'T'. In addition to this speed, the last vehicle that carries the message always keeps moving forward. Therefore, there will be a speed at which the message is traveling in the downstream direction, which is in the opposite direction of traffic. The overall speed of signal will then become

$$v_s = (R+L)/T - (v_{\min} + v_{\max})/2 \tag{5.10}$$

The equation (5.10) estimates the speed of propagation of information. If the negative quantity is higher than the positive part, it would lead to negative speeds, which means that the propagation of infection is taking place in the downstream direction. If the positive quantity in the equation is higher, the propagation takes place in the upstream direction. These results are reasonable because at low densities of instrumented vehicles, the communication is non-existent and the information travels with the last vehicle on the road. If there was no reference line (the green line in figure 5-2), the information is possessed by that vehicle and it moves forward without any communication. With this model, it is also possible to predict a minimum density of instrumented vehicles that is necessary to make the above equation positive so that information propagation takes place.

However, the results, when compared with the results from the simulation indicated a completely different behavior. Upon looking at the model and the simulation results very closely to understand the differences, very important observations were made, which could answer some of the questions raised in the earlier chapter.

First and the foremost observation found in the modeling was the exponential distribution assumption. The vehicles travel with non-zero relative speeds among one another, and possess different driving patterns based on human behavior, making it impossible to follow an exponential distribution all the time. In fact, in order to fit the spacing to a distribution, we used Easyfit 3.0, a tool that automatically compares the given data to a number of distributions and estimates a most appropriate distribution for the data. Unfortunately, in this case the software could not fit the spacing in any of the large number of distributions it can fit to, including exponential distribution.

Secondly, we tried to understand the importance of relative speed in traffic. Upon observing a number of simulations, we could conclude that maximum difference between vehicles did not exceed 7 MPH. At such low speeds it is very unlikely to catch up with vehicles well ahead. This leaves the whole network unconnected; particularly during low densities of instrumented vehicles (that is when the gaps are very large).

This model however answered some of the questions described earlier. Firstly, relative speed does not play a very important role as expected, in maintaining the connectivity of the network, and no distribution could accurately represent the spacing between vehicles in a road network.

CHAPTER 6: THE MODIFIED SUSCEPTIBLE – INFECTED – REMOVED MODEL

In this chapter we present the model that we developed to represent the vehicle-to-vehicle communication behavior. This is analogous to the Susceptible – Infected – Removed model that is used to predict the spread of epidemics in a region. We describe the model in the beginning and draw some similarities with the specific case on hand. Then we describe the analogous model.

6.1 The Original Susceptible – Infected – Removed model for modeling the spread of epidemics (Earn, (2005))

The world has experienced numerous cases of widespread epidemics outbreaks that have resulted in thousands of deaths. These epidemics are caused as a result of spread of infection among people. The infection itself could be disease causing micro-organisms like bacteria, fungi or any kind of viruses. Whenever such a disease causing infection enters the human body and the body is not protected or in other words not immune to the infection, it acts as a host to the infection. In such cases a person experiences sickness and depending on the kind of infection it could be fatal, even leading to death in some cases. In some diseases like measles and cholera, if a person recovers from the illness, he develops immunity for this infection and will be able to resist the attack in the future.

During the period of illness, this infected person also transmits infection to other people around him. This happens in more than one way. For example, bacteria or viruses can be passed on by touching or shaking hands with another person. Touching food with dirty hands allows viruses or bacteria from the intestine to spread. A person with a cold can spread the infection by coughing or sneezing. Some very dangerous viral infections hepatitis and AIDS reside in various bodily fluids and are transmitted by injection or by sexual contact.

It is clear that the infection spreads very rapidly from one person to another if they are not immune to the infection. There are mathematical models that predict this spread of infection by estimating the number of infected persons in a region. These models not only help in understanding the patterns of transmission, but also in estimating the quantity and type of medicine required in a region in order to control the illnesses among the people.

From the above discussion, it is clear that there are three are three different types of people that live in a region. These include the people who are susceptible to the infection but are not infected on the present day, people who are infected and transmit the disease to other susceptible people around them and the third kind are the people who have recovered from the infection and have developed immunity for the disease. In some fatal cases, the infected people die as a result of the disease and are removed from the system as a result of death.

Consider a city with no previous history of existence of a specific disease (for example cholera). The people in this city will all be susceptible to this disease and all of them are likely to contract the infection if an infected person enters it or one of them somehow contacts the disease. This first results in a widespread epidemic resulting in some deaths and a lot of infections. The people who have recovered from the disease will have developed immunity and will not be affected in the future. After every epidemic the number of people susceptible to the infection in the city decreases. With the decrease in the number of susceptible people the disease- causing micro organisms cannot find a potential host and as a result there will be a decrease in the number of infected people. The extent of the epidemic then decreases. During this time the infection still remains dormant in the city. However the number of susceptible people keeps increasing slowly and gradually as a result of births. When the births become sufficiently high that there are a good number of susceptible people in the city, the infection that has been dormant becomes active again and an epidemic outbreak is observed. Thus the epidemic follows a seasonal pattern where the infection remains dormant for a period of time and then an outbreak follows this dormant period with the increase in susceptible population.

If there is an effective vaccine that could prevent this disease, it is administered for all the infants so that they become immune to the infection. This way the susceptible population is always maintained at a very small number and the absence of a potential host will eradicate the infection gradually. However if no such vaccination is available, the seasonal pattern that was explained earlier will be observed. The outbreak of an epidemic is thus governed by the number of susceptible people in the city. If there are too few infected people the chance of an epidemic is low because the chance of coming into contact with others is low, particularly if they are isolated. The rate of spread also depends on the number of infected people that are in easy contact with susceptible population. Thus the immune population does not play any role in the epidemic outbreak.

This made researchers develop the Susceptible – Infected – Removed model for simulating the spread of infection in an epidemic. By obtaining the data related to the number of births over a period of time, the number of infected cases in the city, and the death rate in the city, the model predicted the number of infected people over the next time cycle. The number of people becoming infected depends on a lot of factors, some of which include:

1. *Population of the city:* More is the population; more will be the number of susceptible people.

2. *Population Density:* If the density is very high people are closer and the rate of spread of the epidemic is higher.

3. *Birth and Immigration Rate:* Both these constitute the rate at which new people enter the city that might be susceptible to infections.

4. *Seasonal Variations:* Infections spread faster in more moist and warm conditions than dry and cold conditions. It is more likely that an outbreak starts in the former conditions than later.

5. *Other factors:* When the schools begin just after the end of summer, the children come closer and have a higher chance of catching the infection. Thus an epidemic is likely to occur during a school season than a holiday season.

Over a period of thirty years, the number of cases of Measles virus was recorded in the New York City and the data was plotted. Figure 6-1 shows the pattern of infection or the number of infected people at a point of time. As shown in the figure, the number of monthly cases varied from close to zero to approximately 10000 cases. These values certainly vary from place to place. For example, if we consider any other place (London for example) the number of monthly cases will not necessarily be the same as in New York City.

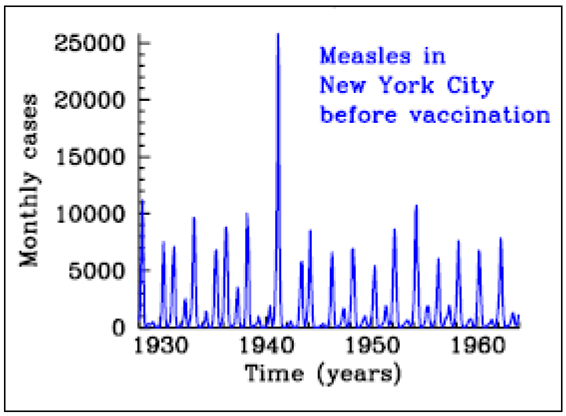


Figure 6-1: Number of monthly cases of Measles in the New York City for a period of thirty years. (Source: Earn, (2005)).

The S-I-R models that were developed were intended to show similar kind of distribution for the number of infected population. The mathematical equation of the model is:

$$\frac{dI}{dt} = \beta SI - \mu I - \gamma I \qquad (6.1)$$

Where,

S is the number of people susceptible to the infection at a time t,

I is the number of persons that are infected at a time t,

β is the infectivity rate, which is defined as the number of susceptible people who could be infected by a single infected person at a given point of time,

μ is the per capita removal rate. This includes people who move out of the city, who die, and every other means by which the population of the city would be reduced, and

γ is the per capita recovery rate.

By varying the values of β, μ and γ different kinds of distributions could be obtained. Each set of values represents a specific city.

6.2 Motivation to develop a vehicular network model analogous to the S-I-R model

The vehicles traveling on a roadway have some similar features to that of the people living in a city. One of the most important factors is the vicinity. Just as people catch infection from other people around them, vehicles that possess the information keep broadcasting it(just like an infected person). The vehicles that are equipped to receive these signals and are close enough to the broadcasting vehicle will receive the signal. This is analogous to the susceptible people who are close to the infected people. Vehicles enter a roadway without any information, catch a wireless signal on their way and leave the system later. This process is similar to the process taking place in a city. Just as in a city the conditions in a road network are governed by factors such as number of instrumented and uninfected vehicles, flow of traffic, speed limit and so on. In addition to all these similarities, there were some other studies that were inspired by these mathematical models and used for different purposes. One such study by Wang et al. (2006) investigated the spread of viruses among mobile phone networks. The model used there was a Susceptible – Infected model (the SI model) to predict the spread of mobile phone viruses. The mobility patterns of the people and hence the spread of the mobile phone virus was predicted by mathematical model.

Owing to these reasons, we assumed that the vehicular networks could also be modeled like a spread of a contagious disease. The analogous model for the vehicular networks has the following parameters. Here the equipped vehicles are equivalent to the susceptible population; vehicles with information about the roadway are similar to the infected people. However, there is no recovery rate as the vehicles that have received the information will possess it as long as they remain in the network. The points below compare the conditions in a city and a vehicular network.

1. Entry rate of vehicles into the roadway that is analogous to the birth rate.
2. Number of infected vehicles is analogous to the number of infected people.
3. Number of uninfected (but equipped) vehicles that is analogous to number of susceptible people.
4. Infectivity rate, which is similar to the infectivity rate in the original model, which is the number of uninformed vehicles that each informed vehicle can communicate with at an instant of time.
5. The rate at which the vehicles leave the network is analogous to the removal or the mortality rate of the population.
6. The difference between the two models is the recovery rate ‘γ’ that exists in the original model and is absent in the analogous model. This is because the informed vehicles stay informed on the road network.

From here onwards we discuss only about the instrumented vehicles present in the network as they are solely responsible for communication. We will use the term vehicles to refer to the instrumented vehicles in the network, infected vehicles to refer to the vehicles that have already received an information regarding the roadway and uninfected vehicles implies the equipped vehicles that have not received any wireless signal and thus possess no information yet.

The birth, immigration and the mortality rates were available from government records that enabled the researchers to model the epidemics efficiently. For the present model, in order to predict the number of infected vehicles, we need information regarding the number of susceptible vehicles and the exit rate of the vehicles. This information was obtained from the Paramics simulation results and was used to predict the infected vehicles present in the network. We developed functions for number of susceptible vehicles and the number of vehicles exiting the network that correctly represented the results from the simulation, and used these functions in the model.

The model then becomes:

$$\frac{dI}{dt} = \beta SI - X \tag{6.2}$$

Where

I is the number of infected vehicles during that time instant.

S is the number of uninfected vehicles during that time instant. Which time instant? Not clear

β is the infectivity rate.

X is the rate of exit of vehicles out of the network.

Just like a set of values for β, μ and γ represent the situation in a specific city, a specific function and the value of the infectivity rate β represents a unique traffic condition on the roadway. The distribution of the number of infected the number of uninfected and the number of vehicles exiting the network varies based on some parameters which are as follows:

1. **Traffic Flow:** When the traffic is high, the vehicles tend to come closer to each other more so when the road is congested. At high traffic volumes, the spread of infection could be better than at low volumes. This results in greater number of infected vehicles.
2. **Market Penetration:** At greater market penetrations for a specific flow rate, the number of equipped vehicles will be greater for greater market penetrations than for lower values. With greater number of equipped vehicles greater is the chance for the propagation of the information.
3. **Number of Lanes:** With increase in the number of lanes, the headways between the vehicles decrease. That is the number of vehicles per mile increases, which reduces the headway. So greater number of lanes will result in greater spread of infection among the vehicles.
4. **Speed Limit:** It is an obvious fact that if the speed limit is high, the vehicles travel at greater speeds. When the speeds are high, the headways become larger. Greater headways means the vehicles are farther apart, which in turn means that the chance of spread of infection drops when the speed limits are higher.

In order to make a complete model, all these parameters will have to be used. For each parameter three different values were used and each of these was used in different combinations to complete the analogous model. The following are the values for each parameter considered:

1. Traffic Volumes:
   i. Low – 1000 vehicles per hour per lane
   ii. Medium – 1500 vehicles per hour per lane
   iii. High – 2000 vehicles per hour per lane
2. Market Penetration:
   i. Low – 5%
   ii. Medium – 10%
   iii. High – 15%
3. Number of Lanes:
   i. 1
   ii. 2
   iii. 3
4. Speed Limit:
   i. 30MPH
   ii. 45MPH
   iii. 60MPH

A traffic scenario consists of, for example, a traffic volume of 1000 vehicles per hour per lane, Market Penetration of 5%, on a three lane roadway which has a speed limit of 45

MPH. The complete model requires all the combinations to be modeled accurately. This would result in 81 different and unique combinations, which will be obtained by using different values for each parameter as a combination with other parameters.

The methodology followed to fit a model for one combination is described here. It should be noted that the same procedure is followed in order to model other combinations. The combination that is being described here consists of three lanes of road, fifteen percent market penetration, with a speed limit of 45 miles per hour and a volume of 4500 vehicles per hour.

6.3 Results from the simulation

Ten simulation runs were performed in Paramics for the combinations specified above. The purpose of performing multiple runs is to reduce the stochastic inconsistency associated with Paramics. A mean and a standard deviation were obtained from all the simulations and the model was developed to match these values as closely as possible.

The length of the road network was set at 10 miles for all the simulations. For each simulation depending on the traffic conditions and the geometry of the road, the network was modified for speed limits, number of lanes, traffic volumes and market penetrations. The length of the road network was not modified. The present network consists of a straight road without any curvature. The simulations were performed on the straight road for the sole purpose of simplicity in developing the model. The results would not vary significantly if there was curvature. This is because of the fact that the whole communication process takes place all along the roadway. For the purpose of evaluating the number of infected vehicles in the network we use the road network itself as the frame of reference. The length of the roadway that would be infected would thus be the actual length of the roadway after taking the curvature into consideration. However, there would be a small variation if the roadway has a high degree of curvature. In this case, a small difference arises during the process of communication, where the distance between the two communicating vehicles is the length of the straight line connecting them and not the length of the roadway. This minor difference makes it a more conservative model. However, for the difference to be significant, the radius of curvature has to be very high. Such high degrees of curvatures are not generally observed in road networks in general, and in uninterrupted traffic flows in particular, which we are dealing with presently.

Another important point to be noted in these results is that they are independent of the length of the roadway. The main aspect of the vehicle to vehicle communication is the communication between vehicles. Greater the number of neighboring vehicles greater will be the interaction and vice versa. For inadequate market penetrations, the entire road network will not be connected. For extremely small market penetrations (say 1%) the equipped vehicles remain far away from one another. As a result of these gaps between equipped vehicles, there will be a large number of 'weak links' (Figure 5-2) in the network that would render the interaction impossible. In such cases the equipped vehicles become aware of the road condition only after they reach this reference position. The average length of spread of infection on the road here is equal to zero. The length of spread is measured upstream of the road from the reference line. For slightly higher but inadequate market penetrations, the scenario is more similar to Figure 5-2. There will be a platoon of infected vehicles followed by a gap and then another bunch of equipped vehicles travel along the road without carrying any information. Over a period of time, the number of infected vehicles (and the number of uninfected vehicles) varies between a maximum and a minimum value. An average value of infected vehicles could thus be estimated from simulation. Depending on the number of lanes, flow rates of the vehicles, market penetration and the speed limit of the roadway, there exists an average number of infected vehicles and hence an average length of the infected roadway. For very high market penetrations the equipped vehicles are in the neighborhood of one another all the time and make the whole network fully connected. In such cases, the whole network is always connected irrespective of the length of the roadway. The length of the road thus does not play an important role in governing the number of infected vehicles. The only binding criterion is that the roadway needs to be longer than the maximum extent to which the infection spreads. For example, in figure 5-2, if the road network ends at the last infected vehicle (at $t = t_0$), it would lead to a misleading conclusion that the whole network is infected, which is not the case.

The output obtained from simulation in Paramics was processed to obtain the number of infected and the number of uninfected vehicles existing in the network at every time cycle. The graph obtained from the simulation results for the present scenario is shown in figures 6-2, 6-3 and 6-4. Figure 6-2 shows the removal rate of vehicles from the network, which is analogous to the mortality rate of people in an epidemic model. Figure 6-3 shows the number of un vehicles in the present in the network at each instant of time as obtained from simulation. This is analogous to the number of susceptible people present in a population, and figure 6-4 shows the number of infected vehicles present in the network at each instant of time, which is analogous to the number of infected people in the network.

This scenario consists of moderate volumes with high market penetration. This scenario contains approximately 140 instrumented vehicles at any point of time during simulation. The number of uninfected vehicles in the network varies between 20 and 60, and the number of infected vehicles varies between 80 and 120. These numbers, as described earlier, differ for different scenarios of traffic. These figures indicate that there is a periodic variation that could be observed. However the variation is fluctuating sometimes and with variable amplitude

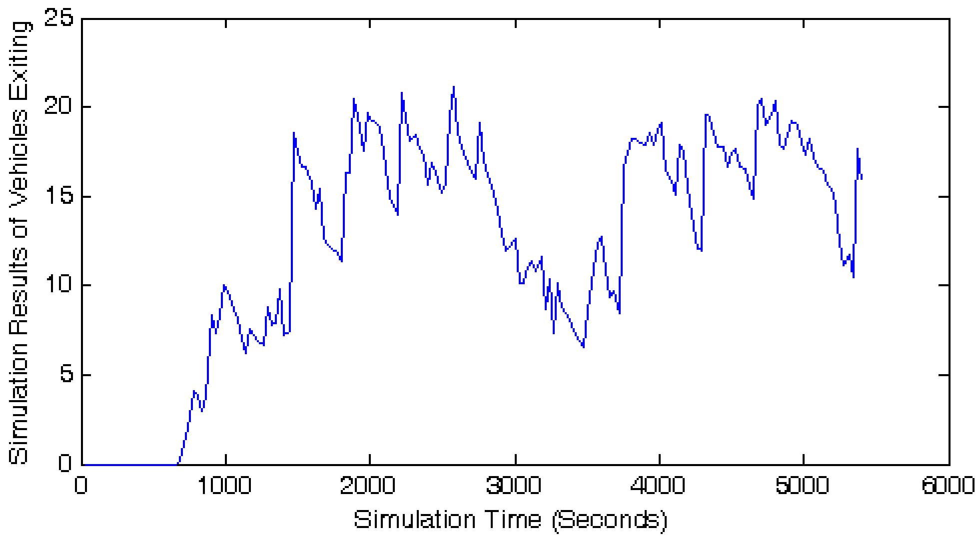


Figure 6-2: Simulation Results for Number of Vehicles Exiting the Network

Certainly there is a random component associated with these results. In the following pages the methodology used to model a similar distribution using the S-I-R model is described.

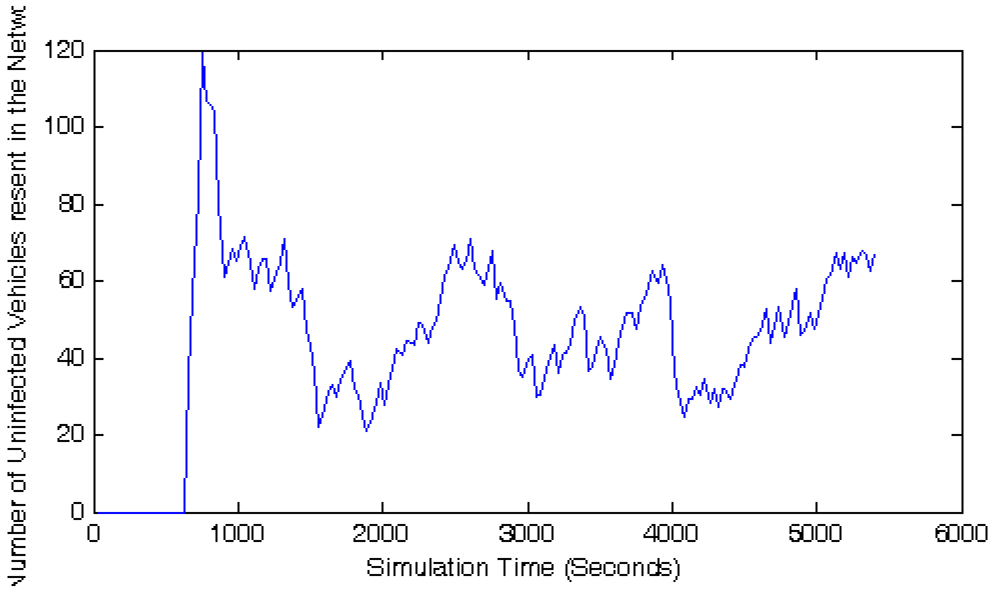


Figure 6-3: Simulation Results for Number of Uninfected Vehicles Existing in the Network

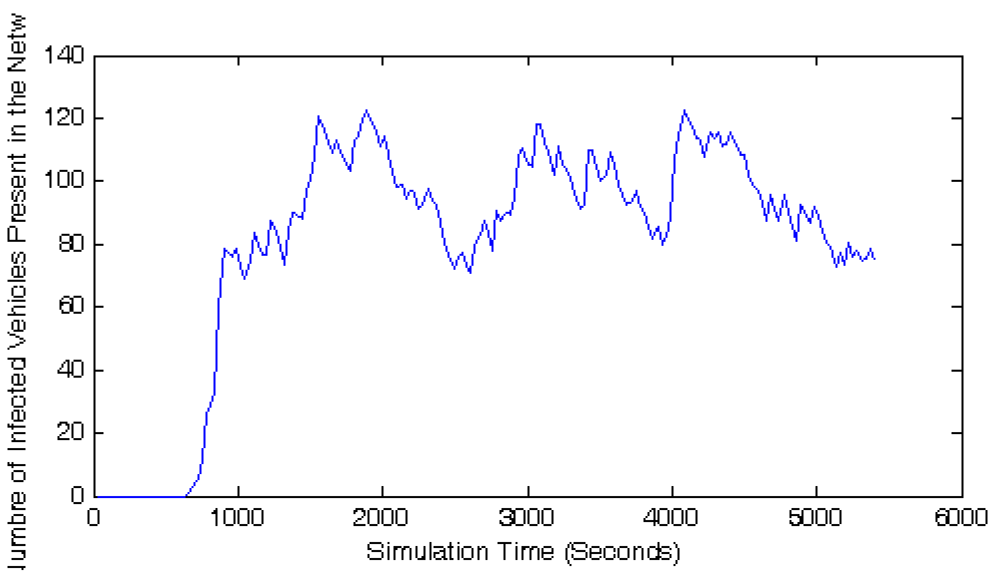


Figure 6-4: Simulation Results for Number of Infected Vehicles Existing in the Network

The complete modeling was done in three phases. In the first phase, a representative model for the removal rate of vehicles was developed. In the second phase, another representative model to predict the number of susceptible vehicles was developed. Upon obtaining these two, the actual S-I-R model was implemented to estimate the number of infected vehicles in the network after making use of the data obtained from the two representative models.

6.4 Developing the analogous model

The figure 6-5 below shows the entire process involved in developing the analogous model. We first develop an analogous model for the mortality rate on a trial and error basis. The results are compared with the simulation results by a t-test. After successfully developing this we develop a model for the susceptible vehicles in a similar manner. These two models act as inputs to the actual SIR model that predicts the number of infected vehicles in the network.

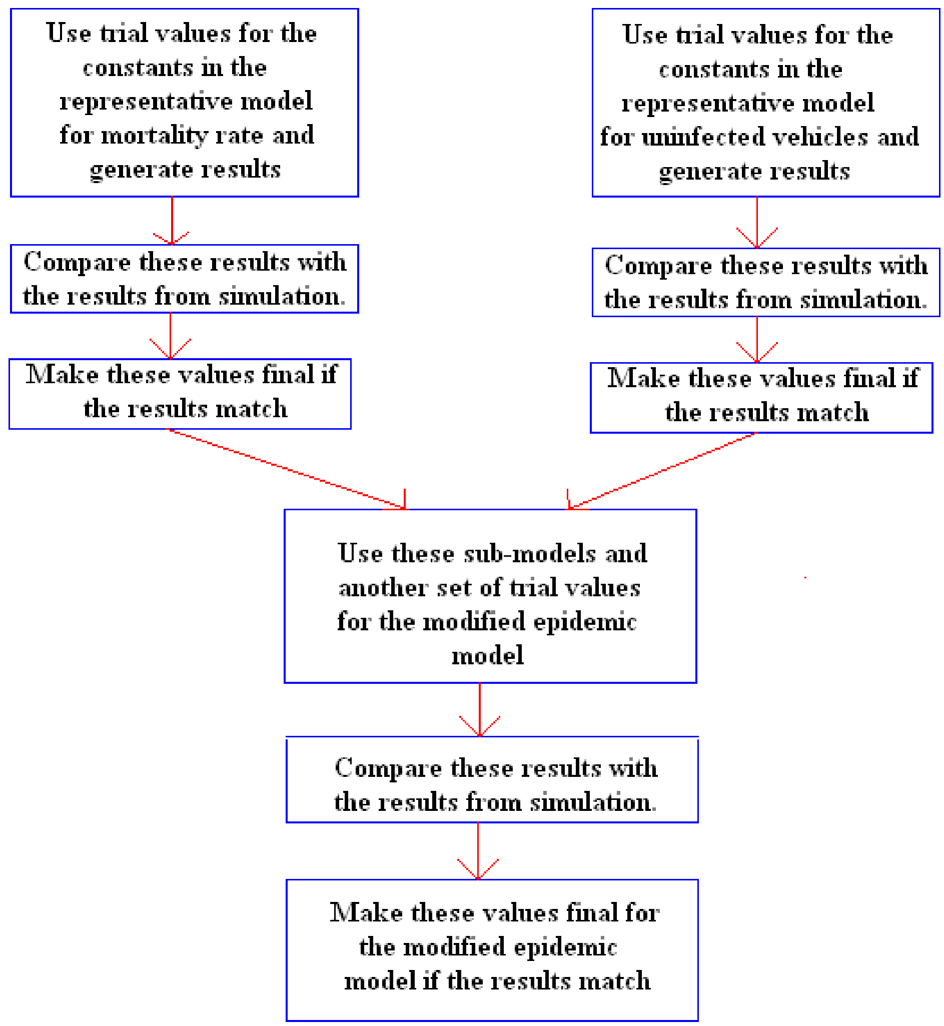


Figure 6-5: The procedure followed to develop the analogous model.

6.4.1 Removal Rate Model

After reaching the steady state, which happens approximately after 1400 seconds of simulation, the number of vehicles exiting the network varied between 10 and 20 vehicles for every 30 seconds, which was the chosen duration of a time cycle. We introduced a random component and a sinusoidal component and developed an equation in the manner shown below.

$$\rho(t) = \tau + \psi(t) \tag{6.3}$$

And

$$\psi(t) = \mathrm{mod}(\alpha\nu\sin(\varpi t + \phi)) + \mathrm{mod}(\alpha\nu\cos(\varpi t + \phi)) \tag{6.4}$$

$\rho(t)$ is the function that represents the removal rate of vehicles (vehicles per minute),

$\psi(t)$ is a function that brings random and periodic behavior to the function ρ and is expressed in vehicles per minute,

ν is a uniformly distributed random number that lies between 0 and 1,

$\tau, \varpi, \phi, \alpha$ are all constants, τ is expressed in vehicles per minute, ϖ is expressed as an inverse of time (min^{-1}) and the rest are dimensionless.

and mod is the modulus function.

From figure 6-3 it could be observed that the removal rate does not fall to values close to zero.

The parameter τ is helpful in maintaining a minimum value for the function ρ. The parameter α maintains the amplitude of the sinusoidal wave for the representative model, the random number ν varies the amplitude for every time step (as '$\alpha\nu$ becomes the effective amplitude for the sinusoidal function). ϖ is helpful in maintaining the wavelength of each of the sinusoidal wave and ϕ takes care of the phase difference between the simulation and the representative model's graphs.

The following values were used to define the model for this scenario:

α = 20; ϖ = 0.08; ϕ = 120; τ = 1.

Using these values for the parameters, the value of the function $\rho(t)$ is obtained. Ten different simulation runs are performed using these parameters and the mean value for $\rho(t)$ obtained by averaging the values obtained from these ten runs. This mean function $\rho(t)$ is the final representative distribution that was compared with the simulation results.

The mean and standard deviation for this averaged function is noted and compared with the mean and standard deviation of values obtained from simulation. This comparison is made using a t-test. The test is conducted at a 95% level of confidence. If the t-test indicates that the results are equal, these values for the parameter are deemed as final for the present scenario and the graphs are plotted. Otherwise, the values are modified and the whole process is repeated until the t-test indicates equal mean and standard deviation.

The figure 6-6 below shows the two distributions superimposed in order to compare them. The graph in blue represents simulation results and the graph in red represents the results from the representative model.

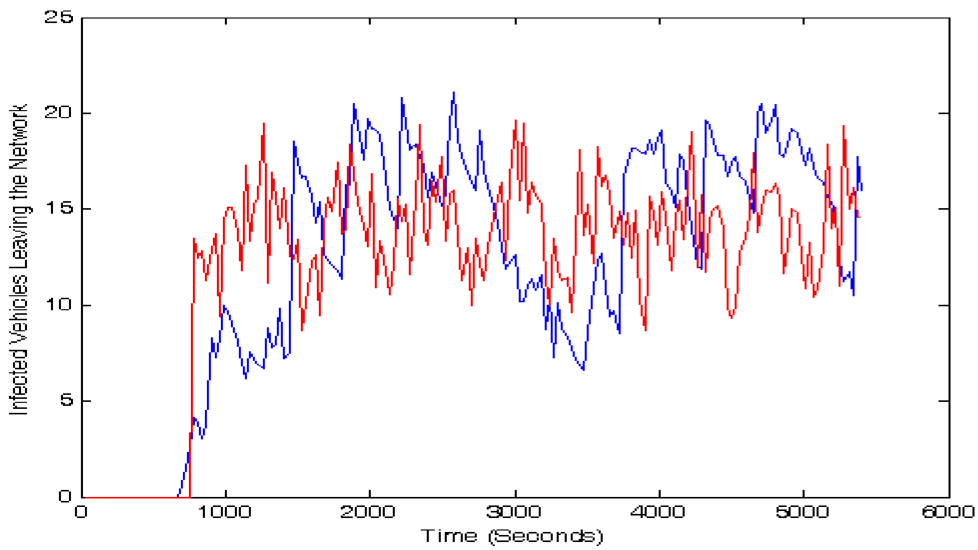


Figure 6-6: Simulation Results and model predicted results for Number of Vehicles Leaving the Network

6.4.2 Susceptible Population Model

Figure 6-3 indicates the variation in number of uninfected vehicles with time. This graph is similar to the graph in Figure 6-2, for the removal rate of vehicles from the network. The number of uninfected vehicles does not fall to values close to zero. There is also a random component associated, as indicated by the fluctuations and the varying amplitude. There is also the periodic behavior that was exhibited by the vehicles leaving the network. Owing to all these reasons, the representative model for uninfected vehicles is modeled in identical lines to the removal rate model. The model used is shown below.

$$\rho_s(t) = \tau_s + \chi_s(t) \tag{6.5}$$

And

$$\psi_s(t) = \mathrm{mod}(\alpha_s v_s \sin(\varpi_s t + \phi)) + \mathrm{mod}(\alpha_s v_s \cos(\varpi_s t + \phi)) \tag{6.6}$$

Where,

$\rho_s(t)$ is the function that represents the number of uninfected vehicles,

$\chi_s(t)$ is a function that brings random and periodic behavior to the function $\rho_s(t)$,

ν_s is a uniformly distributed random number that lies between 0 and 1,

$v_s, \varpi_s, \phi_s, \alpha_s$ are all constants, while all of these are dimensionless, τ_s is expressed as an inverse of time (min^{-1}).

and mod is the modulus function.

The following values were used to define the model for this scenario:

α_s = 190; ϖ_s = 0.12; ϕ_s = 40; τ_s = 20.

The figure 6-7 below shows the distributions for the simulation results and the results for the representative model superimposed in order to compare them. The graph in blue represents simulation results and the graph in red represents the results from the representative model. The mean statistics for the two are compared in table 6-2 at a later part of the section.

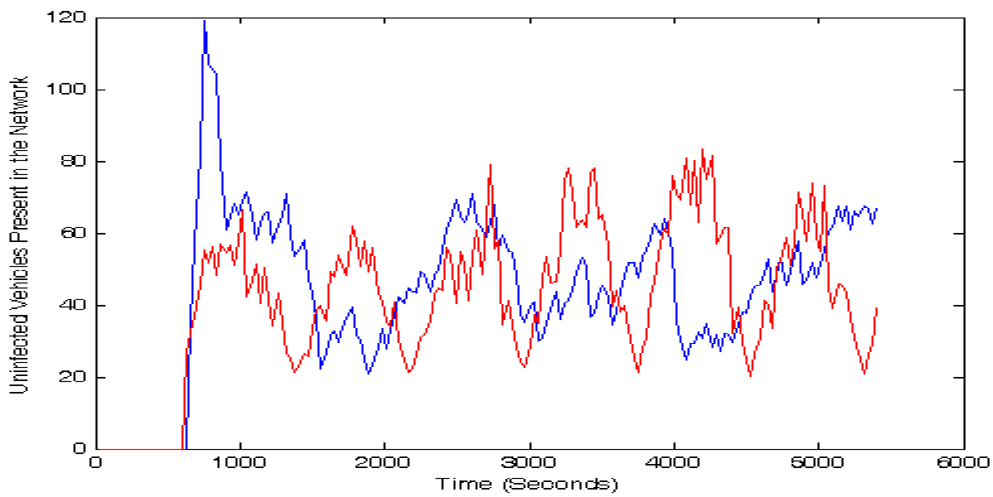


Figure 6-7: Simulation Results and model predicted results for Uninfected Vehicles Present in the Network

With the above two representative models, all the necessary data regarding the uninfected vehicles and the removal rate has become available. Now we move on to the main part of modeling that is to model the infected vehicles using the Susceptible – Infected – Removed model.

6.4.3 Infected Population Model

For the present scenario, which consists of three lanes of roadway at a market penetration of 15%, a speed limit of 45MPH, and a volume of 4500 vehicles per hour, the number of vehicles in consideration are higher than many other scenarios. As a result of the higher count of instrumented vehicles, the spread is also high and so the number of infected vehicles is also fairly high when compared to many other scenarios.

Just as a remainder, figure 6-1 shows the number of people present in the New York City over a period of thirty years. If we compare this graph with the graph in figure 6-4, which shows the simulation results for the number of infected vehicles present in the network, there is one important difference. The values in the epidemic data go down to as low as zero cases for a few months and then rise to as much as 25000 cases per month. In the vehicular network case, the number of infected vehicles oscillates between a maximum and a minimum value, which are close to 80 and 20 for the present scenario.

In addition to the available distributions that is the removal rate and the number of uninfected vehicles, the initial number of infected vehicles present in the system is required for the S-I-R model. This is called as the initial value or the seed value. This seed is not assumed to be a constant but a random number that lies between a maximum value and a minimum value in our model.

During the computer modeling of the epidemic, (Earn, (33)) indicates that certain checks were placed on the number of infected people and the number of susceptible people so that these values do not become negative. In the present model, we modify the check in such a way that the S-I-R model fits the simulation results as closely as possible. The modification is done such that whenever the number of infected vehicles falls below a critical value, the number of infected vehicles is automatically set as the initial value or the seed value. The modeling again continues according to the mathematical equation for the S-I-R model until it drops down to the critical value. This process continues until the end of simulation is reached. From figure 6-4, the variation again contains random and periodic components. The critical value is not a constant but a random variable that varies between a maximum value and a minimum value. Such a random number is assigned for the critical value because the distribution does not exactly have a minimum value but generally drops down to a certain level periodically. For example, in the figure 6-4, the minimum value reached near t = 3000 seconds is different from the value reached at t = 4000 seconds. A varying critical value takes care of this variation. The algorithm used for the model is shown below.

1. Set an initial value or the initial seed for the number of infected vehicles.

$$i(0) = \eta + \gamma v \tag{6.8}$$

2. Use the S-I-R equation to predict the number of infected vehicles present in the network at the present time step.

$$i(t) = i(t-1) + \beta i(t-1)\rho_s(t-1) - \rho(t-1) \tag{6.9}$$

And

$$\beta(t) = \text{mod}(.00010v) * \sin(.1t) \tag{6.10}$$

3. If at any point of time during the simulation the number of infected vehicles drops below a critical value set the number of infected vehicle's value to the seed value.

$$\begin{gathered} \text{If } i(t) < N_c \text{ where} \\ N_c = \kappa + \lambda v \\ \text{Set } i(t) = \sigma + \delta v + \theta \sin(t) \end{gathered} \tag{6.11}$$

Where

$i(0)$ is the seed value or the initial value of the number of infected vehicles,

$i(t)$ is the number of infected vehicles at a time t,

β is the infectivity rate, expressed in min^{-1}.

N_c is the critical value, and

$\eta, \gamma, \kappa, \lambda, \sigma, \theta, \delta$ are all constants.

The following values were used to define the model for this scenario:

$\eta = 20; \gamma = 200; \kappa = 70; \lambda = 70; \sigma = 65; \theta = 3; \delta = 60.$

The figure 6-8 below shows the two distributions superimposed in one figure. The blue graph shows the simulation results and the red graph shows the results from the modified S-I-R model. A t-test was conducted to investigate the statistical significance of the results obtained, just like it was performed earlier for testing the representative models. The graphs were plotted after the model passed the t-test.

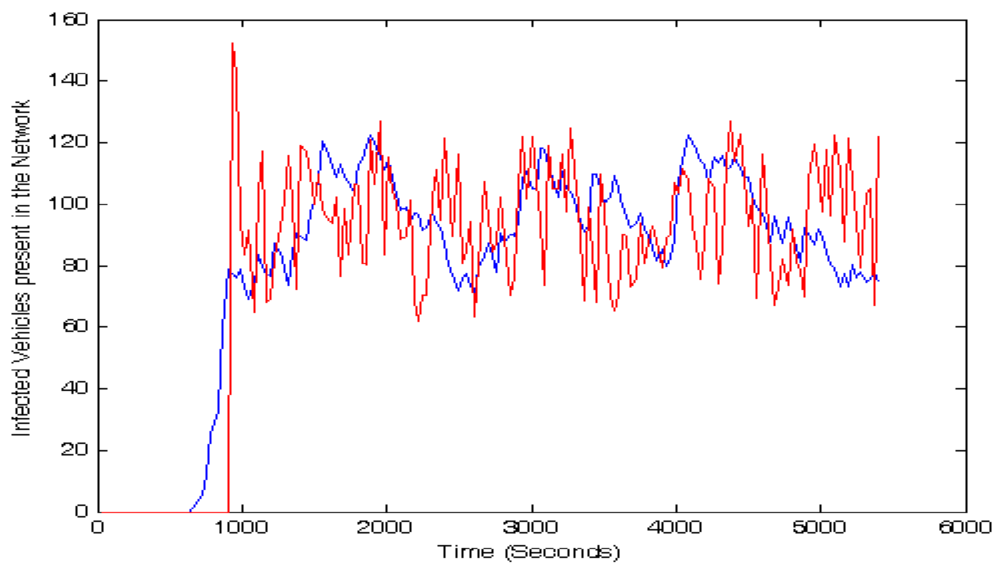


Figure 6-8: Simulation Results and model predicted results for Infected Vehicles Present in the Network

Table 6-1 below shows the traffic and the roadway conditions that were used to present the methodology adopted for the study. Table 6-2 compares the results obtained from the model with the results obtained from the simulation. It can be seen that the two representative models and the modified S-I-R model represent the original simulation results very accurately. The means and standard deviations for these are very close to one another. The similarity in the graphs (figures 6-6, 6-7 and 6-8) also suggests that the distributions are very close. A t-test was performed to statistically compare the means and the standard deviations of the results obtained from the model and from simulation results. The tests confirmed that the means and the standard deviations were not different from each other.

We denote the set of all the constants that constitute the mathematical model for one traffic scenario by the vector represented by **'**ψ**'.** Mathematically it is represented as follows:

$$\psi = \{ \alpha, \varpi, \tau, \phi, \alpha_s, \varpi_s, \tau_s, \phi_s, \eta, \gamma, \sigma, \delta, \theta, \kappa, \lambda \} \tag{6.12}$$

Table 6-1: Combination that was considered for describing the methodology

Volume(VPH)	Market Penetration (Percent)	Speed Limit (MPH)	Number of Lanes
4500	15	45	3

Table 6-2: Comparison of Simulation and Model Predicted Results for the present Scenario

	Simulation Results from Paramics	Results from the Model	Percentage Error
Mean of Infected Vehicles Leaving at Every Instant (Mortality Rate or Removal Rate)	11.66	12.21	5
Standard Deviation of Infected Vehicles Leaving at Every Instant (Mortality Rate or Removal Rate)	6.38	5.12	20
Mean of Uninfected but Instrumented Vehicles (Susceptible)	44.12	44.65	1
Standard Deviation of Uninfected but Instrumented Vehicles (Susceptible)	22.40	23.01	3
Mean of Infected Vehicles (Infected)	80.80	80.65	0
Standard Deviation of Infected Vehicles (Infected)	35.88	39.16	9

In the following pages we present some of the results obtained from the simulation and compared them with the results predicted by the models. The table 6-3 below shows details of the scenario for which the results are presented

Table 6-3: Combinations for scenarios 2 and 3.

Scenario	Volume(VPH)	Market Penetration (Percent)	Speed Limit (MPH)	Number of Lanes
2	6000	5	45	3
3	3000	15	45	3

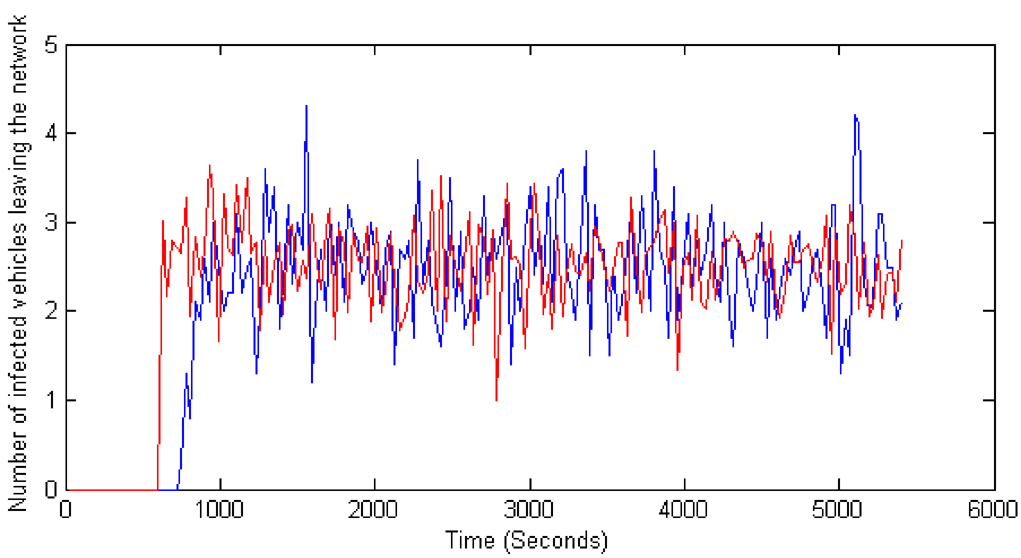


Figure 6-9: Simulation Results and model predicted results for Number of Vehicles Leaving the Network for scenario 2.

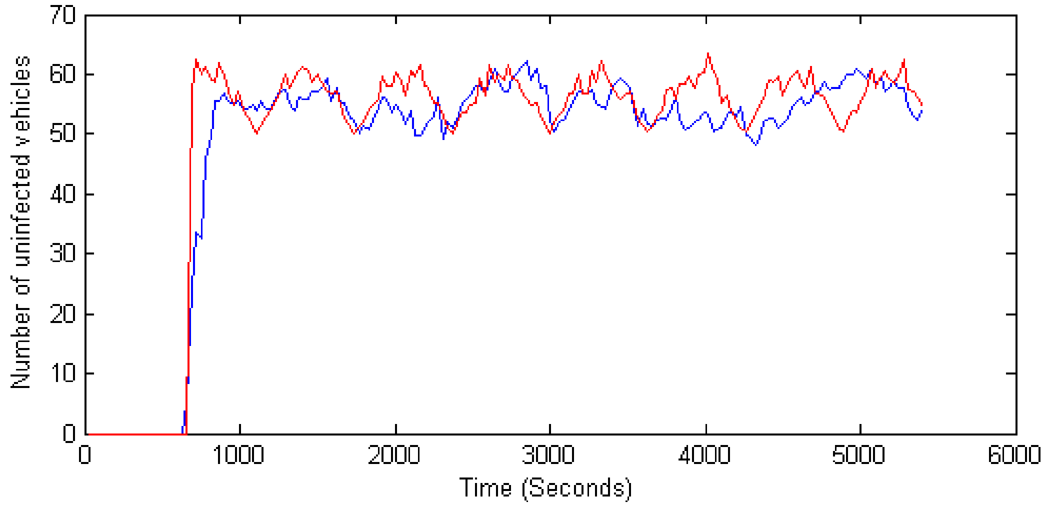


Figure 6-10: Simulation Results and model predicted results for Uninfected Vehicles Present in the Network for scenario 2.

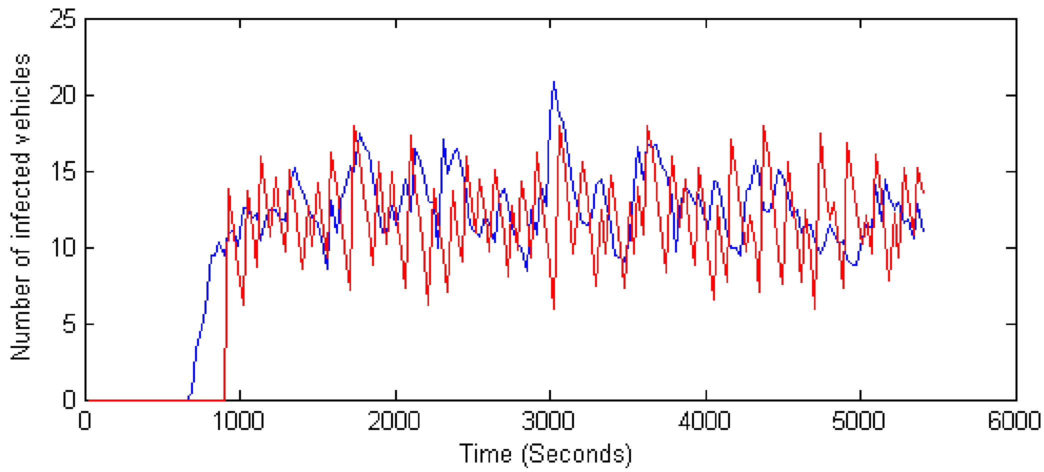


Figure 6-11: Simulation Results and model predicted results for Infected Vehicles Present in the Network for scenario 2.

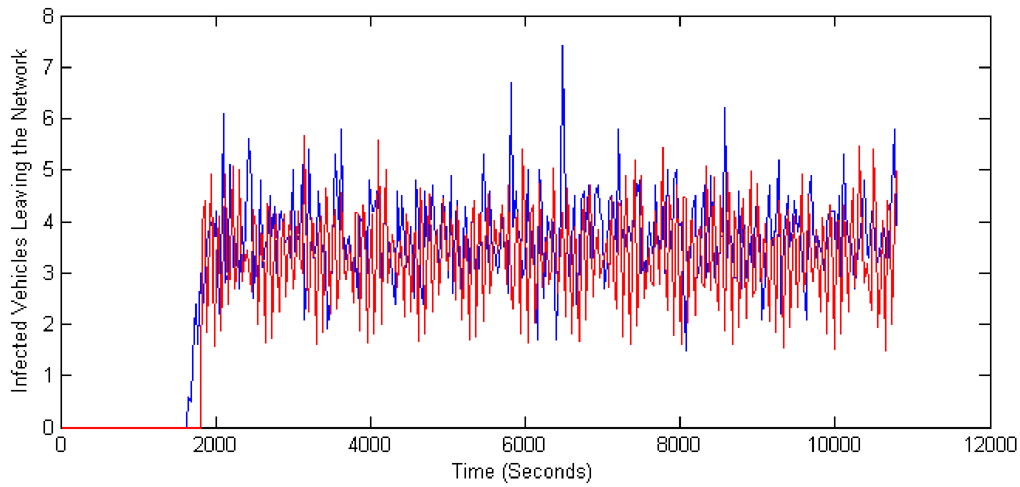


Figure 6-12: Simulation Results and model predicted results for Number of Vehicles Leaving the Network for scenario 3.

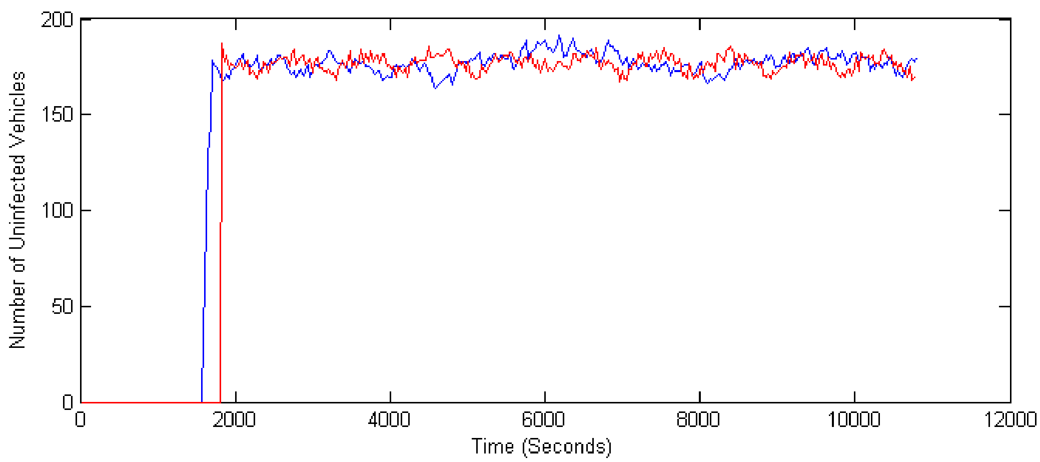


Figure 6-13: Simulation Results and model predicted results for Uninfected Vehicles Present in the Network for scenario 3.

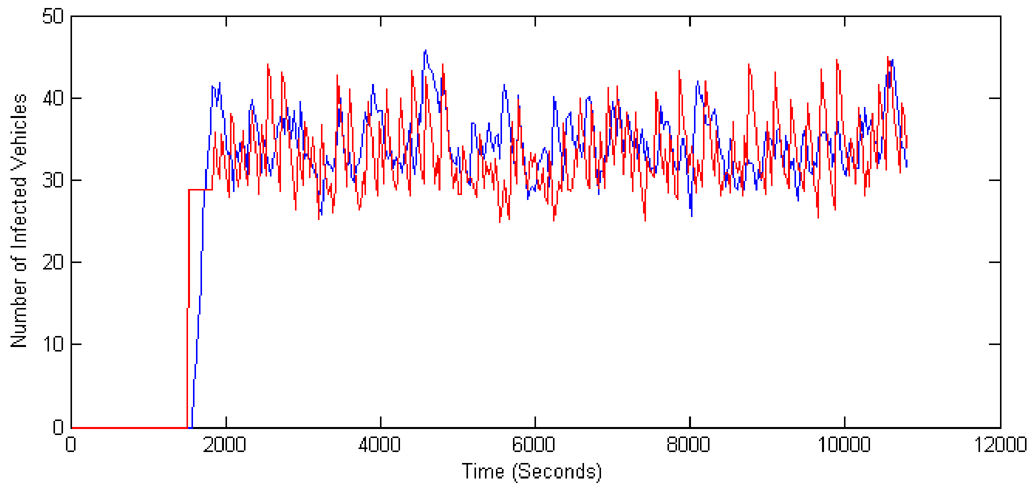


Figure 6-14: Simulation Results and model predicted results for Infected Vehicles Present in the Network for scenario 3.

Table 6-4: Values of all the constants for the model for high volumes (2000 vehicles per hour per lane)

			α	ώ	τ	Φ	αs	ώs	τs	Φs	ή	ν	σ	δ	θ	κ	λ
3 Lanes	Speed 30	M.P. 15	5	1	0	100	0	0.15	0	50	120	10	20	10	10	100	60
		M.P. 10	5	1	4	100	45	0.15	0	50	80	0	180	0	20	160	40
		M.P. 05	4.5	1	0	120	45	0.15	35	50	20	0	60	0	5	10	50
	Speed 45	M.P. 15	5	1	8	120	35	0.15	0	50	80	50	170	0	20	140	40
		M.P. 10	5	1	4	120	60	0.15	25	50	0	10	95	0	3	40	80
		M.P. 05	4	1	0	120	20	0.15	50	50	0	10	15	0	3	5	5
	Speed 60	M.P. 15	4.5	1	8	120	80	0.15	25	50	20	0	120	0	5	90	60
		M.P. 10	4.5	1	4	120	80	0.15	55	50	35	10	40	0	5	20	20
		M.P. 05	4	1	0	120	10	0.15	40	50	0	10	8	0	3	2.5	5
2 Lanes	Speed 30	M.P. 15	5	0.5	0	120	60	0.12	65	40	25	40	25	30	10	10	40
		M.P. 10	5	0.5	-1	120	30	0.12	55	40	6	30	12	7	1	5	30
		M.P. 05	1.75	0.5	0	120	10	0.12	32	40	3	4	4	2	1	3	4
	Speed 45	M.P. 15	5	0.5	0	120	20	0.12	62	40	10	5	12	3	3	10	10
		M.P. 10	4	0.5	-0.5	120	10	0.12	44	40	6	4	7	2	1	4	4
		M.P. 05	3	0.5	-1	120	10	0.12	20	40	1.5	2	2	2	1	1.5	2
	Speed 60	M.P. 15	5	0.5	0	120	20	0.12	48	40	6	6	6	5	1	10	10
		M.P. 10	4	0.5	-0.5	120	15	0.12	30	40	4	4	4	2	1	3	1
		M.P. 05	3	0.5	-1	120	10	0.12	15	40	1.5	2	2	1	0.75	1.5	2
1 Lane	Speed 30	M.P. 15	9	0.5	-1	120	40	0.12	58	40	15	20	16	20	5	15	20
		M.P. 10	5	0.5	-1.5	40	20	0.12	47	40	5	10	10	2	3	5	7
		M.P. 05	5	0.5	-0.5	120	20	0.12	48	40	7	5	9	5	2	6	2
	Speed 45	M.P. 15	5	0.5	-0.75	120	20	0.12	47	40	5	10	8	4	3	5	7
		M.P. 10	5	0.5	-1.5	120	20	0.12	31	40	3	5	4	3	1	3	4
		M.P. 05	5	0.5	-2	120	20	0.12	25	40	3	3	2	2	1	3	3
	Speed 60	M.P. 15	5	0.5	-0.75	120	20	0.12	47	40	5	10	8	4	3	5	7
		M.P. 10	3	0.5	-0.5	120	20	0.12	31	40	3	5	4	3	1	3	4
		M.P. 05	2	0.5	-0.5	120	10	0.12	16	40	1	2	1.5	2	0.5	1	1.5

Table 6-5: Values of all the constants for the model for medium volumes (1500 vehicles per hour per lane)

			α	ώ	τ	Φ	αs	ώs	τs	Φs	ή	ν	σ	δ	θ	κ	λ
		M.P. 15	8	0.5	0	120	130	0.12	25	40	35	20	60	30	3	60	40
	Speed 30	M.P. 10	6	0.08	0	120	100	0.12	15	40	15	10	40	20	3	30	30
		M.P. 05	6	0.08	0	120	100	0.12	10	40	10	6	85	50	3	100	50
		M.P. 15	8	0.5	0	120	100	0.12	35	40	45	45	48	30	3	40	40
3 Lanes	Speed 45	M.P. 10	6	0.08	0	120	50	0.12	60	40	10	20	15	20	3	15	20
		M.P. 05	3	0.08	0	120	20	0.12	39	40	5	5	5	5	3	5	3
		M.P. 15	8	0.5	0	120	40	0.12	62	40	10	10	16	10	3	10	10
	Speed 60	M.P. 10	6	0.08	0	120	35	0.12	52	40	8	20	10	6	3	8	10
		M.P. 05	3	0.5	0	120	20	0.12	29	40	3	3	5	2	3	3	2
		M.P. 15	3	0.5	-0.75	120	10	0.12	33	40	1	4	4	3	0.75	4	4
	Speed 30	M.P. 10	3	0.5	-1	120	15	0.12	30	40	3	5	4	3	1	3	3
		M.P. 05	2.5	0.5	-1	120	15	0.12	29	40	5	3	5	2	1	3	2
2 Lanes		M.P. 15	5	0.5	0	120	30	0.12	60	40	8	5	10	6	0.75	8	5
	Speed 45	M.P. 10	4	0.5	-0.5	120	15	0.12	42	40	5	5	6	4	1	4	3
		M.P. 05	2	0.5	-0.5	120	15	0.12	20	40	2	3	2	2	1	1.5	1.5
		M.P. 15	4	0.5	-0.5	120	15	0.12	30	40	3	5	3	4	1	3	3
	Speed 60	M.P. 10	3.5	0.5	0	120	20	0.12	32	40	3	4	3	4	1	3	4
		M.P. 05	2.5	0.5	-0.5	120	15	0.12	15	40	2	3	1.5	2	1	1.5	1.5
		M.P. 15	2	0.5	0	120	5	0.12	17	20	1	2	2	2	0	2	2
	Speed 30	M.P. 10	2	0.5	-1	120	8	0.12	15	20	2	3	2	2	1	2	2
		M.P. 05	1	0.5	-1	120	8	0.12	15	20	3	2	3	1	1	2	1
		M.P. 15	3	0.5	0	120	20	0.12	37	40	4	6	6	3	2	4	1
1 Lane	Speed 45	M.P. 10	4	0.5	-1.3	120	10	0.12	25	40	4	2	4	1	1	2	2
		M.P. 05	2.5	0.5	-1	120	5	0.12	14	40	2	3	1.5	1	0.5	1	1
		M.P. 15	4.5	0.5	-1	120	20	0.12	31	40	4	10	5	4	3	3	2
	Speed 60	M.P. 10	4	0.5	-1.35	120	10	0.12	21	40	4	3	3	1	1	2	1
		M.P. 05	2.2	0.5	-0.8	120	10	0.12	10	40	0.5	2	1	1	0.5	0.5	2

Table 6-6: Values of all the constants for the model for low volumes (1000 vehicles per hour per lane)

			α	ώ	τ	Φ	αs	ώs	τs	Φs	ή	ν	σ	δ	θ	κ	λ
3 Lanes	Speed 30	M.P. 15	6	0.5	0	120	80	0.12	15	40	100	50	90	40	3	100	50
		M.P. 10	4	0.5	0	120	70	0.12	45	40	10	5	20	30	3	20	20
		M.P. 05	2	0.5	0	120	15	0.12	35	40	4	4	6	1	3	6	1
	Speed 45	M.P. 15	6	0.5	0	120	40	0.12	70	40	30	15	15	10	3	15	20
		M.P. 10	4	0.5	0	120	20	0.12	50	40	5	5	8	5	3	5	10
		M.P. 05	2	0.5	0	120	15	0.12	25	40	2	2	4	1	0	2	1
	Speed 60	M.P. 15	6	0.5	0	120	40	0.12	55	40	5	5	10	5	3	15	20
		M.P. 10	4	0.5	0	120	15	0.12	38	40	4	4	6	1	3	6	1
		M.P. 05	2	0.5	0	120	15	0.12	20	40	2	2	2	2	0	2	1
2 Lanes	Speed 30	M.P. 15	4	0.5	0	120	53	0.12	10	27	67	33	60	27	2	67	33
		M.P. 10	3	0.5	0	120	47	0.12	30	27	7	3	13	20	2	13	13
		M.P. 05	1	0.5	0	120	10	0.12	23	27	3	3	4	1	2	4	1
	Speed 45	M.P. 15	4	0.5	0	120	27	0.12	47	27	20	10	10	7	2	10	13
		M.P. 10	3	0.5	0	120	13	0.12	33	27	3	3	5	3	2	3	7
		M.P. 05	1	0.5	0	120	10	0.12	17	27	1	1	3	1	0	1	1
	Speed 60	M.P. 15	4	0.5	0	120	27	0.12	37	27	3	3	7	3	2	10	13
		M.P. 10	3	0.5	0	120	10	0.12	25	27	3	3	4	1	2	4	1
		M.P. 05	1	0.5	0	120	10	0.12	13	27	1	1	1	1	0	1	1
1 Lane	Speed 30	M.P. 15	4	0.5	-1.3	120	10	0.12	39	40	0.5	4	5.5	2	2	4	3
		M.P. 10	2.5	0.5	-0.75	120	10	0.12	25	40	1.5	4	3.5	1	1	2	2
		M.P. 05	1.8	0.5	-0.75	40	5	0.12	13	40	1	2	1	1	0.25	1	2
	Speed 45	M.P. 15	3.5	0.5	-1	120	10	0.12	25	40	2	3	3	1	1	1.5	1.5
		M.P. 10	3	0.5	-1	120	8	0.12	17	40	1	3	2	1	0.5	1	1
		M.P. 05	2	0.5	-0.85	120	5	0.12	8	40	0.25	1	0.6	1	0.5	0	1
	Speed 60	M.P. 15	4.15	0.5	-1.35	120	20	0.12	19	40	1	4	3	1	1	1	1
		M.P. 10	3.15	0.5	-1.2	120	10	0.12	13	40	0.5	1.5	1.3	1.5	1	0.5	1.5
		M.P. 05	2	0.5	-0.9	120	7	0.12	6.5	40	0.5	1	0.7	0.5	0.25	0	0.5

CHAPTER 7: EXTENSIONS TO THE MODEL

In the earlier chapter we have described the model in detail and validated it using the simulation results from Paramics. In this chapter we try to make the model more comprehensive using a simple method to estimate the number of infected vehicles for intermediate values for flows, market penetrations and speed limits.

Consider a road network that consists of three lanes of road with a flow of 5000 vehicles per hour, market penetration of 12%, and a speed limit of 50MPH. The modeling performed in the previous chapter does not include this kind of a combination of traffic. On the other hand, modeling in the above manner for all kinds of such combinations individually would be impossible because it results in tens of thousands of combinations. It is therefore necessary to make use of these existing combinations and predict the mathematical constants for the modified S-I-R model for the states that fall in between. Making such an interpolation here is again tricky because we have three individual parameters, namely the market penetration, flow and the speed limit. We follow a weighted interpolation procedure that is described here.

7.1 Sensitivity Analysis

For each of such intermediate cases, eight different neighbors exist and the mathematical constants from these models are used to predict the constants for the intermediate traffic scenario. For example, for the current case, the following will be traffic states will be the primary states which would be used to predict the constants:

1. Speed: 45MPH, Market Penetration: 10%, Flow: 4500 VPH, Number of Lanes: 3
2. Speed: 45MPH, Market Penetration: 15%, Flow: 4500 VPH, Number of Lanes: 3

3. Speed: 45MPH, Market Penetration: 10%, Flow: 6000 VPH, Number of Lanes: 3
4. Speed: 45MPH, Market Penetration: 15%, Flow: 6000 VPH, Number of Lanes: 3
5. Speed: 60MPH, Market Penetration: 10%, Flow: 4500 VPH, Number of Lanes: 3
6. Speed: 60MPH, Market Penetration: 15%, Flow: 4500 VPH, Number of Lanes: 3
7. Speed: 60MPH, Market Penetration: 10%, Flow: 6000 VPH, Number of Lanes: 3
8. Speed: 60MPH, Market Penetration: 15%, Flow: 6000 VPH, Number of Lanes: 3

Before starting the process it is good to note that the intermediate points behave closely to the states closer to them. That is, for example, a road network consisting of a speed limit of 50MPH will resemble a network of 45MPH better than a network with a limit of 60 MPH. Greater weight will therefore be given to the mathematical constants of the 45MPH model than the corresponding 60MPH model. The following procedure was adopted for interpolating between the above specified set of states and obtaining the target state.

1. Interpolate between the flows by treating the other two variables as constants. For the present example, we make a set of four intermediate states that have a flow of 5000VPH. We interpolate for flows between states 1 and 3, 2 and 4, 5 and 7 and 6 and 8. By doing so, we get the following intermediate states. The common fact in all these states is that each of these will have 3 lanes of roadway.

   Intermediate State 1: Speed: 45MPH, Market Penetration: 10%, Flow: 5000 VPH

   Intermediate State 2: Speed: 45MPH, Market Penetration: 15%, Flow: 5000 VPH

   Intermediate State 3: Speed: 60MPH, Market Penetration: 10%, Flow: 5000 VPH

   Intermediate State 4: Speed: 60MPH, Market Penetration: 15%, Flow: 5000 VPH

If we look at intermediate state 1 alone, its characteristics (which include the number of infected and uninfected vehicles) will be closer to state 1 than state 3, as the flows in state 1 (4500VPH) are closer to 5000VPH than those of state 2 (6000VPH), and the rest of the parameters are the same. It would be reasonable to assume that the set of constants that define this intermediate state will be close to state 1 than state 3. The interpolation should therefore involve including a weighted factor that estimates intermediate values accurately.

Difference between 4500VPH and 5000VPH (denoted as ‘x’) = 500VPH

Difference between 5000VPH and 6000VPH (denoted as ‘y’) = 1000VPH. We denote

$$w_{4500} = \frac{y}{x+y} \tag{7.1}$$

and

$$w_{6000} = \frac{x}{x+y} \tag{7.2}$$

Where,

w_{4500} = Weight assigned to the constants represented by the state 1, and

w_{6000} = Weight assigned to the constants represented by the state 2.

For a flow of 5000VPH(a value that lies between 4500VPH and 6000VPH) the set of mathematical constants ψ_{int1} are estimated as follows:

$$\psi_{\text{int}1} = \psi_1(w_{4500}) + \psi_2(w_{6000}) \tag{7.3}$$

Where,

$\psi_{\text{int}1}$ = The set of constants defined by the intermediate state that consists of the flow of 5000VPH, market penetration of 10%, speed limit of 45MPH and 3 lanes.

ψ_1 = is the set of mathematical constants defined by state 1.

ψ_2 = is the set of mathematical constants defined by state 2.

A similar procedure is carried out to estimate the constants for the intermediate states 2, 3 and 4. Table 5 shows the values of each of these constants for each of the intermediate states. The number in the left most column of the table indicates the number of the intermediate state and the subsequent columns show the values of the corresponding constants in each state.

Table 7-1: Values of mathematical constants for the intermediate states obtained from the interpolation

	α	ϖ	τ	ϕ	α_s	ϖ_s	τ_s	ϕ_s	η	γ	σ	δ	θ	κ	λ
Intermediate State 1	7	0.67	2.67	120	78.33	0.13	23.33	43.33	56.67	46.67	88.67	20	8.67	73.33	40
Intermediate State 2	5.67	0.39	1.33	120	53.33	0.13	48.33	43.33	6.67	16.67	41.67	13.33	3	23.33	40
Intermediate State 3	6.83	0.67	2.67	120	53.33	0.13	49.67	43.33	13.33	6.67	50.67	6.67	3.67	36.67	26.67
Intermediate State 4	5.5	0.39	1.33	120	50	0.13	53	43.33	17	16.67	20	4	3.67	12	13.33

2. Interpolation between the intermediate states to obtain the values of the constants for the pre-final states. The next step involves interpolating the constants corresponding to the intermediate states 1 and 2 and states 3 and 4 for market penetration. The procedure followed for interpolation will be the same as the weighted interpolation method used for obtaining intermediate flows that was described earlier. This interpolation results in the following two states. We call these states as the pre-final states because they are the final two states that occur just before the final interpolation. These two states have the same number of lanes and flows.

   Pre-final state 1: Speed 45MPH, Market Penetration: 12%, Flow: 5000VPH

   Pre-final state 2: Speed 60MPH, Market Penetration: 12%, Flow: 5000VPH

3. Interpolation between the two pre-final states to obtain values of the constants for the target state. Upon interpolating the sets of constants for the two pre-final states, the corresponding values for the target states could be obtained. The final target state will have the following conditions.

   Target State: Speed 50MPH, Market Penetration: 12%, Flow: 5000VPH, Number of lanes: 3

   The procedure followed for interpolation, again will be the same as the weighted interpolation method used for obtaining intermediate flows that was described earlier.

   Table 6 below shows the values of the constants that define the modified S-I-R model for the two pre-final cases. The first row shows the values for each of the constants for pre-final state ‘1’ and the second row for the pre-final state ‘2’. The third row consists of the constants for the modified S-I-R model for the final required traffic state denoted here as the final target state.

Table 7-2: Values of mathematical constants for the pre-final states and the final target state

	α	ϖ	τ	ϕ	α_s	ϖ_s	τ_s	ϕ_s	η	γ	σ	δ	θ	κ	λ
Pre-final State 1	6.2	0.5	1.87	120	63.33	0.13	38.33	43.33	26.67	28.67	60.47	16	5.27	43.33	40
Pre- final State 2	6.03	0.5	1.87	120	51.33	0.13	51.67	43.33	15.53	12.67	32.27	5.07	3.67	21.87	18.67
Final Target State	6.14	0.5	1.87	120	59.33	0.13	42.78	43.33	22.96	23.33	51.07	12.36	4.73	36.18	32.89

Simulations were performed in Paramics to model the traffic conditions for the final target state. The simulation results were then compared with the results obtained by using the values of constants shown in table 4 in the modified S-I-R model. Table 7 shown below compares some performance measures. The model predicts the average number of infected vehicles leaving the network, the average number of infected vehicles in the network and the average number of uninfected vehicles present in the network very accurately, as the corresponding average values from the simulation results are very close. The corresponding values for the standard deviations are also very close. A t-test was conducted to test the statistical significance of these results and the test confirmed that the model predicted the results accurately.

Table 7-3: Comparison of Simulation Results and Predicted Results for Final Target State

	Simulation Results from Paramics	Results from the Model	Percentage Error
Mean of Infected Vehicles Leaving at Every Instant	4.38	4.97	13
Standard Deviation of Infected Vehicles Leaving at Every Instant	1.89	2.09	11
Mean of Uninfected but Instrumented Vehicles (Susceptible)	46.07	45.36	2
Standard Deviation of Uninfected but Instrumented Vehicles (Susceptible)	18.24	19.05	4
Mean of Infected Vehicles (Infected)	52.66	49.47	6
Standard Deviation of Infected Vehicles (Infected)	21.63	19.84	8

7.2 Extending the Model to two dimensions

We have been modeling the spread of infection on a single road network that consists of a straight road. However, it is obvious that the roads link to each other and form complex networks. These roads are therefore not one-dimensional and it is thus necessary for extending a model to two dimensions so that it becomes complete. For the purpose of extension of the study, we have assumed that the road networks are two-dimensional. This assumption ignores grade separated interchanges as they are in the third dimension.

In order to model the two-dimensional aspect of road networks, we treated both the dimensions as two single dimensions and modeled them individually. Consider the figure 7-1 that is shown below. The figure shown here is similar to the figure 5-1 in chapter 5, with the green line being the reference line and all the red dots are the instrumented vehicles that have been infected. Obviously the vehicles here are close enough for forming a connective chain. As a result the vehicles on the main link, that is the link 1 in the figure need not travel all the way to the reference line. Similarly, the vehicles on the adjacent link need not travel all the way to the reference line. Whenever they approach the junction, they come into contact with an infected vehicle traveling on the main link. This vehicle communicates backwards on the adjacent link in a similar fashion as the vehicles communicate on the main link. However as a result of low market penetrations or very small number of instrumented vehicles, if the information does not reach the place near the junction, there would be no scope for communication as shown in figure 7-2.

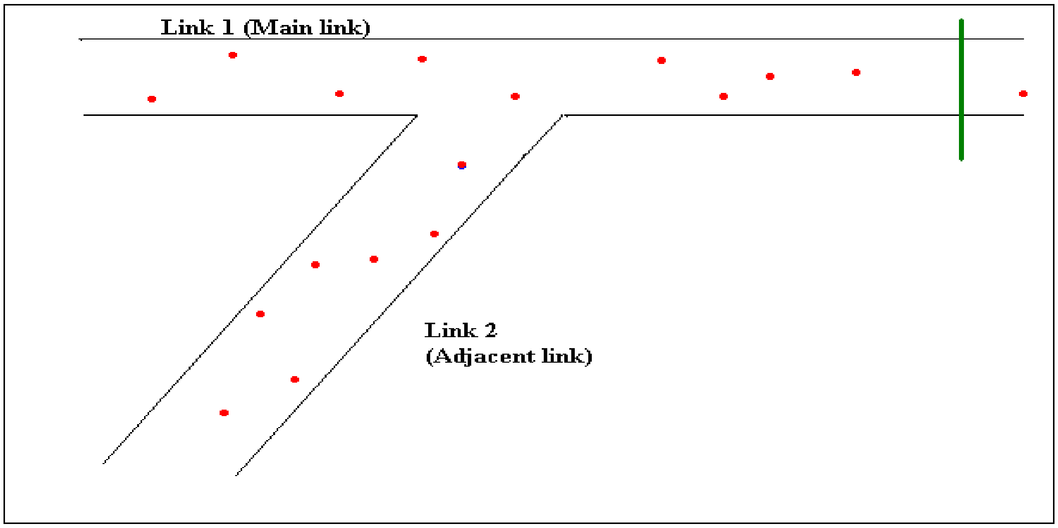


Figure 7-1: Two-dimensional network with all the vehicles infected.

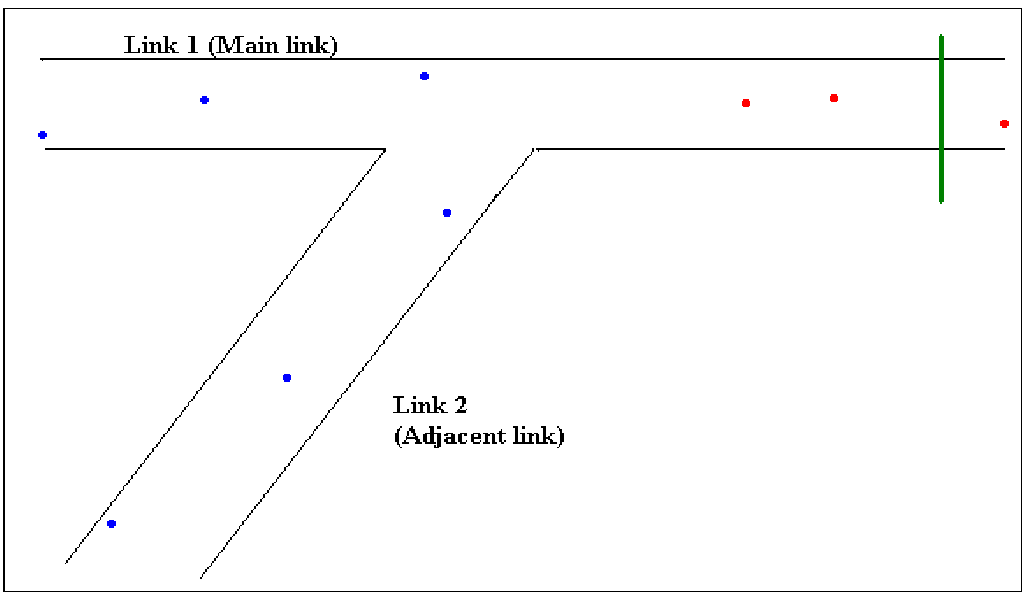


Figure 7-2: Two-dimensional network with some uninfected vehicles.

Thus it is imperative that a sizeable fraction of vehicles be instrumented on each link of the network so that the vehicles spread the infection effectively.

We tried to validate this by using the results from a simulation model developed in Paramics. A small link was constructed adjacent to the main link. This represented the adjacent link of the figures 7-1 and 7-2 above. Here, both the links consisted of similar configuration, consisting of three lanes in each direction with a speed limit of 30MPH and a market penetration of 15%. The simulation was performed for ten times and the results were averaged out. The quantities that were measured included the average number of infected and uninfected vehicles on each of the links. The results matched those predicted by the modified S-I-R model, for the corresponding combination.

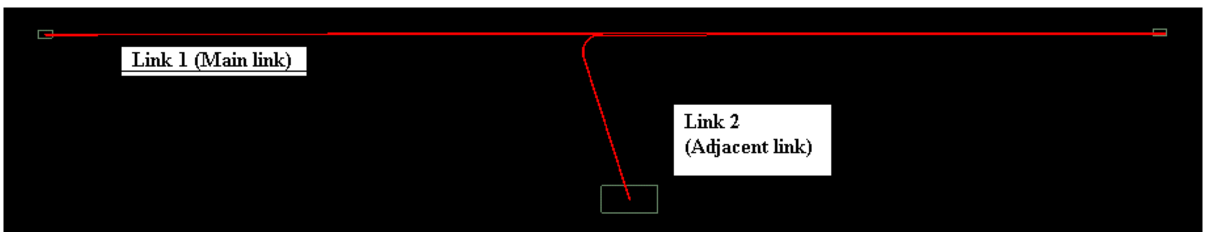


Figure 7-3: A snapshot of the two-dimensional network made in Paramics.

CHAPTER 8: COMPARISON WITH OTHER MODELS

In this chapter we compare the simulation results obtained from Paramics with other simulation studies that were conducted earlier.

Ozbay et al., (2007) studied the specific case of the South Jersey Network. Using Paramics, they calculated the rate of spread of infection over the network. With increasing market penetration values the rate of spread of inspection increased. In addition, as a result of cell-to-vehicle communication, there was a gradual increase in the infected area with time, which was not observed in the case of vehicle-to-vehicle communication In this section, we compare our algorithm with the one used by them.

The figure 8-1 shows the results obtained if the algorithm presented in Ozbay et al. (2007) was used. These results are obtained by simulating traffic on a straight stretch of a road that consists of 2 lanes, with a volume of 3000 vehicles per hour and a speed limit of 45 MPH. An incident occurs at the right end of the road. This incident spreads gradually to the downstream portion of the traffic stream, which is towards left. The uninfected stretch of the entire network is represented in blue and the infected stretch is represented in blue. The series of graphs indicate that there is a finite speed (this speed is not constant) at which the infection spreads. In thirty minutes, the entire network is infected. We performed a simulation in Paramics using the same network but we used our vehicle-to-vehicle communication algorithm (the one that was described in chapter 4) to study and compare the results. The obtained results are shown in the figure 8-2. There is a contrasting difference between the results obtained. The figures suggest that the information has not propagated in the network with progress of time. The spread varied with time but it did not grow with time as seen in the earlier figures.

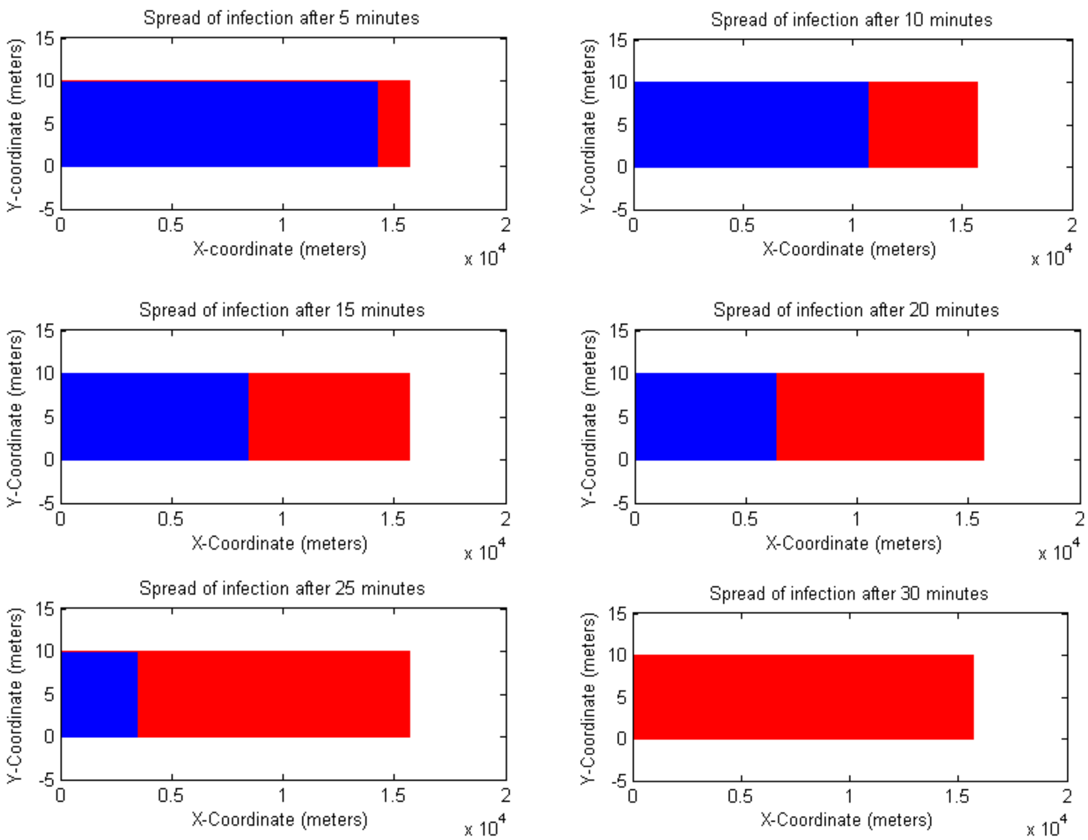
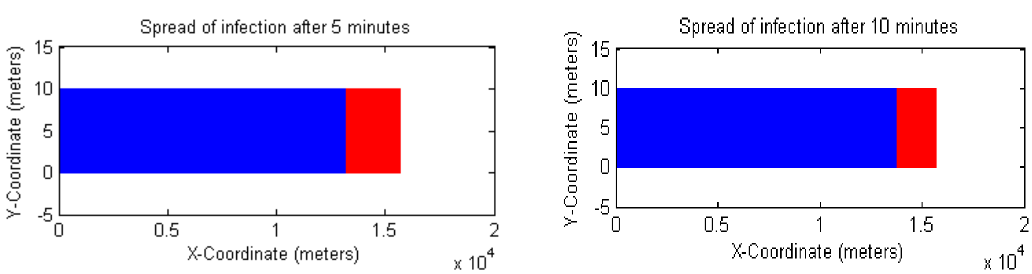


Figure 8-1. View of spread of information after 2 minutes and 5 minutes for a Market penetration: 3% (Modeling based on algorithm used in Ozbay et al., (2007)).



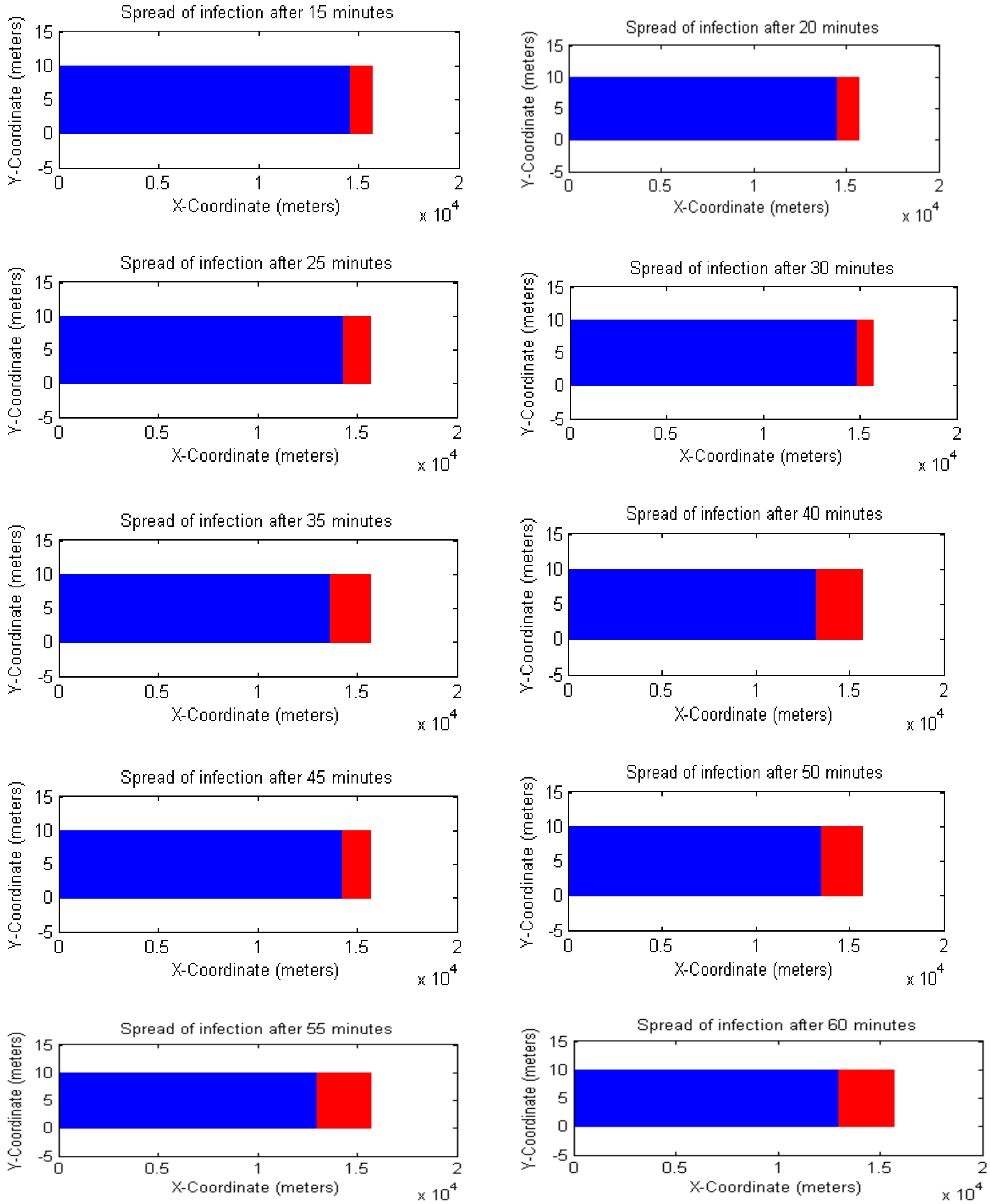


Figure 8-2: Results for Spread of infection during one hour of simulation based on the present study

Table 8-1: Comparison of the extent of spread of infection based on the two different models

Time from start of simulation (minutes)	Extent to which the information is spread	
	Ozbay et al.'s algorithm	Present Study
5	13%	16%
10	31%	13%
15	50%	9%
20	63%	9%
25	75%	13%
30	100%	9%
35	100%	16%
40	100%	19%
45	100%	13%
50	100%	16%
55	100%	19%
60	100%	16%

The main reason for the difference lies in the assumptions made while developing the algorithm, the flowchart of which is shown in figure 8-4 . We followed a vehicle centric approach wherein the vehicle is assumed to be the main and the only carrier of information. Communication is possible only between nearby vehicles. On the other hand, Ozbay et al. followed a cell-centric approach, where the whole network was divided into a number of cells. Whenever an infected vehicle travels in a specific cell, the cell is infected. This cell will remain infected for the rest of the simulation time. In addition whenever an uninfected vehicle passes such a cell, it gets infected too. Thus, the communication takes place in two different ways- namely vehicle-to-vehicle and cell-to-cell. We will now describe the whole process in a qualitative manner using a simple road link. The frequency of transmitting the signal in our study is same as the one that was used by Ozbay et al., namely two broadcasts per second.

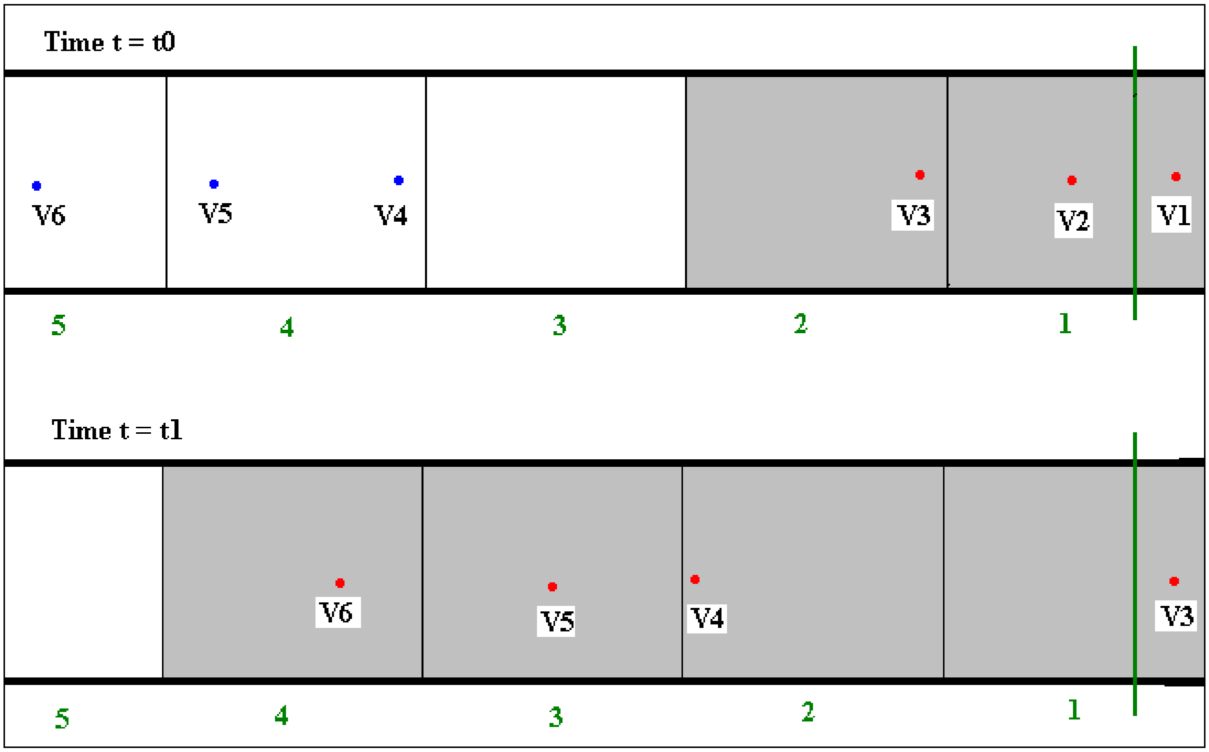


Figure 8-3: Communication process in a cell-based model

The figure 8-3 shows a straight link that was divided into equal-sized cells numbered 1 to 5 from right to left and labeled at the bottom of each cell. The green line at the far right end of the road that is drawn across the road is the reference line is the point of the incident or the hazard as described in earlier chapters. Each of the red dots represents an infected vehicle and a blue dot represents an uninfected but instrumented vehicle. Each vehicle has a name adjacent to it. At time t = t0, the vehicles V1, V2 and V3 that are close to the reference line are all infected. The cells 1 and 2 that contain these vehicles are infected as a result. Other instrumented vehicles are far away from the infected bunch, rendering communication impossible. At time t = t1, vehicle V4 just enters the cell 2. By the process of cell-to-vehicle communication vehicle V4 is now infected. Vehicles V5 and V6 are infected from V4 immediately by virtue of their neighborhood. V5 and V6 are in cells 3 and 4 which were not infected initially and thus are infected by virtue of vehicle-to-cell communication. A similar process continues for subsequent vehicles and the infection keeps spreading all over the network. In the downstream direction, a similar process occurs. In addition to this process, the infected vehicles keep infecting uninfected cells as they move forward on the network.

Precisely, on comparing the process used in the current study and the one used by Ozbay et al. it could be noted that the reference line is fixed in our model while it moves in the upstream direction with time and thus brings the changes in the communication pattern.

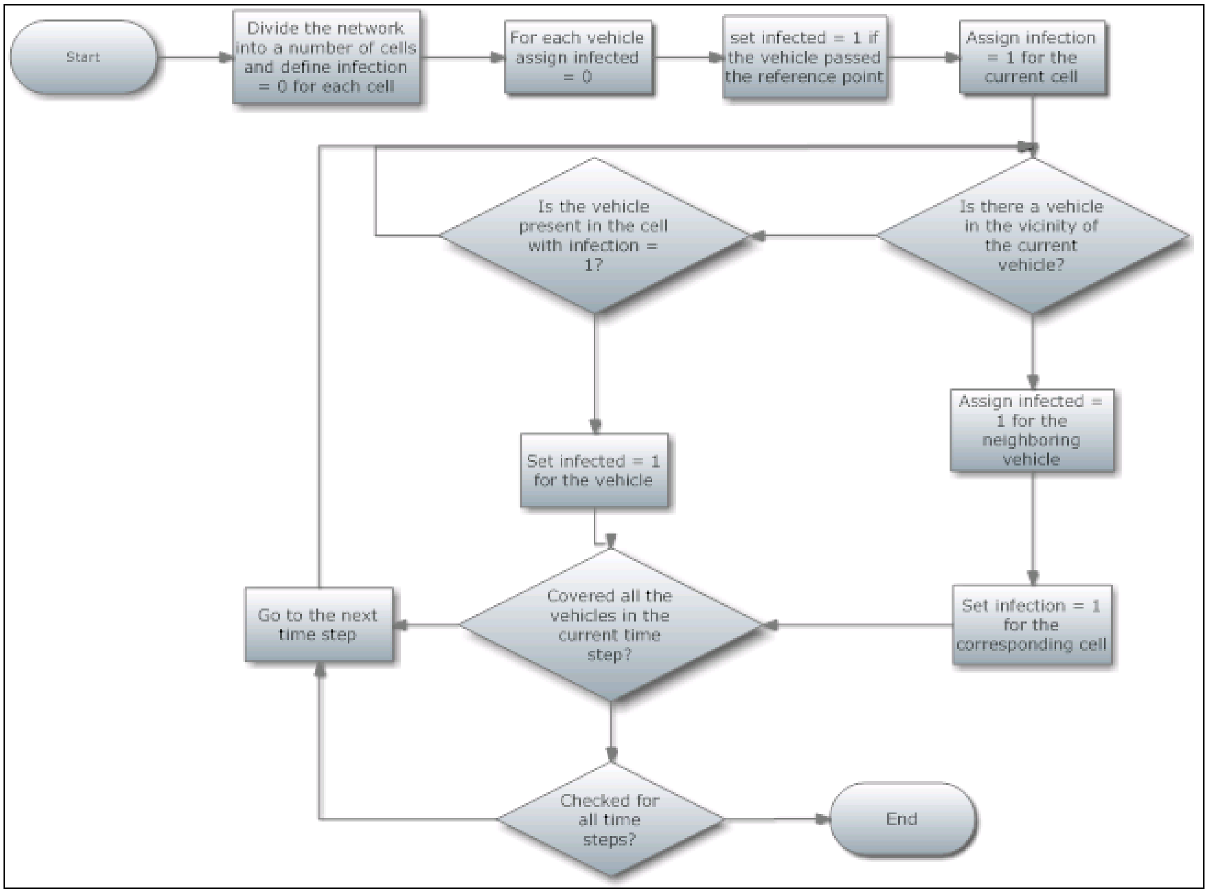


Figure 8-4. The cell-to-vehicle communication algorithm used by Ozbay et al., (2007).

Our general simulation results or the trends in our results appear to be similar to those observed by Zhang et al., (2005). In their study, they used Corsim to obtain the coordinates of vehicles and used a discrete event network simulator to study the communication. Their simulations were carried out on an I-75 model for a stretch in Florida, which is a multi lane roadway. During the A.M. and the P.M peaks when the traffic volumes are generally very high, the network connectivity is maintained for most of the time. On some occasions there were some gaps between vehicles that disabled the connectivity temporarily, however it took a small amount of time for the following vehicles to cover this gap and reconnect the whole traffic network. With high flows and fairly high market penetrations, the instrumented vehicles are very close to one another making connectivity a real possibility. At such high volumes, the gaps between instrumented vehicles (which disconnect the network) are small and can be easily covered by faster moving following vehicles. The relative speeds play an important role here. We have very similar observations from our study. The figure 8-5 below shows a snapshot of the data in Matlab. The figure shows the number of uninfected vehicles present in the network at different simulation time steps, each column represents results from a simulation run. The row number on the left is the number of time steps from the beginning of simulation. In the first run (represented by data in first column), there are no uninfected vehicles in the network (which means the entire network is connected) for the for six time steps. Then there is a gap between the vehicles entering the network in the next time step and the vehicles that were infected in the previous time step. This gap is greater than the radius of communication, which results in a loss of connectivity. As a result the vehicles that enter the network in the subsequent time steps also remain unaware. This happens for the next 5 time steps and the number of uninfected vehicles gets accrued in this time. However, at t = 12, by virtue of relative speed, this gap is closed and the wireless signal is received by one of the following vehicles, enabling the rest of the network gain connectivity. Thus relative speed helped regain connectivity in a small amount of time.

	1	2	3
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
5	0	0	6
6	0	0	14
7	5	0	21
8	15	0	27
9	22	5	0
10	30	9	0
11	39	13	0
12	0	0	0
13	0	0	0
14	0	0	0
15	0	0	0

Figure 8-5: A snapshot of a sample dataset from Matlab that shows the number of uninfected vehicles at different time steps for three different simulation runs.

CHAPTER 9: CONCLUSIONS

Modeling of vehicle-to-vehicle communication behavior is certainly not very straightforward owing to a lot of random components and variations in human driving behavior. In order to model this process accurately it is very important to understand the situation that happens in reality first and then develop models accordingly. For this purpose simulations were performed in Paramics for different values for traffic volumes, market penetrations and so on. This not only helped in developing an accurate model but also in understanding the various issues involved in communication. We answer the questions that were raised in chapter 4 here in the following paragraphs. These answers definitely help in understanding the process in a better way.

Importance of distance of propagation of infection: Consider the figure 9-1 below. In case 1, the instrumented vehicles are lesser in number when compared to case 2. When the first vehicle reaches the reference line, the platoon is infected. But as a result of the gap in between the platoons, this information does not propagate backwards. Thus, the next platoon is infected only when the first vehicle of that platoon reaches the reference line. In this manner, the communication between vehicles is limited and results in an average length of infection. When the number of instrumented vehicles increases, the length of infection increases as seen in case 2 of figure 8-6. When the number of instrumented vehicles is sufficiently high, the whole network becomes connected. Otherwise, the extent of spread of infection remains finite.

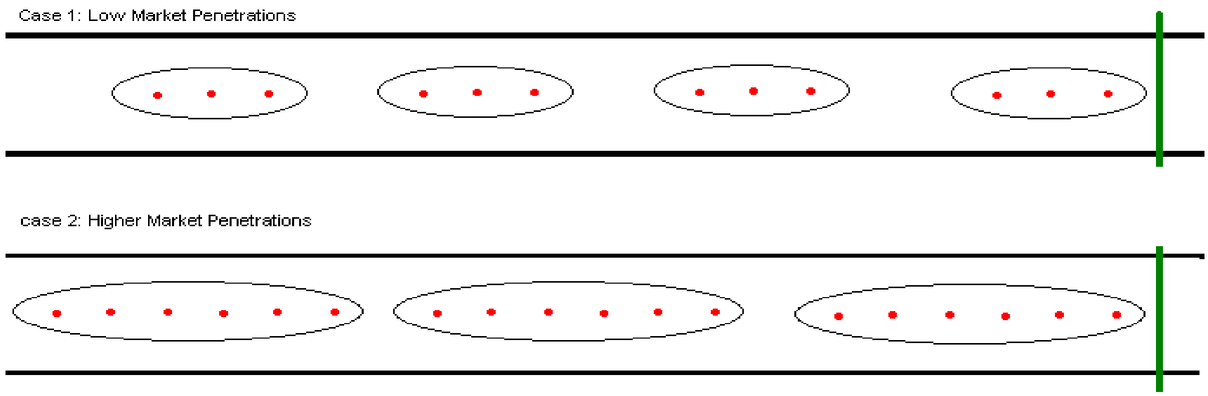


Figure 9-1: Average Distance of propagation of infection

Importance of Relative Speed. In figure 9-1, if case 1 and case 2 were compared, we observe that the gaps between the batches of vehicles are larger for lower market penetrations. Relative speeds play an important role in covering the smaller gaps and maintaining the connectivity and so play an important role in cases with higher market penetrations. At lower magnitudes the role played by relative speeds is less significant. Relative speed plays an important role in maintaining connectivity of the network at higher market penetrations. However, during low values, when the number of instrumented vehicles is low, relative speeds become irrelevant.

In case of an accident that results in slowing down of the traffic, a shock wave moves upstream. There will be greater congestion at the shock wave and at the traffic downstream of the shock wave. The signal is more likely to propagate in these dense conditions than the conditions upstream of the shock wave. In such cases, the signal propagation depends on the conditions upstream of the wave. If there are dense traffic conditions, there would be a negligible effect of shock wave on signal propagation. However, if the traffic is light, propagation becomes difficult as there would be no connectivity. Therefore, the information might not reach a point until the shock wave reaches it. In such cases, the minimum speed of propagation of the signal upstream would be the speed of the shock wave.

Rate of spread of information: The answer to this question is given in chapter 8, where we compared the results of this study with the results from Ozbay et al.(2005). Based on the assumptions made, that is whether the communication between vehicle-to-vehicle only or includes vehicle-to-cell and vice versa, there exists a rate for the spread of information. Otherwise, there is no rate of spread as the length of spread remains constant when there are voids in the network. Smaller voids are covered by faster vehicles and a completely connected network can cover any magnitudes of distances.

Mathematical representation of the distributions of spacing among vehicles: There are well accepted headway distributions for the following for general traffic. But for equipped vehicles this becomes more problematic due to the issues such as market penetration and lack of any real-data. Based on the results obtained from Easyfit, we believe that no mathematical distribution can accurately represent the spacing between vehicles in a traffic network at a level where a successful mathematical model could be developed.

A comprehensive model that predicts the spread of infection: The answer to this question is the main contribution of this study in addition to answering the questions. In the current study, we developed a model that predicts the number of infected vehicles on a road network. This study is based on the mathematical models that were developed to model the patterns of spread of epidemics in a region. We were successful in making a comprehensive model that could be used to predict the number of infected vehicles for a variety of combinations of number of lanes, speed limits, flows and market penetrations. If required, this model could also be extended for four or more lanes.

We believe that one of the main strengths of this study is its completeness. This model successfully avoids the use of simulation models for studying the communication. At low market penetrations, maintaining connectivity is generally difficult. This model helps in predicting the distance on the road to which the infection spreads. At this length a vehicle-to-roadside communicating device could be installed so that the infection spreads further backwards, thus increasing the connectivity. Studying the traffic conditions and installing such devices on a case-by-case basis is definitely more effective than installing them at regular intervals all over the network.

Unfortunately the research on VII is far from complete. A number of research questions related to the design of the wireless systems, reliable traffic information still exist. The impact of instrumented vehicles is not thoroughly studied. For example, if fifteen percent of the vehicles are instrumented and have the necessary information to detour, will it be sufficient to improve the traffic flows on the current roadway? Issues such as these have to be studied and will definitely form an excellent future study.

The large number of studies in the current field itself is a proof of the potential of vehicle-to-vehicle communication in improving the present day road networks. This will definitely be a breakthrough in the field of transportation if it could be implemented successfully.

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APPENDIX - I

The table below shows various traffic and geometric conditions for which the model was made.

Table 1. Different Scenarios

Scenario	Number of Lanes	Speed Limit (Miles Per Hour)	Market Penetration (Percent)	Flow (Vehicles Per Hour Per Lane)
1	3	30	15	2000
2	3	30	10	2000
3	3	30	5	2000
4	3	45	15	2000
5	3	45	10	2000
6	3	45	5	2000
7	3	60	15	2000
8	3	60	10	2000
9	3	60	5	2000
10	2	30	15	2000
11	2	30	10	2000
12	2	30	5	2000
13	2	45	15	2000
14	2	45	10	2000
15	2	45	5	2000
16	2	60	15	2000
17	2	60	10	2000
18	2	60	5	2000
19	1	30	15	2000
20	1	30	10	2000
21	1	30	5	2000
22	1	45	15	2000
23	1	45	10	2000

Table 2. Different Scenarios (Contd)

Scenario	Number of Lanes	Speed Limit (Miles Per Hour)	Market Penetration (Percent)	Flow (Vehicles Per Hour Per Lane)
24	1	45	5	2000
25	1	60	15	2000
30	3	30	5	1500
31	3	45	15	1500
32	3	45	10	1500
33	3	45	5	1500
34	3	60	15	1500
35	3	60	10	1500
36	3	60	5	1500
37	2	30	15	1500
38	2	30	10	1500
39	2	30	5	1500
40	2	45	15	1500
41	2	45	10	1500
42	2	45	5	1500
43	2	60	15	1500
44	2	60	10	1500
45	2	60	5	1500
46	1	30	15	1500
47	1	30	10	1500
48	1	30	5	1500
49	1	45	15	1500
50	1	45	10	1500
51	1	45	5	1500
52	1	60	15	1500
53	1	60	10	1500
54	1	60	5	1500

Table 3. Different Scenarios (contd)

Scenario	Number of Lanes	Speed Limit (Miles Per Hour)	Market Penetration (Percent)	Flow (Vehicles Per Hour Per Lane)
55	3	30	15	1500
56	3	30	10	1500
57	3	30	5	1500
58	3	45	15	1500
59	3	45	10	1000
60	3	45	5	1000
61	3	60	15	1000
62	3	60	10	1000
63	3	60	5	1000
64	2	30	15	1000
65	2	30	10	1000
66	2	30	5	1000
67	2	45	15	1000
68	2	45	10	1000
69	2	45	5	1000
70	2	60	15	1000
71	2	60	10	1000
72	2	60	5	1000
73	1	30	15	1000
74	1	30	10	1000
75	1	30	5	1000
76	1	45	15	1000
77	1	45	10	1000
78	1	45	5	1000
79	1	60	15	1000
80	1	60	10	1000
81	1	60	5	1000

Table 4. Results for Scenario 1

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	1.99	2.33
Standard Deviation – Mortality Rate	1.16	1.25
Mean – Susceptible Vehicles	36.77	36.25
Standard Deviation – Susceptible Vehicles	19.9	18.52
Mean - Infected Vehicles	40.48	42.85
Standard Deviation - Infected Vehicles	22.95	21.90

Table 5. Results for Scenario 2

	Simulation Results from Paramics	Results from S-I-R Analogous Model
Mean – Mortality Rate	2.15	2.26
Standard Deviation – Mortality Rate	1.04	0.89
Mean – Susceptible Vehicles	47.87	49.67
Standard Deviation – Susceptible Vehicles	18.35	18.86
Mean - Infected Vehicles	10.91	9.93
Standard Deviation - Infected Vehicles	4.80	5.19

Table 6. Results for Scenario 3

	Simulation Results from Paramics	Results from S-I-R Analogous Model
Mean – Mortality Rate	2.17	2.22
Standard Deviation – Mortality Rate	0.93	0.89
Mean – Susceptible Vehicles	37.92	38.77
Standard Deviation – Susceptible Vehicles	12.48	13.05
Mean - Infected Vehicles	7.11	6.33
Standard Deviation - Infected Vehicles	2.94	2.92

Table 7. Results for Scenario 4

	Simulation Results from Paramics	Results from S-I-R Analogous Model
Mean – Mortality Rate	3.90	4.19
Standard Deviation – Mortality Rate	2.10	2.16
Mean – Susceptible Vehicles	7.35	8.31
Standard Deviation – Susceptible Vehicles	7.10	6.76
Mean - Infected Vehicles	144.0	146.3
Standard Deviation - Infected Vehicles	71.77	72.63

Table 8. Results for Scenario 5

	Simulation Results from Paramics	Results from S-I-R Analogous Model
Mean – Mortality Rate	4.22	4.63
Standard Deviation – Mortality Rate	1.85	1.76
Mean – Susceptible Vehicles	41.4	39.7
Standard Deviation – Susceptible Vehicles	18.54	16.55
Mean - Infected Vehicles	75.4	74.9
Standard Deviation - Infected Vehicles	32.05	34.12

Table 9. Results for Scenario 6

	Simulation Results from Paramics	Results from S-I-R Analogous Model
Mean – Mortality Rate	4.39	4.33
Standard Deviation – Mortality Rate	1.65	1.64
Mean – Susceptible Vehicles	58.76	61.29
Standard Deviation – Susceptible Vehicles	19.82	21.56
Mean - Infected Vehicles	31.39	32.24
Standard Deviation - Infected Vehicles	13.42	12.36

Table 10. Results for Scenario 7

	Simulation Results from Paramics	Results from S-I-R Analogous Model
Mean – Mortality Rate	5.89	5.86
Standard Deviation – Mortality Rate	3.17	3.00
Mean – Susceptible Vehicles	0	0
Standard Deviation – Susceptible Vehicles		
Mean - Infected Vehicles	(All vehicles in the system)	(All vehicles in the system)
Standard Deviation - Infected Vehicles		

Table 11. Results for Scenario 8

	Simulation Results from Paramics	Results from S-I-R Analogous Model
Mean – Mortality Rate	6.41	6.15
Standard Deviation – Mortality Rate	2.63	2.74
Mean – Susceptible Vehicles	8.30	9.28
Standard Deviation – Susceptible Vehicles	7.13	6.68
Mean - Infected Vehicles	146.24	144.69
Standard Deviation - Infected Vehicles	60.75	59.23

Table 12. Results for Scenario 9

	Simulation Results from Paramics	Results from S-I-R Analogous Model
Mean – Mortality Rate	6.58	6.55
Standard Deviation – Mortality Rate	2.48	2.52
Mean – Susceptible Vehicles	35.37	35.66
Standard Deviation – Susceptible Vehicles	17.02	14.27
Mean - Infected Vehicles	100.92	104.26
Standard Deviation - Infected Vehicles	36.61	37.29

Table 13. Results for Scenario 10

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	2.51	2.60
Standard Deviation – Mortality Rate	1.60	1.36
Mean – Susceptible Vehicles	59.93	60.05
Standard Deviation – Susceptible Vehicles	29.79	29.93
Mean - Infected Vehicles	32.1	31.8
Standard Deviation - Infected Vehicles	17.34	17.60

Table 14. Results for Scenario 11

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate		
Standard Deviation – Mortality Rate		
Mean – Susceptible Vehicles		
Standard Deviation – Susceptible Vehicles		
Mean - Infected Vehicles		
Standard Deviation - Infected Vehicles		

Table 15. Results for Scenario 12

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	0.83	0.9
Standard Deviation – Mortality Rate	0.54	0.48
Mean – Susceptible Vehicles	26.62	27.11
Standard Deviation – Susceptible Vehicles	13.46	13.38
Mean - Infected Vehicles	4.04	3.99
Standard Deviation - Infected Vehicles	2.16	2.11

Table 16. Results for Scenario 13

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	2.62	2.72
Standard Deviation – Mortality Rate	1.27	1.22
Mean – Susceptible Vehicles	56.46	56.25
Standard Deviation – Susceptible Vehicles	21.31	22.71
Mean - Infected Vehicles	11.67	11.5
Standard Deviation - Infected Vehicles	5.24	5.03

Table 17. Results for Scenario 14

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	1.77	1.77
Standard Deviation – Mortality Rate	0.83	0.83
Mean – Susceptible Vehicles	38.93	39.33
Standard Deviation – Susceptible Vehicles	15.01	15.87
Mean - Infected Vehicles	6.68	6.29
Standard Deviation - Infected Vehicles	2.86	2.81

Table 18. Results for Scenario 15

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	0.83	0.77
Standard Deviation – Mortality Rate	0.49	0.44
Mean – Susceptible Vehicles	18.98	18.42
Standard Deviation – Susceptible Vehicles	7.53	7.45
Mean - Infected Vehicles	2.71	2.58
Standard Deviation - Infected Vehicles	1.36	1.31

Table 19. Results for Scenario 16

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	2.83	2.83
Standard Deviation – Mortality Rate	1.26	1.13
Mean – Susceptible Vehicles	46.28	45.74
Standard Deviation – Susceptible Vehicles	14.86	16.33
Mean - Infected Vehicles	8.15	7.54
Standard Deviation - Infected Vehicles	3.24	3.04

Table 20. Results for Scenario 17

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	1.78	1.78
Standard Deviation – Mortality Rate	0.83	0.75
Mean – Susceptible Vehicles	30.29	28.41
Standard Deviation – Susceptible Vehicles	9.83	10.14
Mean - Infected Vehicles	4.62	4.21
Standard Deviation - Infected Vehicles	1.95	1.78

Table 21. Results for Scenario 18

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	0.89	0.82
Standard Deviation – Mortality Rate	0.45	0.43
Mean – Susceptible Vehicles	15.48	14.68
Standard Deviation – Susceptible Vehicles	5.38	5.27
Mean - Infected Vehicles	2.07	2.14
Standard Deviation - Infected Vehicles	0.9	0.93

Table 22. Results for Scenario 19

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	3.9	3.71
Standard Deviation – Mortality Rate	2.72	2.05
Mean – Susceptible Vehicles	52.22	52.38
Standard Deviation – Susceptible Vehicles	26.48	26.01
Mean - Infected Vehicles	21.25	20.66
Standard Deviation - Infected Vehicles	12.4	11.65

Table 23. Results for Scenario 20

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	1.26	1.3
Standard Deviation – Mortality Rate	0.76	0.8
Mean – Susceptible Vehicles	40.85	40.12
Standard Deviation – Susceptible Vehicles	21.06	19.82
Mean - Infected Vehicles	8.62	8.34
Standard Deviation - Infected Vehicles	4.74	4.53

Table 24. Results for Scenario 21

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	2.12	2.16
Standard Deviation – Mortality Rate	1.33	1.15
Mean – Susceptible Vehicles	41	41.15
Standard Deviation – Susceptible Vehicles	21.16	20.33
Mean - Infected Vehicles	8.73	8.32
Standard Deviation - Infected Vehicles	4.88	4.54

Table 25. Results for Scenario 22

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	2.02	2.1
Standard Deviation – Mortality Rate	0.97	1.01
Mean – Susceptible Vehicles	43.43	42.95
Standard Deviation – Susceptible Vehicles	17.24	17.36
Mean - Infected Vehicles	8.75	8.36
Standard Deviation - Infected Vehicles	3.99	4.01

Table 26. Results for Scenario 23

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	1.34	1.45
Standard Deviation – Mortality Rate	0.68	0.77
Mean – Susceptible Vehicles	29.55	29.48
Standard Deviation – Susceptible Vehicles	12.1	11.99
Mean - Infected Vehicles	4.79	4.7
Standard Deviation - Infected Vehicles	2.23	2.17

Table 27. Results for Scenario 24

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	1.73	1.78
Standard Deviation – Mortality Rate	0.85	0.88
Mean – Susceptible Vehicles	37.52	36.6
Standard Deviation – Susceptible Vehicles	15.11	14.86
Mean - Infected Vehicles	6.97	6.41
Standard Deviation - Infected Vehicles	3.19	3.06

Table 28. Results for Scenario 25

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	2.11	2.11
Standard Deviation – Mortality Rate	1.01	0.99
Mean – Susceptible Vehicles	45.49	43.71
Standard Deviation – Susceptible Vehicles	18.13	17.72
Mean - Infected Vehicles	9.15	8.12
Standard Deviation - Infected Vehicles	4.14	3.95

Table 29. Results for Scenario 26

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	1.37	1.24
Standard Deviation – Mortality Rate	0.63	0.53
Mean – Susceptible Vehicles	29.32	30.63
Standard Deviation – Susceptible Vehicles	9.82	11.03
Mean - Infected Vehicles	4.48	4.64
Standard Deviation - Infected Vehicles	1.98	2.13

Table 30. Results for Scenario 27

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	0.72	0.71
Standard Deviation – Mortality Rate	0.4	0.33
Mean – Susceptible Vehicles	15.73	15.7
Standard Deviation – Susceptible Vehicles	5.36	5.64
Mean - Infected Vehicles	1.85	2.04
Standard Deviation - Infected Vehicles	0.85	0.97

Table 31. Results for Scenario 28

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	20.25	18.73
Standard Deviation – Mortality Rate	10.31	9.38
Mean – Susceptible Vehicles	3.2	3.32
Standard Deviation – Susceptible Vehicles	3.94	2.61
Mean - Infected Vehicles	165.08	166.09
Standard Deviation - Infected Vehicles	80.89	82.19

Table 32. Results for Scenario 29

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	12.38	13.72
Standard Deviation – Mortality Rate	7.38	6.89
Mean – Susceptible Vehicles	21.88	20.75
Standard Deviation – Susceptible Vehicles	13.39	12.71
Mean - Infected Vehicles	90.91	86.77
Standard Deviation - Infected Vehicles	45.38	45.23

Table 33. Results for Scenario 30

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	2.95	3.1
Standard Deviation – Mortality Rate	1.65	1.65
Mean – Susceptible Vehicles	23.7	20.9
Standard Deviation – Susceptible Vehicles	14.06	12.93
Mean - Infected Vehicles	87.42	88.87
Standard Deviation - Infected Vehicles	44.18	45.73

Table 34. Results for Scenario 31

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	12.21	11.77
Standard Deviation – Mortality Rate	6.38	5.09
Mean – Susceptible Vehicles	44.15	42.77
Standard Deviation – Susceptible Vehicles	22.4	21.52
Mean - Infected Vehicles	80.8	79.72
Standard Deviation - Infected Vehicles	35.89	39.24

Table 35. Results for Scenario 32

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	3.13	3.31
Standard Deviation – Mortality Rate	1.41	1.46
Mean – Susceptible Vehicles	60.39	60.61
Standard Deviation – Susceptible Vehicles	23.06	21.87
Mean - Infected Vehicles	23.6	22.31
Standard Deviation - Infected Vehicles	10.98	9.44

Table 36. Results for Scenario 33

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	1.58	1.65
Standard Deviation – Mortality Rate	0.76	0.73
Mean – Susceptible Vehicles	35.97	36.47
Standard Deviation – Susceptible Vehicles	13.62	14.79
Mean - Infected Vehicles	6.27	6.3
Standard Deviation - Infected Vehicles	2.8	3.28

Table 37. Results for Scenario 34

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	2.42	2.53
Standard Deviation – Mortality Rate	1.05	1.04
Mean – Susceptible Vehicles	44.19	44.61
Standard Deviation – Susceptible Vehicles	15.33	15.5
Mean - Infected Vehicles	9.22	8.87
Standard Deviation - Infected Vehicles	3.81	3.99

Table 38. Results for Scenario 35

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	3.27	3.42
Standard Deviation – Mortality Rate	1.33	1.36
Mean – Susceptible Vehicles	52.41	52.75
Standard Deviation – Susceptible Vehicles	17.05	16.22
Mean - Infected Vehicles	12.17	11.45
Standard Deviation - Infected Vehicles	4.82	4.71

Table 39. Results for Scenario 36

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	1.61	1.69
Standard Deviation – Mortality Rate	0.76	0.66
Mean – Susceptible Vehicles	27.91	28.65
Standard Deviation – Susceptible Vehicles	9.29	10.31
Mean - Infected Vehicles	4.43	4.74
Standard Deviation - Infected Vehicles	1.94	2.53

Table 40. Results for Scenario 37

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	0.87	0.96
Standard Deviation – Mortality Rate	0.55	0.57
Mean – Susceptible Vehicles	27.92	28.05
Standard Deviation – Susceptible Vehicles	14.01	13.85
Mean - Infected Vehicles	4.34	4.44
Standard Deviation - Infected Vehicles	2.45	2.38

Table 41. Results for Scenario 38

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	0.83	0.74
Standard Deviation – Mortality Rate	0.51	0.47
Mean – Susceptible Vehicles	25.93	26.37
Standard Deviation – Susceptible Vehicles	13	13.07
Mean - Infected Vehicles	4.29	4.26
Standard Deviation - Infected Vehicles	2.31	2.31

Table 42. Results for Scenario 39

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	0.81	0.86
Standard Deviation – Mortality Rate	0.51	0.49
Mean – Susceptible Vehicles	25.82	25.37
Standard Deviation – Susceptible Vehicles	13.07	12.56
Mean - Infected Vehicles	4.1	4.3
Standard Deviation - Infected Vehicles	2.3	2.31

Table 43. Results for Scenario 40

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	2.65	2.71
Standard Deviation – Mortality Rate	1.28	1.19
Mean – Susceptible Vehicles	56.96	56.35
Standard Deviation – Susceptible Vehicles	21.62	21.21
Mean - Infected Vehicles	11.3	10.82
Standard Deviation - Infected Vehicles	4.88	4.71

Table 44. Results for Scenario 41

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	1.69	1.79
Standard Deviation – Mortality Rate	0.86	0.84
Mean – Susceptible Vehicles	38.18	38.04
Standard Deviation – Susceptible Vehicles	14.09	15.36
Mean - Infected Vehicles	6.39	6.33
Standard Deviation - Infected Vehicles	2.87	2.85

Table 45. Results for Scenario 42

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	0.64	0.68
Standard Deviation – Mortality Rate	0.37	0.34
Mean – Susceptible Vehicles	19.13	19.28
Standard Deviation – Susceptible Vehicles	7.52	7.86
Mean - Infected Vehicles	2.69	2.5
Standard Deviation - Infected Vehicles	1.28	1.25

Table 46. Results for Scenario 43

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	1.82	1.84
Standard Deviation – Mortality Rate	0.82	0.77
Mean – Susceptible Vehicles	30.52	28.97
Standard Deviation – Susceptible Vehicles	10.23	10.35
Mean - Infected Vehicles	4.72	4.45
Standard Deviation - Infected Vehicles	1.91	2.05

Table 46. Results for Scenario 44

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	1.85	2.01
Standard Deviation – Mortality Rate	0.86	0.79
Mean – Susceptible Vehicles	31.34	31.06
Standard Deviation – Susceptible Vehicles	10.55	11.12
Mean - Infected Vehicles	4.84	4.31
Standard Deviation - Infected Vehicles	2.02	1.94

Table 47. Results for Scenario 45

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	0.89	0.99
Standard Deviation – Mortality Rate	0.46	0.43
Mean – Susceptible Vehicles	15.53	15.54
Standard Deviation – Susceptible Vehicles	5.54	5.67
Mean - Infected Vehicles	2.12	2.21
Standard Deviation - Infected Vehicles	0.95	1.14

Table 48. Results for Scenario 46

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	1.86	1.84
Standard Deviation – Mortality Rate	0.89	0.69
Mean – Susceptible Vehicles	37.9	36.77
Standard Deviation – Susceptible Vehicles	14.49	14.62
Mean - Infected Vehicles	6.95	6.65
Standard Deviation - Infected Vehicles	3.17	2.84

Table 49. Results for Scenario 47

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	2.83	2.68
Standard Deviation – Mortality Rate	1.33	0.96
Mean – Susceptible Vehicles	60.27	58
Standard Deviation – Susceptible Vehicles	23.43	23.57
Mean - Infected Vehicles	11.79	11.08
Standard Deviation - Infected Vehicles	5.38	4.53

Table 50. Results for Scenario 48

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	2.24	2.14
Standard Deviation – Mortality Rate	1.07	0.83
Mean – Susceptible Vehicles	47.86	46.29
Standard Deviation – Susceptible Vehicles	18.72	18.79
Mean - Infected Vehicles	8.97	8.55
Standard Deviation - Infected Vehicles	4.1	3.56

Table 51. Results for Scenario 49

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	1.64	1.6
Standard Deviation – Mortality Rate	0.82	0.71
Mean – Susceptible Vehicles	35.44	34.59
Standard Deviation – Susceptible Vehicles	14	14.02
Mean - Infected Vehicles	6.15	6.01
Standard Deviation - Infected Vehicles	2.82	2.58

Table 52. Results for Scenario 50

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	1.05	1.06
Standard Deviation – Mortality Rate	0.56	0.59
Mean – Susceptible Vehicles	23.03	22.88
Standard Deviation – Susceptible Vehicles	9.29	9.25
Mean - Infected Vehicles	3.34	3.47
Standard Deviation - Infected Vehicles	1.55	1.6

Table 53. Results for Scenario 51

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	0.55	0.48
Standard Deviation – Mortality Rate	0.33	0.32
Mean – Susceptible Vehicles	12.56	12.74
Standard Deviation – Susceptible Vehicles	5.19	5.15
Mean - Infected Vehicles	1.6	1.71
Standard Deviation - Infected Vehicles	0.8	0.81

Table 54. Results for Scenario 52

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	1.7	1.66
Standard Deviation – Mortality Rate	0.8	0.73
Mean – Susceptible Vehicles	31	30.43
Standard Deviation – Susceptible Vehicles	10.05	10.95
Mean - Infected Vehicles	6.14	5.84
Standard Deviation - Infected Vehicles	3.02	3.04

Table 55. Results for Scenario 53

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	1.08	1.07
Standard Deviation – Mortality Rate	0.55	0.58
Mean – Susceptible Vehicles	20.59	19.98
Standard Deviation – Susceptible Vehicles	6.93	7.13
Mean - Infected Vehicles	3.19	3.06
Standard Deviation - Infected Vehicles	1.48	1.31

Table 56. Results for Scenario 54

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	0.57	0.53
Standard Deviation – Mortality Rate	0.32	0.3
Mean – Susceptible Vehicles	10.28	10.3
Standard Deviation – Susceptible Vehicles	3.69	3.75
Mean - Infected Vehicles	1.31	1.3
Standard Deviation - Infected Vehicles	0.65	0.66

Table 57. Results for Scenario 55

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	3.04	3.09
Standard Deviation – Mortality Rate	1.68	1.65
Mean – Susceptible Vehicles	22.87	24.45
Standard Deviation – Susceptible Vehicles	15.91	14.06
Mean - Infected Vehicles	89.95	89.4
Standard Deviation - Infected Vehicles	45.55	45.13

Table 58. Results for Scenario 56

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	2.01	2.06
Standard Deviation – Mortality Rate	1.15	1.09
Mean – Susceptible Vehicles	45.53	46.19
Standard Deviation – Susceptible Vehicles	23.4	23.51
Mean - Infected Vehicles	28.85	28.62
Standard Deviation - Infected Vehicles	16	15.37

Table 59. Results for Scenario 57

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	0.95	1.02
Standard Deviation – Mortality Rate	0.57	0.54
Mean – Susceptible Vehicles	30.26	29.85
Standard Deviation – Susceptible Vehicles	15.06	14.74
Mean - Infected Vehicles	5.36	5.16
Standard Deviation - Infected Vehicles	3.01	3.04

Table 60. Results for Scenario 58

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	3.2	3.22
Standard Deviation – Mortality Rate	1.47	1.58
Mean – Susceptible Vehicles	65	65.82
Standard Deviation – Susceptible Vehicles	24.12	26.7
Mean - Infected Vehicles	18.6	17.57
Standard Deviation - Infected Vehicles	8.12	7.92

Table 61. Results for Scenario 59

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	2.11	2.1
Standard Deviation – Mortality Rate	1.03	1.01
Mean – Susceptible Vehicles	46.43	45.54
Standard Deviation – Susceptible Vehicles	17.57	18.4
Mean - Infected Vehicles	8.93	8.68
Standard Deviation - Infected Vehicles	4.09	4.19

Table 62. Results for Scenario 60

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	1.05	1.11
Standard Deviation – Mortality Rate	0.54	0.49
Mean – Susceptible Vehicles	23.93	23.56
Standard Deviation – Susceptible Vehicles	9.23	9.57
Mean - Infected Vehicles	3.44	3.31
Standard Deviation - Infected Vehicles	1.49	1.51

Table 63. Results for Scenario 61

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	3.4	3.44
Standard Deviation – Mortality Rate	1.46	1.38
Mean – Susceptible Vehicles	54.09	54.98
Standard Deviation – Susceptible Vehicles	17.45	19.78
Mean - Infected Vehicles	11.63	11.19
Standard Deviation - Infected Vehicles	4.78	4.73

Table 64. Results for Scenario 62

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	2.21	2.27
Standard Deviation – Mortality Rate	0.92	0.91
Mean – Susceptible Vehicles	36.17	35.97
Standard Deviation – Susceptible Vehicles	11.85	12.82
Mean - Infected Vehicles	6.2	5.49
Standard Deviation - Infected Vehicles	2.39	2.9

Table 65. Results for Scenario 63

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	1.08	1.07
Standard Deviation – Mortality Rate	0.53	0.48
Mean – Susceptible Vehicles	18.76	19.21
Standard Deviation – Susceptible Vehicles	6.36	7.84
Mean - Infected Vehicles	2.61	2.49
Standard Deviation - Infected Vehicles	1.11	1.14

Table 66. Results for Scenario 64

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	1.22	1.3
Standard Deviation – Mortality Rate	0.66	0.64
Mean – Susceptible Vehicles	29.23	29.42
Standard Deviation – Susceptible Vehicles	13.06	13.8
Mean - Infected Vehicles	6.2	6.18
Standard Deviation - Infected Vehicles	3.26	3.29

Table 67. Results for Scenario 65

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	1.35	1.52
Standard Deviation – Mortality Rate	0.79	0.8
Mean – Susceptible Vehicles	39.7	39.62
Standard Deviation – Susceptible Vehicles	19.77	19.76
Mean - Infected Vehicles	9.8	9.86
Standard Deviation - Infected Vehicles	5.41	5.45

Table 68. Results for Scenario 66

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	0.65	0.74
Standard Deviation – Mortality Rate	0.43	0.48
Mean – Susceptible Vehicles	21.1	22.08
Standard Deviation – Susceptible Vehicles	10.86	10.94
Mean - Infected Vehicles	3.19	3.15
Standard Deviation - Infected Vehicles	1.83	1.72

Table 69. Results for Scenario 67

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	1.04	1.1
Standard Deviation – Mortality Rate	0.59	0.63
Mean – Susceptible Vehicles	26.47	27.16
Standard Deviation – Susceptible Vehicles	11.55	11.99
Mean - Infected Vehicles	4.13	3.84
Standard Deviation - Infected Vehicles	2.08	1.96

Table 70. Results for Scenario 68

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	1.42	1.47
Standard Deviation – Mortality Rate	0.76	0.78
Mean – Susceptible Vehicles	31.84	32.23
Standard Deviation – Susceptible Vehicles	12.23	13.04
Mean - Infected Vehicles	5.08	4.54
Standard Deviation - Infected Vehicles	2.32	2.21

Table 71. Results for Scenario 69

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	0.7	0.79
Standard Deviation – Mortality Rate	0.43	0.43
Mean – Susceptible Vehicles	16.17	16.16
Standard Deviation – Susceptible Vehicles	6.31	6.57
Mean - Infected Vehicles	2.22	2.18
Standard Deviation - Infected Vehicles	1.08	1.15

Table 72. Results for Scenario 70

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	1.1	1.16
Standard Deviation – Mortality Rate	0.57	0.61
Mean – Susceptible Vehicles	20.77	20.62
Standard Deviation – Susceptible Vehicles	7.28	7.77
Mean - Infected Vehicles	2.98	3
Standard Deviation - Infected Vehicles	1.33	1.42

Table 73. Results for Scenario 71

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	1.49	1.53
Standard Deviation – Mortality Rate	0.71	0.79
Mean – Susceptible Vehicles	25.36	25.08
Standard Deviation – Susceptible Vehicles	8.25	8.96
Mean - Infected Vehicles	3.75	3.82
Standard Deviation - Infected Vehicles	1.57	1.7

Table 74. Results for Scenario 72

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	0.72	0.83
Standard Deviation – Mortality Rate	0.39	0.43
Mean – Susceptible Vehicles	12.53	12.04
Standard Deviation – Susceptible Vehicles	4.29	4.34
Mean - Infected Vehicles	1.68	1.67
Standard Deviation - Infected Vehicles	0.76	0.87

Table 75. Results for Scenario 73

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	0.98	1
Standard Deviation – Mortality Rate	0.63	0.61
Mean – Susceptible Vehicles	32.11	32.92
Standard Deviation – Susceptible Vehicles	16.39	16.24
Mean - Infected Vehicles	5.32	5.28
Standard Deviation - Infected Vehicles	2.88	2.98

Table 76. Results for Scenario 74

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	0.62	0.69
Standard Deviation – Mortality Rate	0.44	0.44
Mean – Susceptible Vehicles	21.43	21.34
Standard Deviation – Susceptible Vehicles	11.15	10.54
Mean - Infected Vehicles	2.98	3.18
Standard Deviation - Infected Vehicles	1.71	1.73

Table 77. Results for Scenario 75

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	0.32	0.31
Standard Deviation – Mortality Rate	0.26	0.23
Mean – Susceptible Vehicles	11	11.07
Standard Deviation – Susceptible Vehicles	5.73	5.47
Mean - Infected Vehicles	1.33	1.24
Standard Deviation - Infected Vehicles	0.81	0.7

Table 78. Results for Scenario 76

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	1.02	1.01
Standard Deviation – Mortality Rate	0.58	0.54
Mean – Susceptible Vehicles	22.6	23.11
Standard Deviation – Susceptible Vehicles	9.09	9.36
Mean - Infected Vehicles	3.19	2.99
Standard Deviation - Infected Vehicles	1.48	1.42

Table 79. Results for Scenario 77

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	0.72	0.77
Standard Deviation – Mortality Rate	0.41	0.44
Mean – Susceptible Vehicles	16.35	15.7
Standard Deviation – Susceptible Vehicles	6.49	6.36
Mean - Infected Vehicles	2.09	2.16
Standard Deviation - Infected Vehicles	0.97	0.97

Table 80. Results for Scenario 78

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	0.34	0.35
Standard Deviation – Mortality Rate	0.24	0.25
Mean – Susceptible Vehicles	7.58	7.62
Standard Deviation – Susceptible Vehicles	3.05	3.1
Mean - Infected Vehicles	0.93	0.94
Standard Deviation - Infected Vehicles	0.51	0.57

Table 81. Results for Scenario 79

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	1.1	1.17
Standard Deviation – Mortality Rate	0.59	0.55
Mean – Susceptible Vehicles	19.76	19.53
Standard Deviation – Susceptible Vehicles	6.67	7.11
Mean - Infected Vehicles	3.05	3.09
Standard Deviation - Infected Vehicles	1.51	1.31

Table 82. Results for Scenario 80

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	0.72	0.72
Standard Deviation – Mortality Rate	0.47	0.41
Mean – Susceptible Vehicles	12.85	12.85
Standard Deviation – Susceptible Vehicles	4.67	4.63
Mean - Infected Vehicles	1.85	1.82
Standard Deviation - Infected Vehicles	0.97	1.03

Table 83. Results for Scenario 81

	Simulation Results from Paramics	Results from the Model
Mean – Mortality Rate	0.35	0.33
Standard Deviation – Mortality Rate	0.23	0.25
Mean – Susceptible Vehicles	6.69	6.75
Standard Deviation – Susceptible Vehicles	2.49	2.46
Mean - Infected Vehicles	0.86	0.82
Standard Deviation - Infected Vehicles	0.49	0.4

APPENDIX – II

This section contains the C++ and the Matlab programs used for generating and analyzing results from Paramics.

Part 1. The C++ code to extract coordinates from the Paramics Network:

```
#include <stdlib.h>
#include <stdio.h>
#include <string.h>
#include <math.h>

#include "programmer.h"

/* include our function definitions explicit to this example */
#include "plugin_p.h"
#include "LT_p.h"


// Output file parameters
FILE *g_InfoFilePtr = NULL;
FILE *g_TrajFilePtr = NULL;
FILE *g_SpeedFilePtr = NULL;
FILE *g_FilePtr = NULL;
FILE *g_TravelTimePtr = NULL;
static char		*path;
FILE *readfile, *readfile2, *writefile, *writefile2;
int number_of_timesteps;
int counter = 0;
int vehicle_number_counter = 0;
char fullfilename[200], fullfilename3[200];
int vehicle_count = 0;
float percent = 0.10;
int length = 0;
int total = 0;
//float time;

// store the distances traveled for each vehicle in order to generate output
typedef struct distancerecord_s distancerecord;
struct distancerecord_s
{
	float xcood;
```

```
        float ycood;
        int vehID;
        int travtime;
        int check;
        int entry_time;
        int exit_time;

};




//InfoRecord *vehrecord = NULL;


/* Start control function calls */

/* -----------------------------------------------------------------
 * call api_setup once when the full network has been read into modeller
 * ----------------------------------------------------------------- */
void qpx_NET_postOpen(void)
{
        int f;


        number_of_timesteps = 0;

        path = qpg_NET_dataPath();
        strcpy(fullfilename, path);
        strcat(fullfilename,"/");
        strcat(fullfilename, "timings");
        strcat(fullfilename, ".");
        strcat(fullfilename, "txt");




        path = qpg_NET_datapath();
        strcpy(fullfilename3, path);
        strcat(fullfilename3,"/");
        strcat(fullfilename3, "results");
        strcat(fullfilename3, ".");
        strcat(fullfilename3, "txt");
```

```
            writefile = fopen(fullfilename3, "w");



    // Prepare Log Files
    pp_prepare_log_files();



}

void qpx_NET_timeStep()
{
    // count the number of time steps
        number_of_timesteps = number_of_timesteps + 1;



    //print the information about the time steps and the number of vehicles in the network in
a separate file.
{
        fprintf(writefile2, "%d, %d\n",number_of_timesteps/2, vehicle_number_counter);
  vehicle_number_counter = 0;
        }





}



void  qpx_VHC_timeStep(VEHICLE* vehicle)
{
      distancerecord *distanceinfo = NULL;
      distanceinfo = (distancerecord*)qpg_VHC_userdata(vehicle);
      if(!vehicle) return;
        if(distanceinfo != NULL)
        {
              if(distanceinfo->check == 0)
              {
                  //calculate the travel time of each vehicle
                    distanceinfo->travtime = distanceinfo->travtime + 1;
```

```
                    }
            }
}


void qpx_LNK_vehicleTimeStep(LINK* link, VEHICLE* vehicle)
{
                    distancerecord *distances = NULL;
      distancerecord *distanceinfo = NULL;
            //nalrecord *records_transfer = NULL;
            int k,j;
            float x,y,z,b,g;
            distanceinfo = (distancerecord*)qpg_VHC_userdata(vehicle);




            if(!vehicle) return;
            if(distanceinfo != NULL)
            {

          //extract the coordinates of vehicles here
qpg_POS_vehicle(vehicle, link, &x, &y,&z, &b, &g);

{distanceinfo->xcood = 1*x;
distanceinfo->ycood = y;
}



if(distanceinfo->check == 0)
                    {
          if(counter>=1)
          {

// print the coordinates of each of the vehicle  in a separate file
if(number_of_timesteps % 6 == 0)
{
          fprintf(g_InfoFilePtr,"%d, %d, %d \n", qpg_VHC_uniqueID(vehicle),
(int)distanceinfo->xcood, number_of_timesteps/2);

          //fprintf(g_InfoFilePtr,"hello");
          //qps_GUI_printf("hello");
}
```

```
}
}

            }

}

void  qpx_VHC_transfer(VEHICLE* vehicle, LINK* link1, LINK* link2)
{
          distancerecord *distanceinfo = NULL;
          distanceinfo = (distancerecord*)qpg_VHC_userdata(vehicle);
          if(!vehicle) return;
            if(distanceinfo != NULL)
            {
                      //this check ensures the vehicle entered the main network
                      if(strcmp(qpg_LNK_name(link1),"1:2") == 0)
                      {
                                if(strcmp(qpg_LNK_name(link2),"2:3") == 0)
                                {

                                distanceinfo->check = 0;
                                distanceinfo->entry_time = (int)qpg_CFG_simulationTime();

                                }
                      }

                      if(strcmp(qpg_LNK_name(link1),"2:3") == 0)
```

```
                { //this check ensures that  recording the data ends after the vehicle leaves
the main network
                        if(strcmp(qpg_LNK_name(link2),"3:4") == 0)
                        {
                        counter = counter + 1;
                        distanceinfo->check = 2;
                        distanceinfo->exit_time = (int)qpg_CFG_simulationTime();
                        distanceinfo->travtime = distanceinfo->exit_time - distanceinfo-
>entry_time;

                       // fprintf(writefile2, "%d, %d\n", distanceinfo->vehID,
length/distanceinfo->travtime);
                        }
                }
        }
}




void qpx_VHC_release(VEHICLE *vehicle)
{

//      InfoRecord *vehrecord = NULL;
        distancerecord *distanceinfo = NULL;
//      finalrecord *records = NULL;
        int j;
        float time;



    float Marker;


    /* check for a bad vehicle */
  if(!vehicle) return;




//generate the vehicles with wireless equipped functionalities according  to the market
penetration value

                Marker = qpg_UTL_randomFloat(APIRNG_RELEASE, 1.0);
```

```
   // if(Marker < 0.08)
                    //for all vehicles, use this, or use the above condiiton
                    if(Marker < percent)
   {


//Assign initial values to each of the vehicles as soon as it is released
   distanceinfo = (distancerecord*)malloc(sizeof(distancerecord));


   distanceinfo->xcood=0;
distanceinfo->ycood = 0;
distanceinfo->travtime = 0;
distanceinfo->check = 2;
distanceinfo->entry_time = 0;
distanceinfo->exit_time = 0;
distanceinfo->vehID = qpg_VHC_uniqueID(vehicle);
vehicle_count = vehicle_count + 1;
time = qpg_CFG_simulationTime();
fprintf(writefile,"%d,%f\n", qpg_VHC_uniqueID(vehicle), qpg_CFG_simulationTime());








   qps_VHC_userdata(vehicle, (VHC_USERDATA*) distanceinfo);
   //fprintf(g_InfoFilePtr, "hello\n\n");

   }
   }

   void  qpx_VHC_arrive(VEHICLE* vehicle, LINK* link, ZONE* zone)
   {
//Make note of the vehicles that have completed the journey
      distancerecord *distanceinfo = NULL;
         distanceinfo = (distancerecord*)qpg_VHC_userdata(vehicle);
         if(!vehicle) return;
           if(distanceinfo != NULL)
           {
```

```
                vehicle_number_counter = vehicle_number_counter + 1;
            }
    }



void pp_prepare_log_files(void)
{
    char fullFileName[200];
    char temp_string[20];
        char fullfilename2[200];
    int randomInteger;

    /* Prepare a log file for writing messages */
    path = qpg_NET_dataPath();
    randomInteger = qpg_UTL_randomInteger(APIRNG_MISC, 1000);

    /* copy the fully qualified name of the file in another variable */


    /* Prepare a log file for writing messages */
    path = qpg_NET_dataPath();

        strcpy(fullfilename2, path);
      strcat(fullfilename2,"/");
      strcat(fullfilename2, "traveltimes");
      itoa(randomInteger,temp_string,10);
      strcat(fullfilename2, temp_string);
      //strcat(fullfilename2, ".");
      strcat(fullfilename2, ".txt");
      qps_GUI_printf("\nLog File:%s\n", fullfilename2);
      writefile2 = fopen(fullfilename2, "w");

    /* copy the fully qualified name of the file in another variable */
    strcpy(fullFileName, path);
    strcat(fullFileName, "/");
    strcat(fullFileName, "InformationFile");
    itoa(randomInteger,temp_string,10);
    strcat(fullFileName, temp_string);
    strcat(fullFileName,".txt");
    qps_GUI_printf("\nLog File:%s\n", fullFileName);


       // path = qpg_NET_datapath();
```

```
    /* Prepare Log file for travel times to each bridges */
    /* Open the file in WRITE mode */
    g_InfoFilePtr = fopen(fullFileName, "w");
    if (g_InfoFilePtr == NULL) {
        qps_GUI_printf("File: %s not found!", fullFileName);
        exit(-1);
    }

}
```

Part 2. Matlab code for analyzing the extracted data

```
% First import the file containing the coordinates of vehicles
 and name it as data. All the values
% can be changed if required by changing the initialized variables.

 %radius of communication;

Radius = 600;
%Arrange the coordinates by increasing vehicle ID
coordinates = sortrows(data,1);
coordinates(:,2) = coordinates(:,2)*-1;
first_coordinate = min(coordinates(:,2));

coordinates(:,2) = coordinates(:,2) - first_coordinate;
last_coordinate = max(coordinates(:,2));
coordinates = sortrows(coordinates,1);
%coordinates(1,1) = 1;
flow_out(:,3) = flow_out(:,1);
flow_out(:,1) = flow_out(:,2);
flow_out(:,2) = flow_out(:,3);
flow_out = flow_out(:,1:2);
Make the vehicle Ids continuous for easier processing
vector(1:length(coordinates),1) = 1;
for i = 1:length(coordinates) - 1
    if coordinates(i+1,1) > coordinates(i,1)
```

```
        vector(i+1,1) = vector(i,1) + 1;
    end
    if coordinates(i+1,1) == coordinates(i,1)
        vector(i+1,1) = vector(i,1);
    end
end
coordinates(:,1) = vector;

Sort vehicle coordinates according to time steps in order to read each
time step separately
coordinates = sortrows(coordinates,3);
first_time = coordinates(1,3);
current_row = 1;
current_time = 1;
last_time = coordinates(length(coordinates),3);
last_vehicle = max(coordinates(:,1));
infection(1:length(coordinates),1) = 0;
vehicle(1:last_vehicle,1:last_time) = 0;
vehcood(1:last_vehicle,1:last_time) = -2;
minimum(1:last_time,1) = -1;
Set the reference point and assign the information to the vehicle if it
crossed the reference point.
for i = 1:length(coordinates)
    if coordinates(i,2) >= 0.90*last_coordinate
        vehicle(coordinates(i,1),coordinates(i,3):last_time) = 1;
        vehcood(coordinates(i,1),coordinates(i,3)) = coordinates(i,2);
        infection(i,1) = 1;
    end
end
t = 1;
Start processing for each time step
while t < last_time + 1
    if t == coordinates(length(coordinates),3)
            break;
        end
    for i = current_row:length(coordinates)
        if t < coordinates(i,3)
                t = coordinates(i,3);
                current_row = i;
                break;
        end
        if i == length(coordinates)
            break;
        end
        for j = i:length(coordinates)
check if the vehicles being compared are in the same time step
            if coordinates(i,3) < coordinates(j,3)
                break;
            end
 check if at least one of the vehicle pairs is infected

             if (infection(i,1) + infection(j,1)) >= 1
calculate the distance between vehicles
```

```
                    distance = abs(coordinates(i,2) - coordinates(j,2));
check for vicinity of the vehicles

                    if distance <= Radius
                        random = rand();
                        if random < Probability
                            infection(i,1) = 1;
                            infection(j,1) = 1;
                            i = i;
                            if i >= 20000

                                i = i;

                            end

Assign the infection state value for the vehicle according to the result
obtained from above comparison

vehicle(coordinates(i,1),coordinates(i,3):last_time) = 1;
                            vehcood(coordinates(i,1),coordinates(i,3)) =
coordinates(i,2);

vehicle(coordinates(j,1),coordinates(j,3):last_time) = 1;
                            vehcood(coordinates(j,1),coordinates(j,3)) =
coordinates(j,2);

                        end

                    end
             end

         end

    end
end

     If a vehicle is infected at one time step, set it to remain infected
for the rest of its journey.

for i = 1:length(coordinates)
    if infection(i,1) == 1
        present_vehicle = coordinates(i,1);
    Assign the variable called infection for the vehicle for each time
step

    for k = i:length(coordinates)
        if coordinates(k,1) == present_vehicle
            infection(k,1) = 1;
        end
    end
    end
end
```

```
coordinates(:,4) = infection;
t = 1;
Separate the infected vehicles from the uninfected vehicles at each time
step, the variable 'new' represents infected vehicles
for k = 1:length(coordinates)
    if coordinates(k,4) == 1
        new(t,1:3) = coordinates(k,1:3);
        t = t + 1;
    end
end
for i = 1:180
    %infected(i,1) = i*30;
    %total_count(i,1) = i*30;
    time_count(i,1) = i*30;
    infected(i,count) = 0;
total_count(i,count) = 0;
end

 Obtain the number of infected and uninfected vehicles at each time step

m = 1;
for t = 1:180
for i = m:length(new)

    if new(i,3) == time_count(t,1)
        infected(t,count) = infected(t,count) + 1;

    end
    if new(i,3) > time_count(t,1)
        m = i;
        break;
    end

end
end

m = 1;

for t = 1:180
for i = m:length(coordinates)

    if coordinates(i,3) == time_count(t,1)
        total_count(t,count) = total_count(t,count) + 1;

    end
    if coordinates(i,3) > time_count(t,1)
        m = i;
        break;
    end

end
end
```

```
clear the unnecessary spac

     clear coordinates new final i t first_coordinate infection k
present_time final current_row current_time first_time j distance
present_vehicle minimum vehcood vehicle vector random m last_vehicle
last_time Probability data smallest;
     %should remove comments or unclear data, smallest and total_count.
    for t = 2:180
    if infected(t-1,count) >= flow_out(t,1)
        infected_leaving(t,count) = flow_out(t,1);
    end
    if infected(t-1,count) > 0
        if infected(t-1,count) < flow_out(t,1)
            infected_leaving(t,count) = infected(t,count);
        end
    end
    if infected(t-1,count) == 0
        infected_leaving(t,count) = 0;
    end

    if infected(t-1,count) > 0
%beta(t,1) = (infected(t,2) - infected(t-1,2) +
infected_leaving(t,1))/(infected(t-1,2)*(total_count(t-1,2) -
infectedtot(t-1,2)));
    else
        %beta(t,1) = 0;
    end
    end
    for i = 1:180
        uninfected(i,count) = total_count(i,count) - infected(i,count);
    end
    count = count + 1;
clear t flow_out i Radius last_coordinate;
```