

ABSTRACT

PATWA, PRITESH. Integrated Modeling of Mobility and Communication in Vehicular Wireless Networks. (Under the direction of Dr. Rudra Dutta).

Due to global increase in urbanization, improving the transportation facilities has become a challenge for governments and researchers. Increasing rates of traffic congestion on the roads have resulted in a significant increase in the travel times, the expenditure of fuel and other resources. These growing concerns about traffic conditions have motivated researchers towards enabling intelligence in the vehicles, so that the drivers can be warned beforehand about the adverse driving conditions that lie far ahead of them. This intelligence has come in the form of equipping the vehicles with computing technologies and wireless communication devices that enables them to communicate with other vehicles and network infrastructure in their proximity. A wide range of traffic flow models have been developed since past half a century to study the operations of road traffic. These existing traffic flow models assume that drivers are aware only of their immediate surroundings that are limited by the range of a human eye-sight. Hence, the drivers' decisions in such models are based on the traffic conditions prevailing in the neighborhood of the vehicle. With the introduction of communication networks, e.g. Vehicular Ad hoc Networks, the visibility of the drivers will increase as they will be able to gather the traffic information at locations that are far ahead of them. This increased visibility will influence the drivers' decisions and the way in which the traffic operations are predicted and modeled. Hence, with the introduction of communication capabilities in the vehicles, there is a need to define new traffic flow models that will take into consideration the impact of communication on the drivers' decisions and the traffic mobility. Till date, however, no work has been done towards the joint consideration of the two areas of traffic mobility and communication. In the research presented in this thesis, we mathematically formulate an integrated traffic flow model based on the partial-differential fluid dynamic equations. This traffic flow model predicts the traffic behavior on the road when a fraction of the vehicles are equipped with the communication capabilities. We also, numerically investigate the predictions made by this model in various traffic scenarios and compare their nature with the actual road traffic simulations that trace the behavior of each individual car.

**Integrated Modeling of Mobility and Communication in Vehicular
Wireless Networks**

by

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To my family ...

Biography

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Chapter 1

Introduction

With increasing industrialization, vehicular traffic flow and congestion has become one of the main societal and economical problems related to transportation. As presented in a report by U.S. Department of Transportation[13], increasing rates of traffic congestion have resulted in a significant increase in the travel times and the expenditure of gas.

This growing concern about traffic conditions have motivated researchers towards enabling intelligence in the vehicles, such that the drivers could be warned beforehand, about the adverse driving conditions that lie ahead of them. Such warnings, can provide drivers with enough time to take decisions to opt for alternate routes. This intelligence has come in the form of equipping the vehicles with computing technologies and wireless communication devices, commonly referred to as *telematics*. The *telematics* will enable the vehicles to communicate with the other equipped vehicles and the network infrastructure in their vicinity. In the literature[99], such modes of communication are commonly referred to as Vehicle to Vehicle communication (V2V) and Vehicle to Roadside communication (V2R), respectively. We refer to the cars equipped with *telematics* like radios and GPS, as Communication Enabled Cars (CECs). In the near future, the number of CECs is poised to increase and it is predicted[1] that the number of *telematics* subscribers in the United States will reach more than 15 million by 2009. By acquiring and exchanging information, vehicles gather knowledge about the local traffic situation that can improve the driving conditions and reduce the travel times. In our work, we consider cases where no network infrastructure is installed on the road-side and hence, only V2V communication is possible.

This is important because during the initial phases of deployment of such technologies on the road, a well established network infrastructure on the road-side will incur a high cost overhead and therefore, might not be available.

Since the vehicle speeds are very high, and their relative positions change very quickly, V2V communication happens on an ad-hoc basis. Research done in this direction, development and deployment projects[27][28][26][29][4] and standardization efforts[3][11] show the growing interest in Vehicular Ad-hoc Networks (VANETs). VANETs are a special kind of Mobile Ad-Hoc Network (MANET), where wireless-equipped vehicles form a network with no additional infrastructure. In comparison to other communication networks, VANETs have unique requirements with respect to self-organization and management, networking protocols and applications. Although, there are several unique features of VANETs that distinguish them from conventional wireless networks, following features provide a brief overview of the important aspects involved:

1. *Self-organization and management:* Like MANETs in general, a VANET requires fully decentralized network control since no central entity can organize such a network. Moreover, VANETs hold an additional complexity due to special conditions like timing and reliability requirements, together with probable saturation when VANET technology is fully deployed.
2. *High mobility and frequent topology changes:* Nodes potentially move with high speeds along the streets and freeways. Hence, in certain scenarios, such as when vehicles move in different directions, the duration of time that remains for exchange of data packets is very small. Also, intermediate nodes in a wireless multi-hop chain of forwarding nodes can move quickly. Hence, established routes between two nodes are frequently interrupted and a network can be partitioned. Due to very high speeds of mobile nodes, the communication links break and come up very often. Additionally, with the initial deployment of this technology on the road, not all the vehicles will be equipped with such capabilities resulting into sparsely connected networks.
3. *Networking Protocols:* Research community is working towards deployment of existing communication technologies like Bluetooth and IEEE 802.11 for VANETs, as well as towards development of new standards to better suit their specific needs. Many papers have proposed new protocols for VANETs at physical, MAC and network layer. In

this thesis, we have limited ourselves to the routing protocols that use geographical positions of the vehicles to address them. Such routing is called as *Geocast* routing[7]. A VANET platform includes on-board sensors like GPS (Global Positioning System), to be utilized by such routing protocols.

4. *Wide range of applications:* VANETs can be used in many applications for V2V and V2R communication. In addition, the technology might be used for various other purposes. For example, to connect to a home network when the car is in the garage. However, the focus of deployment of this technology in vehicles is limited to improving the driving conditions and the vehicular safety applications, with specific requirements for simultaneous reliability and timeliness.

A wide range of traffic flow models have been developed since past half a century to study the operations of road traffic. Researchers in vehicular traffic theory, broadly distinguish these models amongst three levels of description: microscopic, mesoscopic, and macroscopic. The most basic type of modeling approach is presented by microscopic or follow-the-leader models[5][19][16]. A microscopic model describes the movement of a single vehicle by its space and speed coordinates at a given time. When modeling on macroscopic scale[5][14], density, mean speed and flow of vehicles, are the parameters of interest. An example of a macroscopic movement model is the fluid flow model, that is based on the fluid dynamic equations[5]. This family of analytical models describes the mobility in terms of the average number of users crossing a given area. At the mesoscopic level, the homogenized movement behavior of several vehicles is reflected. For example, a distribution function is derived that describes the number of vehicles at a certain location or speed at any time. Mesoscopic models based on Kinetic or Boltzmann like equations[5] present an intermediate step between the microscopic and macroscopic models. This is because, the macroscopic models can be derived from such mesoscopic equations that can in turn be derived from the microscopic rules. Refer [25] for a concise summary of nearly fifty years of work in vehicular traffic flow modeling.

These existing traffic flow models assume that drivers are aware only of their immediate surroundings that are limited by the range of human eye-sight. Hence, drivers' decisions in such models are based on the traffic conditions prevailing in the neighborhood of the vehicle. With introduction of communication networks like, VANETs, the visibility of the drivers increases as they become aware of the traffic conditions at locations far

ahead of them by exchanging information with other vehicles in proximity. This increased visibility influences the drivers' decisions and the way in which traffic operations should be predicted and modeled by the traffic flow models. As an example, vehicles inside a traffic jam learn about it and communicate this to those vehicles that have not joined the jam, thus giving them an option to take alternate routes. Such phenomenon affects the rate at which congestion grows and resolves. In this scenario, the traffic state predictions by the existing models would be inconsistent with the reality, as these models do not take into consideration the effect of communication on the traffic mobility.

Hence, with the introduction of communication capabilities in the vehicles, there is a need to define new traffic flow models to reflect the impact of communication on drivers' decisions and the manner in which road traffic operates. Till date, however, there has been no work towards the joint consideration of the two areas of communication and traffic mobility. In this thesis, we propose a new integrated macroscopic model based on the fluid dynamic equations, which predicts the traffic behavior when a fraction of the vehicles are equipped with communication capabilities.

The rest of this thesis is arranged as follows. In Chapter 2, we briefly describe the context of this thesis and other related work, including the protocols and algorithms related to VANETs, and the vehicular traffic flow models. In Chapter 3, we present a formal definition of the identified problem. This is followed by Chapter 4, which presents the formulation of the new proposed model that addresses this problem. In Chapter 5, we present the numerical investigations done with the new macroscopic model and their comparisons with the corresponding microscopic simulations. Finally, Chapter 6 discusses possible directions for future research and concludes this thesis.

Chapter 2

Context

2.1 Communication Protocols for VANETs

VANETs are emerging as a new network environment for Intelligent Transportation Systems (ITS). Such systems can enable a wide range of applications, such as collision avoidance, emergency message dissemination, dynamic route scheduling, real-time traffic condition monitoring, incident detection and propagation, and other miscellaneous information sharing between the vehicles. Traditional vehicular networks[29][4] for reporting accidents or traffic conditions rely on certain infrastructures, such as road-side traffic sensors reporting data to a central database, or cellular wireless communication between vehicles and a monitoring center. The problem with such solutions is that they require expensive infrastructures installed on every road in which the system is going to be used. Additionally, they are not scalable owing to their centralized design. VANETs are emerging as the preferred network design for ITS. VANETs are based on short-range wireless communication between vehicles, e.g., Dedicated Short Range Communication (DSRC)[26] and IEEE 802.11[2]. Unlike infrastructure-based networks (e.g., cellular networks), these networks are constructed on-the-fly and do not require any investment besides the wireless network interfaces that are expected to be a standard feature in the next generation of vehicles. Furthermore, VANETs enable a new class of applications that require time-critical responses and high data transfer rates.

2.1.1 MAC Layer Protocols

There are several network access technologies that are being considered for deployment to enable V2V communication in VANETs. These technologies include but are not limited to: IEEE 802.11, Bluetooth and cellular networks. These technologies have their pros and cons when applied to V2V communication as they are not specifically designed for such an application. The IEEE 802.11 MAC layer, is by far the most commonly used MAC layer protocol to evaluate the performance of IVC systems. Bluetooth is a widely known standard for limited range wireless communication of data. Several researchers have proposed Bluetooth based V2V communication systems. The most attractive solution on the MAC layer is the already existing cellular communication infrastructure. The limitations of such a technology are that it is centrally managed and it can not support a huge volume of traffic. Recently, DSRC[26] standard for vehicular communications has been proposed and approved. The MAC layer of DSRC is comparable to 802.11a[2]. In this thesis, we do not dwell into MAC layer issues of V2V communication and assume that an efficient network access technology is already deployed.

2.1.2 Network Layer Protocols

Network layer has the responsibility of routing and forwarding packets through existing links. It also takes care of uniquely addressing the nodes. In VANETs, addressing the vehicles has been done in two ways - fixed addressing and geographical addressing. In our work, we limit ourselves to the use of geographical addressing as it has lower overhead than fixed addressing and is also more scalable. In the case of geographical addressing, positions of the vehicles are used to address them.

Routing and forwarding in VANETs is unique due to high mobility of nodes, that results in frequently changing network topology. Several routing protocols[30][24][10][7] have been specifically proposed for V2V communication. One such algorithm, Role Based Multicast (RBM)[10], involves multicasting messages among highly mobile hosts in ad hoc networks. Authors consider that the vehicle must be ensured of the existence of a neighbor within its transmission range before broadcasting a message. Therefore, as long as the vehicle does not have neighbors, it does not broadcast the message. This avoids redundant broadcasts of messages. However, this method requires that each vehicle maintains a list

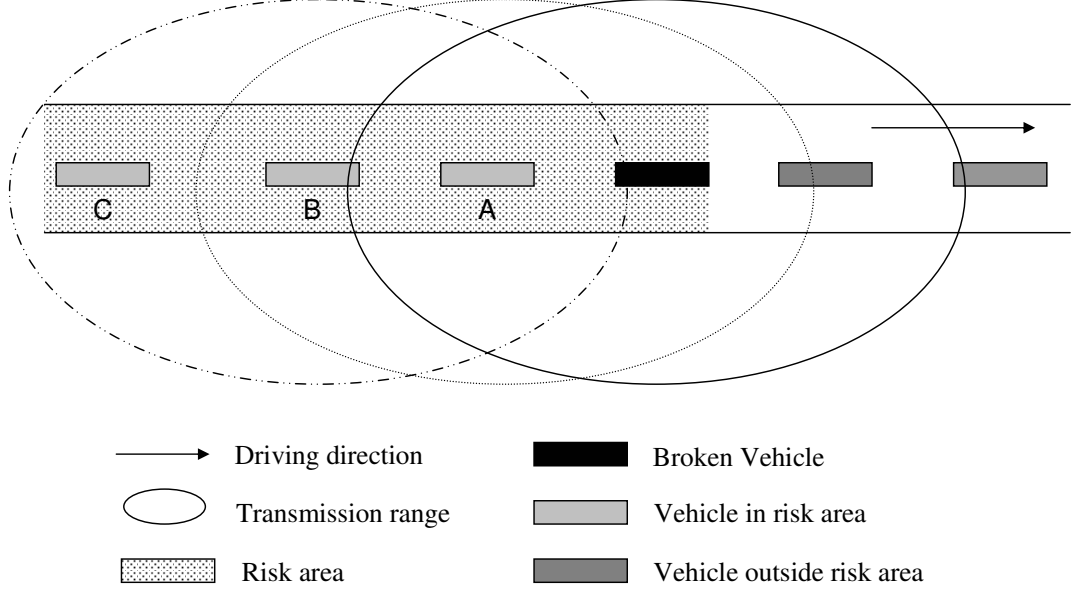


Figure 2.1: Inter-Vehicle Geocast: Relay Selection

of all its neighbors. During the initial deployments of V2V communication, when only a few fraction of cars are CECs, these overheads will be acceptable, but when this fraction increases, overhead will also increase significantly. Moreover, due to high speeds of vehicles, such information about neighbors will become antiquated very frequently.

Several protocols have been proposed in the literature, that resort to flooding messages in a region of interest based on the positions and driving direction of the nodes without maintaining a list of neighbors or routing information. One such algorithm, Inter-Vehicle Geocast (IVG)[7], informs all the target vehicles in risk area on a freeway, about any incident such as an accident or traffic congestion. IVG is an algorithm that does an effective scalable dissemination of alarm messages based on message broadcasting, where the vehicles define a restricted broadcast group, called a *multicast* group. In VANETs, *multicast* group is defined ephemerally and dynamically by the location, speed and driving direction of the vehicles. This is contrary to the typical methods that use node identities. Figure 2.1 shows the risk areas and target vehicles for a given accident.

In IVG algorithm, first, the broken vehicle begins to broadcast an alarm message.

The way in which a node is designated as a relay (next node to broadcast the message) is based on the defer time algorithm. The node that receives an alarm message does not rebroadcast it immediately but waits for some time, called defer time, to take a decision about rebroadcast. When this defer time expires and if it does not receive the same alarm message from another node behind it, it concludes that there is no relay node behind it. Thus, it designates itself as a relay and starts broadcasting alarm message to inform the vehicles which might be behind it. The defer time for a node receiving a message from another node is inversely proportional to the distance between them, i.e., the farthest node waits for the least time to broadcast the message so that the message can be forwarded to greater lengths of road in shorter durations of time. In the scenario shown by Figure 2.1, when the broken vehicle begins the broadcast of an alarm message, node B is selected as a relay, so that node C could be reached in the second broadcast of the message, done by node B. This wouldn't have been achieved if node A was selected as a relay. Moreover, the broken vehicle addresses the destination location up to which the alarm message would be relevant and not any specific node on the road. This avoids the need of maintaining list of neighbors for each vehicle.

In our model, we assume that an efficient *Geocast* routing protocol like IVG, is installed on all the CECs, and hence, all such cars are able to communicate with each other, based on their positions and driving directions.

2.2 Congestion Detection Algorithms

Traffic congestion occurs when the volume of traffic on the road is high enough to become detrimental to its performance. In congested conditions, vehicle speeds are reduced and drive times are increased. Moreover, vehicles burn unnecessary fuel when in congestion. Three fundamental parameters[18] that have been consistently used to measure the performance of incident detection algorithms on the roads are:

1. *Detection Rate*: The detection rate is generally defined as the ratio of the number of detected incidents to the total number of incidents.
2. *Time to Detect*: Time to detect is considered as the time from when the incident occurs until it is detected.

3. *False Alarm Rate:* The false alarm rate is defined as the percentage of incorrect detection signals relative to the total number of algorithm decisions.

There are several incident detection algorithms that are being currently deployed on the freeways. An exhaustive list of these can be found in [21]. For the simulation purposes with respect to V2V communication, these algorithms are too complex to be used. Moreover, for this thesis the main focus being integrated modeling of mobility and communication, the congestion detection algorithms are not primal. Hence, a simpler algorithm for congestion detection via V2V communication as presented in [8] and [9] is used in this thesis. Here, authors have proposed a “Localized Group Membership Service (LGMS)”, that tracks the membership of only the adjacent neighbors. In LGMS, vehicles within a local group exchange information and become aware of their local surroundings. Moreover, changes in the localized group membership happens when existing neighbors join or leave the group on voluntary basis, or any new members move into the vicinity of a vehicle. The information about the local group exists in the form of local views, that are installed at each host. Authors have incorporated LGMS into inter-vehicle communication for traffic jam detection on freeways. The traffic jam is detected when the speed of a communication equipped vehicle falls below a minimum threshold. Authors have also proposed an algorithm to find the extent of congestion by defining a protocol for communication between the vehicles that belong to the same local group inside the congestion. They have focused on the cases where a fraction of the vehicles have communication capabilities.

2.3 Traffic Flow Models

Traffic flow operations on roads can be improved by field research of real-life traffic flow. However, apart from the scientific problem of reproducing such experiments[25], costs and safety plays a dominant role. Therefore, traffic flow models are designed to characterize the behavior of the complex traffic flow systems. Today, these models have become an essential tool in traffic flow analysis and experimentation. The application area of these traffic flow models is very broad and depends on the type of model.

The traffic models can be classified[25] according to the following fundamental characteristics:

1. *Scale of independent variables:* A model can define quantities which are continuous,

discrete or semi-discrete.

2. *Level of detail:* Model can be of microscopic, mesoscopic or macroscopic type, based on the quantities that it defines.
3. *Representation of the processes:* In this respect, models can be deterministic or stochastic. The former models have no random variables implying that all quantities in the model are defined by deterministic relationships. Stochastic models incorporate processes that include random variants.
4. *Operationalization:* Models can be either analytical solutions of sets of equations, or they can be simulation based.
5. *Area of application:* The model may describe the dynamics of its entities for a single lane or a multi-lane freeway, a downtown street, an entire traffic network, etc.

In the following section we focus on the classification based on the level-of-detail, as it is the main criteria on which the new integrated model is based. Other classifications are referred as and when needed.

2.3.1 Microscopic Traffic Flow Models

Microscopic traffic flow models describe the behavior of the individual vehicles in two dimensions of space and time, as well as their interactions with each other. Such models can be based on single lane or multi-lane roads. In the former case, model defines rules of acceleration and deceleration operations that happen within a lane, and in the later case, additional rules for lane changing to the left and right lanes are modeled. For instance, for each vehicle on the road a lane-change is described as a detailed chain of drivers' decisions based on a set of if-then rules. From the driver's behavior and the vehicle characteristics, position and speed of each vehicle is calculated for every time step. Due to higher level of detail involved in microscopic models, they are computation intensive. In literature[19][16][5], several such models have been proposed.

Trieber et al.[19] have simulated a continuous microscopic single-lane car-following model, named Intelligent Driver Model (IDM), using empirical boundary conditions that are defined essentially by its acceleration function. In IDM, the acceleration V_γ for a vehicle γ , is a continuous function of its velocity v_γ , the actual gap s_γ and the desired minimum

gap s^* to the leading vehicle, the desired velocity $v_{0(\gamma)}$, the maximum acceleration $a^{(\gamma)}$ and the velocity difference or approach rate Δv_γ to the leading vehicle:

$$V_\gamma = a^{(\gamma)}[1 - (v_\gamma/v_{0(\gamma)})] - a^{(\gamma)}[(s^*(v_\gamma, \Delta v_\gamma)/s_\gamma)^2] \quad (2.1)$$

This equation is the interpolation of tendency to accelerate (as represented by the first term on right hand side) and tendency to decelerate (as represented by the second term on right hand side).

Kesting et al.[16] have proposed a general scheme of lane-changing rules for a wide class of microscopic single lane models. An essential parameter in this lane-changing model is the ‘politeness factor’ (p) that represents the degree of cooperation when considering lane changes. Through the politeness, the advantages and disadvantages of neighboring drivers on the same and adjacent lanes are taken into account. Depending on this parameter, either a local driver optimum or a system optimum with respect to lane choice is achieved. The following equation defines the incentive condition for a lane-changing decision of the driver of a vehicle c :

$$\tilde{a}_c - a_c + p(\tilde{a}_n - a_n + \tilde{a}_o - a_o) > 0 \quad (2.2)$$

The first two terms denote the advantage of a possible lane change for the driver himself, where a_c refers to the current acceleration, and $\tilde{a}_c$ refers to the new acceleration after a prospective lane change, for a vehicle c . The subsequent term with the politeness factor (p), denotes the total advantage (acceleration gain or loss) of the affected neighbors. The incentive criterion is fulfilled if the own advantage (acceleration gain) is higher than the weighted sum of the disadvantages (acceleration losses) of the affected neighbors. Authors have applied these lane changing equations to the IDM and have presented the agreement between simulation results and empirical data.

Klar et al.[5] have used a unique approach to define the rules in their microscopic traffic flow model. Their model is based on the reaction thresholds that are dependent on the velocities of cars. The cars change velocity and lanes instantaneously once certain reaction thresholds are crossed, i.e., once the distance between a car and its following or leading car becomes larger or smaller than the threshold distance, driver takes a decision whether to accelerate, decelerate or do a lane change. E.g., a driver accelerates when it crosses the acceleration threshold, defined by:

$$H_A(v) = H_0 + \delta + vT_A \quad (2.3)$$

where, H_0 is the minimum distance between the vehicles, T_A is the reaction time, δ accounts for the fact that acceleration is done with a certain delay in comparison with braking, and v is current velocity of the vehicle. This equation states that, if the distance between the vehicle and its leading vehicle on the same lane exceeds $H_A(v)$, the driver decides to accelerate to a new velocity.

As long as no threshold is crossed, the cars move with their respective velocities. This model will be described in a greater detail in Section 3.1.2.

2.3.2 Mesoscopic Traffic Flow Models

Mesoscopic traffic flow models do not distinguish between individual vehicles[25], but specify their behavior in probabilistic and stochastic terms. Traffic is represented by groups of traffic entities, the activities and interactions of which are described at a medium level of detail. For example, a lane-change maneuver is represented for an individual vehicle as an instantaneous event, where the decision to perform a lane-change is defined in a probabilistic manner based on quantities like relative lane densities and speed differentials. Generally, mesoscopic models are derived in analogy to gas-kinetic theory and they describe the dynamics of velocity and vehicle distributions.

Several mesoscopic models[15][5] have been proposed in literature. In [5], authors have derived a new kinetic multi-lane model that is based on the rules defined in the underlying microscopic model. In this kinetic model, the correlations between the vehicles are taken into account by a mathematical assumption for the leading vehicle distribution that determines the probability for lane changing. From the multi-lane model a cumulative single-lane model is developed. The equilibrium solution of the homogeneous cumulative kinetic equation is later used to determine the equilibrium coefficients in the fluid dynamic macroscopic equations that are described in Sections 2.3.3 and 3.1.1.

2.3.3 Macroscopic Traffic Flow Models

Macroscopic traffic flow models describe traffic at a high level of aggregation as a flow without distinguishing its constituent parts. For instance, the traffic is represented in an aggregate manner using flow, density, and velocity as fundamental quantities. Individual vehicle maneuvers, such as lane change are not explicitly represented. Macroscopic traffic

flow models assume that the aggregate behavior of drivers depends on the traffic conditions in the drivers' immediate environments and therefore predict traffic flow in terms of aggregate variables. Usually, these models are derived from the analogy between vehicular flow and flow of continuous media (e.g. fluids), yielding flow models with partial differential equations. Since the model to be established in this paper is a macroscopic model, the discussion will be elaborate.

The independent variables of a continuous macroscopic flow model are location x and time t . To introduce the dependent traffic flow variables, consider a small segment $[x, x+\Delta x)$ of a roadway referred to as x and a small time interval $[t, t+\Delta t)$ referred to as t such that, $\Delta x, \Delta t \rightarrow 0$. Most macroscopic traffic flow models describe the dynamics of the density $\rho = \rho(x, t)$, the velocity $u = u(x, t)$, and the flow $\rho u = \rho(x, t)u(x, t)$. The density ρ describes the expected number of vehicles on the roadway segment x at time t . The flow ρu equals the expected number of vehicles flowing past x during time t . The velocity u is the expected velocity of vehicle defined by $\frac{\rho(x, t)u(x, t)}{\rho(x, t)}$. Hence, given any of the two quantities, we can deterministically obtain the third quantity. Additionally, some macroscopic traffic flow models also consider the velocity variance $\Theta(x, t)$ and the traffic pressure $P = P(x, t)$ of continuous media, to model the vehicular flow.

Helbing[14] has presented a single-lane macroscopic model, consisting of flow, density, velocity and velocity variance (θ), which is derived from gas-kinetic equations and consists of the following equations:

1. *Equation for conservation of vehicles:*

$$\partial \rho + \partial \rho u = 0 \quad (2.4)$$

2. *The velocity dynamics equation:*

$$V = \partial_t u + u \partial_x u \quad (2.5)$$

The total time derivative of velocity, V describes the rate of velocity changes experienced by a moving observer who observes the traffic flow while moving along with the stream at the same velocity u . The total time derivative is composed of a true time derivative $\partial_t u$ and a convection term $u \partial_x u$. The later term describes changes in the velocity u due to inflowing vehicles with a different velocity.

3. The equation describing the dynamics of the variance Θ :

$$\partial_t \theta + u \partial_x \theta = -2(P/r) \partial_x u + 2(\theta^e - \theta)/T - (1/r) \partial_x J \quad (2.6)$$

Here, the flux of velocity variance $J = J(x, t) = r(x, t) \Gamma(x, t)$ is defined by the product of the density (r) and the skewness of the velocity distribution (Γ). Rather than being experimentally determined, the equilibrium velocity V^e and variance θ^e are determined by considering the interaction process between vehicles.

Another macroscopic model has been presented by Klar et al.[5], where authors have proposed fluid-dynamic equations to represent the vehicular traffic flow for a multi-lane and a single lane road. These fluid dynamic equations are derived from underlying gas-kinetic equations at mesoscopic level, explained in Section 2.3.2 above. The single-lane model is presented by the following equations:

$$\partial_t(\rho) + \partial_x(\rho u) = 0 \quad (2.7)$$

$$\partial_t(\rho u) + \partial_x(p^e(\rho) + \rho u^2) + \partial_x(A^e(\rho)) = \frac{1}{T^e(\rho)} \rho [u^e(\rho) - u] \quad (2.8)$$

Here, A^e is the enskog coefficient, p^e is the pressure, u^e is the average velocity and T^e represents acceleration and braking interaction frequencies between the vehicles, all in equilibrium state. More detailed description of these quantities and the multi-lane model is presented in Section 3.1.1. In this work, we have built upon these multi-lane fluid-dynamic equations to model the effect of communication on traffic flow.

2.4 Our Contribution

Our primary contribution is in recognizing the need for integrated modeling of communication and mobility for vehicular traffic flow, that has not been addressed in the past. The overall focus of this thesis is towards defining the dynamics of the macroscopic parameters to address the impact of *telematics* on the nature of traffic operations in a scenario of traffic congestion. To allow a joint consideration of mobility and communication, we mathematically integrate these parameters with an existing macroscopic traffic flow model[5]. Also, the nature of predictions made by this new macroscopic traffic model are compared and contrasted with the microscopic simulations.

Chapter 3

Problem Description

In this chapter, we discuss the need for joint consideration of mobility and communication for the traffic flow modeling. We also define the integrated problem and the various assumptions and the notations used in this thesis.

3.1 Mobility

As briefly explained in Section 2.3, traffic flow models describe the nature of traffic flow operations at various levels of detail. We focus our work at the macroscopic level, where traffic flow operations are treated as that of a continuous media. Such a model provides predictions of traffic state based on the aggregated representations of interactions between the vehicles without individually addressing them. At the microscopic level, behavior of individual vehicles is traced and therefore it provides a more realistic representation of the traffic operations. In Chapter 5, we compare and contrast the predictions made by the macroscopic model with the corresponding microscopic simulations.

3.1.1 Macroscopic Models

Macroscopic traffic flow models describe traffic at the highest level of aggregation, representing it in an aggregate manner using flow, density, and mean velocity as fundamental characteristics. In the past, macroscopic traffic flow models[5][14] have assumed that the

drivers' decisions depend on the traffic conditions in their immediate surroundings. With the introduction of *telematics*, visibility of the drivers increases beyond human eye-sight and therefore drivers' decisions are influenced by traffic conditions that lie far ahead of them. This has motivated us to define a new traffic flow model, which captures the effect of communication on the mobility of vehicles.

The proposed model in this thesis, is based on the fluid-dynamic macroscopic traffic flow model presented by Klar et al.[5]. Klar et al. have presented a hierarchy of traffic flow models, deriving the fluid dynamic (macroscopic) model from the underlying kinetic equations (mesoscopic) that are based on the microscopic rules. The approach used for deriving gas kinetic equations, at the mesoscopic level, resembles Enskog's theory of a dense gas rather than more commonly used Boltzmann-type treatment. It has been cited that a Boltzmann-type treatment leads to completely wrong results even for simple inhomogeneous situations. Since, in this thesis we consider traffic inhomogeneities and resultant congestion, Enskog's-type treatment serves as a better approach. Moreover, since the authors have derived the macroscopic equations from kinetic and microscopic model, it has led to a better foundation of the macroscopic model and an insightful explanation of the coefficients in the model. Klar et al.'s single-lane road model has been explained in Section 2.3.3. In this section, we focus on details related to their multi-lane model. The fundamental macroscopic quantities that are derived by this macroscopic model are, ρ_α (density on lane α), u_α (mean velocity on lane α) and $\rho_\alpha u_\alpha$ (flow on lane α). Here, $\alpha \in \{1 \dots N\}$, where N is the total number of lanes on the road, with lane numbers increasing from right to left. The multi-lane fluid dynamic equations derived in this model are:

Density Equation:

$$\begin{aligned} \partial_t(\rho_\alpha) + \partial_x(\rho_\alpha u_\alpha) = & \left(\frac{1}{T_{\alpha-1}^L} \rho_{\alpha-1} - \frac{1}{T_\alpha^R} \rho_\alpha \right) (1 - \delta_{\alpha,1}) \\ & + \left(\frac{1}{T_{\alpha+1}^R} \rho_{\alpha+1} - \frac{1}{T_\alpha^L} \rho_\alpha \right) (1 - \delta_{\alpha,N}) \end{aligned} \quad (3.1)$$

Flow Equation:

$$\begin{aligned} \partial_t(\rho_\alpha u_\alpha) + \partial_x(p^e(\rho_\alpha) + \rho_\alpha u_\alpha^2) + \partial_x(A^e(\rho_\alpha)) = & \\ & \left(\frac{1}{T_{\alpha-1}^L} \rho_{\alpha-1} u_{\alpha-1} - \frac{1}{T_\alpha^R} \rho_\alpha u_\alpha \right) (1 - \delta_{\alpha,1}) \\ & + \left(\frac{1}{T_{\alpha+1}^R} \rho_{\alpha+1} u_{\alpha+1} - \frac{1}{T_\alpha^L} \rho_\alpha u_\alpha \right) (1 - \delta_{\alpha,N}) \end{aligned}$$

$$+ \frac{1}{T^e(\rho_\alpha)} \rho_\alpha [u^e(\rho_\alpha) - u_\alpha] \quad (3.2)$$

Following are the parameters that define the dynamics of the fundamental quantities in these equations:

$\frac{1}{T_\alpha^L}$: Rate of lane change to the left, from lane α to $\alpha + 1$

$\frac{1}{T_\alpha^R}$: Rate of lane change to the right, from lane α to $\alpha - 1$

$\delta_{i,j}$: The Kronecker symbol that accounts for the asymmetry at the boundary lanes, as, no lane change to the left is possible on the left-most lane and no lane change to the right is possible on the right-most lane

$$\delta_{i,j} = \begin{cases} 1 & \text{if } i = j \\ 0 & \text{otherwise} \end{cases}$$

$\frac{1}{T^e(\rho_\alpha)}$: Sum of braking and acceleration interaction frequencies between vehicles at equilibrium

$u^e(\rho_\alpha)$: Mean velocity at equilibrium

$p^e(\rho_\alpha)$: Equilibrium pressure

$A^e(\rho_\alpha)$: Integrated Enskog coefficient at equilibrium

The Density equation (Equation 3.1), predicts the rate of change of density (ρ_α) and is influenced by the densities in the immediate surroundings on the same lane and the adjacent lanes. Terms on the right-hand side of the equations, define the sources and sinks due to lane changing, e.g., $\frac{1}{T_{\alpha-1}^L} \rho_{\alpha-1}$ is the gain in the density on lane α , due to left lane change from lane $\alpha - 1$ and $\frac{1}{T_\alpha^R} \rho_\alpha$ is the loss in the density on lane α , due to right lane change from lane α . Similarly, the $\partial_x(\rho_\alpha u_\alpha)$ term on left hand side of the equation defines the effect due to the densities at immediate surroundings on the same lane.

The Flow equation (Equation 3.2) can be interpreted in a similar way, as Equation 3.1. It models the rate of change of flow ($\rho_\alpha u_\alpha$) and is influenced by the flows in the immediate surroundings on the same lane and the adjacent lanes.

In the model, it is assumed that the lane changes occur only due to a desire to avoid braking, and therefore, the lane changing rates ($\frac{1}{T_\alpha^L}$ and $\frac{1}{T_\alpha^R}$) are dependent on the probability of a lane change and the braking interaction frequencies between the vehicles. While deriving macroscopic fluid dynamic equations, authors have defined closure relations for the gas-kinetic equations using the stationary (equilibrium) solutions. Due to such

an approach, equilibrium parameters like $u^e(\rho_\alpha)$, $A^e(\rho_\alpha)$, $p^e(\rho_\alpha)$ and $\frac{1}{T^e(\rho_\alpha)}$ influence the dynamics of fundamental quantities even in inhomogeneous conditions. That is, the assumption of *quasi-static equilibrium*, standard in gas dynamics, has been made; and the Enskog modeling lends confidence that this assumption remains a good one even though the condition of the flow can clearly become inhomogeneous.

We refer to [5] and [6], for a detailed explanation of the derivation procedure and the numerical investigations done with this model.

3.1.2 Microscopic Models

The nature of predictions made by the macroscopic model can be validated with an individual car based description by a microscopic simulation. In this thesis, to compare and contrast the predictions of the proposed macroscopic model, we use the underlying microscopic model[5] which is the basis for the macroscopic model described in Section 3.1.1.

This microscopic model is based on the reaction thresholds, where the vehicles change their velocity and lanes instantaneously once a certain threshold is crossed. Until no threshold is crossed, the vehicles move with their respective velocities in free motion. The thresholds are determined with the velocities of the vehicles and the drivers' reaction times. Authors have introduced the thresholds for lane change, braking and acceleration operations. The acceleration threshold definition has been presented in Section 2.3.1. Here, we briefly describe the threshold for lane changing to the left lane, $H_L(v)$ which is formulated as:

$$H_L(v) = H_0 + vT_L \quad (3.3)$$

In Equation 3.3, T_L is the reaction time, H_0 is the minimal distance between the vehicles and v is the vehicle velocity. When the distance between a car and its leading car on the same lane becomes smaller than $H_L(v)$, car tries to switch to the left lane. Moreover, authors have introduced additional rules to determine the minimum gap required on the left lane, for a changing car. This space threshold is represented by:

$$H_L^S(v) = H_0 + vT_L^S \quad (3.4)$$

In Equation 3.4, T_L^S is the reaction time. When a car attains $H_L(v)$ threshold, the change of lane to the left is only possible if, the distance between this car and its leading and

following car on the new lane is greater than the minimum threshold, defined by $H_L^S(v)$. These two rules (Equations 3.3 and 3.4) define the lane changing operation to the left lane. Similar rules are defined for lane changing to the right lane. More detailed description of the microscopic rules can be found in [5].

3.2 Effect of Communication on Traffic Flow Modeling

Integration of communication capabilities in the vehicles has led to realization of various applications like file sharing, accessing external network infrastructure while on the road, etc. But, the research community has been widely focusing on building intelligence in the vehicles to achieve co-operative driving by sharing, gathering and processing the information related to traffic conditions. Such a phenomenon renders increased visibility to the drivers by making them aware of the traffic conditions that lie at locations far ahead of them. This increased visibility influences drivers' decisions and the way in which overall traffic operations happen on the road.

3.2.1 Motivation for an Integrated Model

A model based on fundamental macroscopic quantities can predict the behavior of traffic operations when vehicles are equipped with *telematics*. As explained above in Section 3.1, in the existing models, the dynamics of the traffic flow at any location are modeled based on the conditions at its immediate surroundings. When cars have communication capabilities, their motion will additionally be affected by the traffic conditions at distant locations. Similarly at macroscopic level, the dynamics of fundamental quantities at a position will also be affected by conditions at the distant locations.

This results in realization of a feedback loop between the Information Plane (communication network) and Physical Plane (mobility patterns of the vehicles), as identified in Figure 3.1. Hence, there is a need to define traffic flow models that capture the effect of communication on traffic mobility.

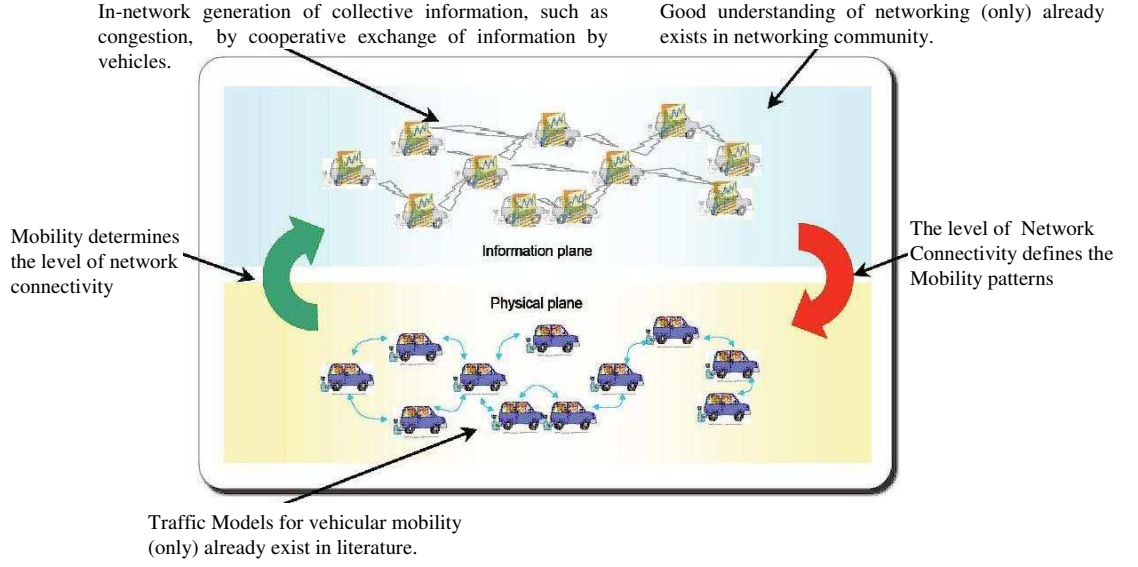


Figure 3.1: The Feedback Loop between Mobility and Communication

3.2.2 Communication Based Parameters

In the existing macroscopic traffic flow models, density, flow and mean velocity are the fundamental quantities. There are several aspects related to communication that will affect the traffic mobility in inhomogeneities like traffic congestion. The effect of communication on the traffic mobility is primarily dependent on the extent of communicability amongst the CECs. Such communicability is dependent on the number of CECs, as well as their relative positions. Moreover, the efficiency of communication protocols will also play an important role towards the timely delivery of messages.

Other than density, flow and velocity, we identify a new fundamental quantity, density of CECs (ρ_{α}^{com}). Density of CECs is defined as the number of CECs in a region of unit length. It can be determined by a product of total density (ρ_{α}) with the fraction of CECs (f_{α}^{com}). The ρ_{α}^{com} will define the extent up to which communication affects the traffic mobility. This is described in a greater detail in Sections 4.1 and 4.2. To summarize, we identify following criterions that need to be addressed so as to formulate a new integrated macroscopic model:

1. *Fraction of CECs (f_{α}^{com})*: During the initial deployment of *telematics* in the market,

not all the vehicles will be equipped with radios and GPS. Therefore, the effect of f_{α}^{com} on the network connectivity and subsequently on the traffic mobility needs to be modeled.

2. *Efficiency of the protocols on Network, MAC and Physical layers:* The efficiency of communication protocols in VANET environment will determine the extent up to which *telematics* are able to influence the driving conditions. Also, the robustness of routing and MAC layer algorithms will determine the timely delivery of warning messages to the target vehicles. As we mentioned above, there has been significant research in this context, and efficient strategies are likely to be available.
3. *Efficiency of the Incident detection algorithms:* Incidents e.g., congestion, bad weather, accidents etc., can be detected via driver assistance, or automatically by equipping the vehicles with appropriate capabilities. Research community[20] has widely focused on Automatic Incident Detection (AID) algorithms, and it can be safely assumed that incident detection will be very efficient. The efficiency of AID algorithms defines the latency with which the incidents are detected, and the warning messages are generated and propagated. This latency will affect the traffic mobility.
4. *Driver behavior in response to the warning messages:* The manner in which drivers respond to the warning messages depends on the severity of the incident and its impact on the safety and travel times of the driver. The drivers' decisions in response to the warning messages will define the traffic mobility. Since there is insufficient history regarding this, our model should accommodate various possible extent of driver response.

3.3 Assumptions

Motivated by the considerations presented in the previous section, we make the assumptions listed below in order to proceed with our modeling. In general, in this first work on the modeling topic, our approach has been to assume a perfect or nearly perfect network operation. This attitude not only reflects a practical confidence in V2V networking technology of the near future, but also reflects the different timescales operative at the mobility and communication planes. Network timescales are much smaller than typical

driver reaction timescales, so even if some messages are re-transmitted upon loss, or routed through non-optimal paths, the immediacy of the message on the drivers is likely to remain the same.

Assumptions in this thesis are classified into two broad categories depending on, whether they are related to communication networking or to the traffic flow modeling. Following sections define these assumptions.

3.3.1 Communication Network Based Assumptions

With regard to communication networking, we make following assumptions:

1. All the CECs are equipped with similar radios (having omni-directional antenna) and GPS, and therefore have similar communication ranges and consistent position co-ordinates. Also, CECs always know their current positions and can detect other CECs within the communication range in negligible time.
2. The efficient network layer protocols and the network access (MAC and physical layer) protocols are already deployed. At the network layer, geographical positions and directions of motion of the vehicles are used for addressing the vehicles and the routing algorithm is similar to IVG (described in Section 2.1.2). For the sake of simplicity, it has been assumed that addressing and routing are flawless. If communication links exist, packets are always delivered successfully to their destinations. No loss of packets due to collisions happen in the network. Also, it is assumed that communication delays are in the range of milliseconds and therefore can be neglected.
3. All the CECs have consistent communication and congestion detection algorithms installed on them, hence, they can always correctly interpret the messages that are forwarded to them.
4. CECs are always able to communicate with other CECs within their communication range, e.g., there are no obstacles like heavy weight vehicles between CECs to obstruct the wireless communication between them.

3.3.2 Traffic State Based Assumptions

With regard to the traffic flow modeling, traffic patterns, and traffic states, we make the following assumptions:

1. In this thesis, traffic congestions of continuous form are addressed. In the continuous form, only a single region is congested and the area under this region increases and decreases as the congestion grows and resolves, respectively. On the contrary, in the non-continuous congested states, the congested stretches of road are separated by non-congested regions.
2. The inflow of vehicles is uniform on all the lanes. Moreover, at the inlet, CEC density is also uniformly distributed across all the lanes.
3. No vehicle breakdown happens on the freeway. Thus, drops in the velocity of vehicles are solely influenced by the traffic conditions on the road.
4. After reaching the location of the exit, drivers can exit the freeway instantaneously, irrespective of the lane on which they are driving. This is a simplifying assumption that is consistent with previous literature[12], and is known to not significantly impact the realistic nature of the model.

3.4 Notations

The notations used in this thesis are mostly consistent with [5] and [6]. The four fundamental macroscopic quantities that are defined in the new model are, ρ , ρ^{com} , ρu and u . We use ρ , ρu and u , to represent density, flow and mean velocity, respectively. Moreover, fraction of CECs is represented as f^{com} and the density of CECs is represented as $\rho^{com} = \rho f^{com}$. The lanes on the freeway are numbered from 1 to N , with numbers increasing from the right to the left lane. The lane numbers are denoted by α and, ρ_α , ρ_α^{com} , ρu_α and u_α are the macroscopic quantities on a lane α . We define $U_{average}(x)$, as a continuous function that represents, average velocity at any position x on the freeway. The $u_{threshold}$ defines the minimum velocity threshold, such that, if the average velocity at any position on the freeway drops below this velocity, it is declared congested. At microscopic level, if the velocity of a CEC drops below $u_{threshold}$, it detects that it is in traffic congestion. The quantities with

superscript “ e ”, e.g., $u^e(\rho)$, $A^e(\rho)$ etc., denote the value of the corresponding quantity at equilibrium. At equilibrium, traffic attains a stationary state and all the vehicles move at zero relative velocity. In such a state, the density and the flow remain constant at every position in the space.

L represents the length of the unidirectional stretch of the freeway, and X_{Exit} represents the position of the exit on the freeway. The direction of motion of the vehicles on the considered freeway cross-section is from the left end to the right end. In our model, we define two kinds of congestion, represented by the actual traffic congestion ($Cong_a$) and the detected traffic congestion ($Cong_d$). In this thesis, the term congestion implicitly means actual traffic congestion. The head ($Cong_a^{head}$) and the tail ($Cong_a^{tail}$) are defined as the rightmost and the leftmost ends of the congested region on the freeway, respectively. Whereas, the head ($Cong_d^{head}$) and the tail ($Cong_d^{tail}$) are defined as the rightmost and the leftmost ends of the freeway section where the congestion has been detected. Moreover,

$$Cong_a^{tail} \leq Cong_d^{tail} \leq Cong_d^{head} \leq Cong_a^{head}$$

The congestion ($Cong_d$) warning information is propagated through the Congestion Warning Message ($CWMsg$). The $CWMsg$ essentially consists of the information about length of the congestion, its position and the position on the freeway up to which this message would be relevant and therefore, should be propagated. The ψ represents the fraction of drivers that choose to exit the freeway in response to the $CWMsg$. Length of the actual and detected congestions are represented by $\Delta Cong_a$ and $\Delta Cong_d$, respectively, and are the distances between the corresponding heads and tails. Moreover,

$$\Delta Cong_d \leq \Delta Cong_a$$

The length of congestion and its proximity to X_{Exit} determines the Severity of Congestion (SoC). The number of CECs between any two positions (x and y) on a N lane freeway is represented as, $Num_{car}^{com}(x, y, N)$. R represents the transmission range of the radio that is installed on the vehicles.

By the very nature of this thesis, the terms “traffic” and “congestion” have two meanings, one in the context of the actual roadway and physical vehicles, the other as computer networking terms. In general, we have occasion in this thesis to use these terms only in the first sense.

Chapter 4

Integrated Model Formulation

4.1 Macroscopic Network Algorithms

In this section, we propose a macroscopic fluid dynamic model that integrates the effect of communication on vehicular traffic mobility in a state of traffic congestion. While deriving this model, we have considered an unidirectional multi-lane freeway of length L , with an exit located at X_{Exit} . This section proposes communication networking algorithms and their integration with a traffic flow model.

4.1.1 Congestion Detection Algorithm at Macroscopic Level

In VANETs, the congestion detection and subsequent warning message propagation, is dependent on the number of CECs and their relative positions on the freeway. For example, consider two scenarios, one with large number of randomly distributed CECs forming connected groups that are not inter-connected to one another, and second scenario with smaller number of uniformly distributed CECs that are connected to one another.

At the macroscopic level, presence of CECs in traffic congestion needs to be determined in order to detect congestion. This is required due to the fact that in VANETs, only V2V communication is possible and no external network infrastructure or information source exists. Thus, cars themselves detect the occurrence of a congestion. Similarly, the communicability between the CECs determines whether the Congestion Warning Message

($CWMsg$) can be propagated to the target vehicles. Target vehicles in our case, are the vehicles that are located at a position x such that, $x \leq X_{Exit}$, and are capable of opting for an alternate route. We assume here that the congestion occurs at a position x such that, $x > X_{Exit}$.

Determining Traffic Congestion

Algorithm 1 Determining Traffic Congestion

```

{ $Cong_a$ : actual traffic congestion}
{ $Cong_a^{head}$ : head of actual congestion}
{ $Cong_a^{tail}$ : tail of actual congestion}
{ $\Delta Cong_a$ : length of actual congestion}
{ $Z$ : set of points in the space where, average velocity( $u$ )= $u_{threshold}$ }
{ $U_{average}(x)$ :  $\frac{\sum_{\alpha=1}^N \rho_{\alpha} u_{\alpha}}{\sum_{\alpha=1}^N \rho_{\alpha}}$ }
 $Z = U_{average}^{-1}(u_{threshold})$ 
if  $Z = \{\phi\}$  then
     $Cong_a \leftarrow 0$ 
else
     $Cong_a \leftarrow 1$ 
     $Cong_a^{tail} = \text{minimum}[Z]$ 
     $Cong_a^{head} = \text{maximum}[Z]$ 
     $\Delta Cong_a = Cong_a^{head} - Cong_a^{tail}$ 
end if

```

In our model, we first find the presence ($Cong_a$) and extent ($\Delta Cong_a$) of traffic congestion, and then determine whether it will be detected based on the presence of at least one CEC in the congested region.

Algorithm 1 finds the presence and extent of traffic congestion by determining the region on the freeway where the average velocity is less than the threshold velocity ($u_{threshold}$). Such a definition is consistent with [8], where congestion is defined as the drop in the velocity below a minimum threshold. As mentioned above in Section 3.3, drop in the velocity of a vehicle occurs only due to the traffic conditions in its surroundings and therefore, it deterministically defines the occurrence of a traffic congestion. We have also assumed that the congestion is of a continuous form and therefore, there is only a single region on the freeway that is congested. The area under this region increases and decreases as the congestion grows and resolves, respectively.

Congestion Detection Algorithm

Algorithm 2 Determining Detected Traffic Congestion ($Cong_d$)

```

{ $Cong_d$ : detected traffic congestion}
{ $Cong_d^{head}$ : head of detected congestion}
{ $Cong_d^{tail}$ : tail of detected congestion}
{ $\Delta Cong_d$ : length of detected congestion}
{ $R$ : transmission range of radio}
if  $Cong_a = 1$  then
  if  $Num_{car}^{com}(Cong_a^{head}, Cong_a^{tail}, N) \geq 1$  then
     $Cong_d \leftarrow 1$ 
    if  $\Delta Cong_a < R$  then
       $Cong_d^{head} \leftarrow Cong_d^{tail} \leftarrow Cong_a^{head}$ 
       $\Delta Cong_d \leftarrow Cong_d^{head} - Cong_d^{tail}$ 
    else
       $j \leftarrow Cong_a^{tail}, k \leftarrow Cong_a^{tail} + R$ 
      while  $Num_{car}^{com}(k, j, N) \geq 1$  and  $k \leq Cong_a^{head}$  do
         $Cong_d^{tail} \leftarrow Cong_a^{tail} + R$ 
         $Cong_d^{head} \leftarrow k$ 
         $\Delta Cong_d \leftarrow Cong_d^{head} - Cong_d^{tail}$ 
         $j \leftarrow k$ 
         $k \leftarrow k + R$ 
      end while
      if  $Cong_a^{head} < k < Cong_a^{head} + R$  then
         $j \leftarrow k - R$ 
         $k \leftarrow Cong_a^{head}$ 
        if  $Num_{car}^{com}(k, j, N) \geq 1$  then
           $Cong_d^{head} \leftarrow k$ 
           $\Delta Cong_d \leftarrow Cong_d^{head} - Cong_d^{tail}$ 
        end if
      end if
    end if
  end if
end if
  end if
end if
  
```

In VANETs, CECs detect congestion ($Cong_d$) and its length ($\Delta Cong_d$), through communication with their neighbors. This information is communicated through the CWM_{sg} . In [8], author has presented an algorithm that determines the presence and the length of the traffic congestion using V2V communication. In this thesis, we assume that similar algorithm is installed on all the CECs. The delay with which the congestion and its extent are detected, is inversely proportional to the CEC density ($\rho^{com} = \rho f^{com}$). Here, f^{com} de-

notes the fraction of the total density that is equipped with *telematics*. In the new model, we propose ρ^{com} as a fundamental macroscopic quantity along with ρ , u and ρu . In rest of the thesis, the term congestion refers to the actual traffic congestion ($Cong_a$), and the term detected congestion refers to the congestion that is detected ($Cong_d$) by CECs.

In order to detect congestion and its length, the presence of CECs in the congested region ($\Delta Cong_a$) has to be determined. This requires formulation of number of CECs located between any two positions. $Num_{car}^{com}(x, y, N)$ (Equation 4.1), represents the number of CECs located between positions x and y on a N lane freeway such that, $x \geq y$.

$$Num_{car}^{com}(x, y, N) = \sum_{\alpha=1}^N \int_y^x \rho_{\alpha}^{com}(x) dx \quad (4.1)$$

In order for CECs (inside congestion) to determine $\Delta Cong_d$ by communicating with each other, we need to determine the connectivity of the network in $\Delta Cong_a$ region. We define connected network in this area, by the presence of at least one CEC in each of the $\lceil \frac{\Delta Cong_a}{R} \rceil$ segments within $\Delta Cong_a$. Here, R is the transmission range of the radio. We assume that if present, the CEC is located at the right most end of such R length segment. For the sake of simplicity, if multiple CECs are present in a segment, we only consider one CEC and disregard the presence of others. This congestion detection method is presented in Algorithm 2. Here, it is assumed that the cars can address each other using their geographical positions[7][10]. Also, cars can broadcast the packets without any initial connection set up using similar routing algorithm as presented in [7].

This algorithm can be mapped to a microscopic congestion detection algorithm where, when a CEC detects that its velocity has dropped below $u_{threshold}$ and it has not heard the $CWMsg$ from any car in front of it, then it broadcasts a $CWMsg$ with its own position as head ($Cong_d^{head}$) and tail ($Cong_d^{tail}$). If any other CEC in congested area behind this car receives this $CWMsg$, it replaces the $Cong_d^{tail}$ to its own position, recomputes $\Delta Cong_d$ and broadcasts this updated $CWMsg$. This way, the $Cong_d^{tail}$ is set to the position of the hindmost CEC in the $\Delta Cong_a$ region. Also, the $Cong_d^{head}$ is set to the position of the farthest CEC in the $\Delta Cong_a$ that is connected to $Cong_d^{tail}$. $Cong_d^{head}$ and $Cong_d^{tail}$ define the length of the detected congestion ($\Delta Cong_d$).

4.1.2 Message Propagation Algorithm at Macroscopic Level

The $CWMsg$ is propagated to the target vehicles through communication amongst CECs that are already inside the congestion and those that lie between the congestion ($Cong_d^{tail}$) and the target vehicles. Propagation happens ($prop = 1$) only if these CECs form a connected network. If the network is not connected ($prop = 0$), the $CWMsg$ can not be propagated to the target CECs. We determine the propagability of the $CWMsg$

Algorithm 3 Determining Propagability of the $CWMsg$

```

{ $prop$ : propagability}
{ $R$ : transmission range of radio}
if  $Cong_d = 1$  then
   $j \leftarrow Cong_a^{tail} - R$ 
   $k \leftarrow Cong_a^{tail}$ 
   $prop \leftarrow 1$ 
  if  $j \leq X_{Exit}$  and  $k \geq X_{Exit}$  then
    if  $Num_{car}^{com}(k, X_{Exit}, N) < 1$  then
       $prop \leftarrow 0$ 
    end if
  else
    while  $j \geq X_{Exit}$  and  $prop = 1$  do
      if  $Num_{car}^{com}(k, j, N) \geq 1$  then
         $k \leftarrow j, j \leftarrow j - R$ 
      else
         $prop \leftarrow 0$ 
      end if
    end while
    if  $X_{Exit} - R < j$  and  $prop = 1$  then
      if  $Num_{car}^{com}(k, X_{Exit}, N) < 1$  then
         $prop \leftarrow 0$ 
      end if
    end if
  end if
end if

```

at macroscopic level (Algorithm 3), by locating the CECs in each of the $\lceil \frac{Cong_d^{tail} - X_{Exit}}{R} \rceil$ segments between the $Cong_d^{tail}$ and the X_{Exit} . Similar to Algorithm 2, if multiple CECs are present in a segment, we only consider one CEC and disregard the presence of others. Moreover, the $CWMsg$ is last updated by $Cong_d^{tail}$ and is forwarded till a position up to where it will be relevant (for example, information may be useful 10 miles from the point of congestion, but is unlikely to be useful 100 miles behind). In our algorithm, the message

is propagated up to $Cong_d^{tail}-M$ where, M is a constant and for small L considered in this thesis, $M>L$. If the network is connected, the propagation delay is assumed to be in the range of milliseconds and therefore it is neglected. In our algorithms, we have not considered the possibility of congestion extending beyond the X_{Exit} .

4.2 Macroscopic Fluid Dynamic Equations

In this section, we present the macroscopic fluid dynamic equations that model the effect of communication on the traffic mobility. This is achieved by modeling the driver behavior (in response to the $CWMsg$) and integrating it with a traffic flow model to reflect its impact on the traffic dynamics. The $CWMsg$ is generated and forwarded using the congestion detection and propagation algorithms presented in Section 4.1. The integrated model equations apply to a freeway with an exit (X_{Exit}) such that, the traffic congestion happens at an $x > X_{Exit}$.

Modeling Driver Behavior (ψ)

When the target vehicles receive the $CWMsg$, the drivers may or may not choose to exit the freeway. Fraction of the drivers choosing to exit is influenced by the Severity of Congestion (SoC), which is defined below:

$$SoC = \frac{q\Delta Cong_d}{(Cong_d^{tail} - X_{Exit})} \quad (4.2)$$

Here, $Cong_d^{tail} > X_{Exit}$ and the parameter $q(>1)$ is a scale factor that models the greater impact of $\Delta Cong_d$ on the SoC than its closeness to the X_{Exit} .

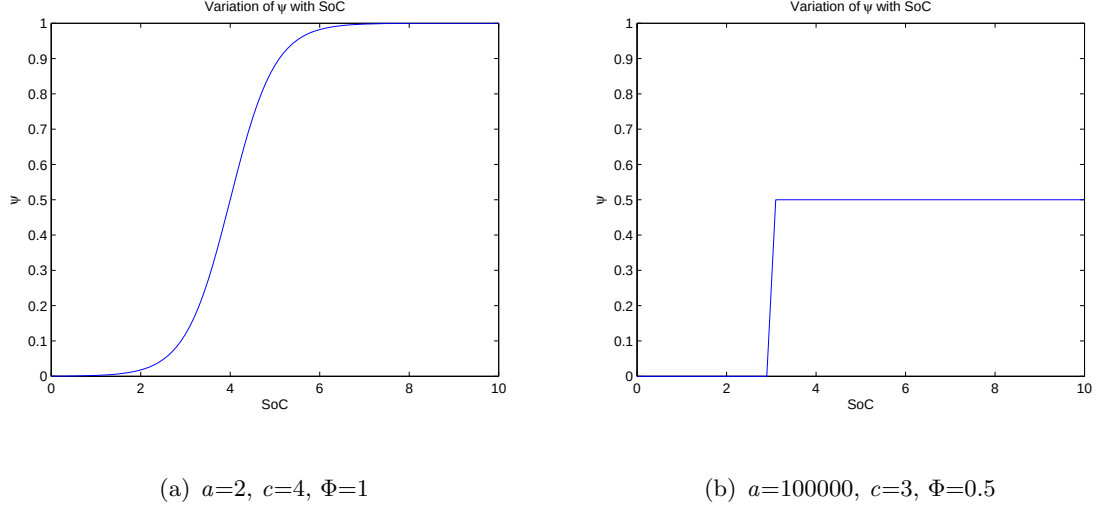
In the macroscopic equations that follow, ψ represents the driver behavior i.e., the fraction of the cars that choose to exit in response to the SoC and is defined as follows:

$$\psi = prop \left[\Phi \frac{1}{1 + e^{-a(SoC-c)}} \right] \quad (4.3)$$

Where,

$$prop = \begin{cases} 1 & \text{if, the } CWMsg \text{ can be propagated} \\ 0 & \text{otherwise} \end{cases}$$

Φ represents the maximum fraction of CECs that can exit the freeway at any given time

Figure 4.1: Variations in ψ with SoC

and therefore represents the maximum value that ψ can attain. Moreover, a and c are the constants. Here, ψ is modeled as a sigmoid function (Equation 4.3), which is useful in this context because it correctly represents the non-linearity and saturation of reaction to congestion that may be naturally expected, but does not involve discontinuous changes in the function derivative. Figure 4.1 shows the different variations of ψ (with respect to SoC) considered in this thesis. Here, SoC is scaled to a severity rating of 0-10 such that, $SoC \geq 10$ represents severe congestion states and $SoC=0$ represents no congestion state.

Effect of Driver Behavior (ψ) on Flow and Density

When CECs exit in response to the $CWMsg$, they affect the dynamics of macroscopic fundamental quantities, ρ_α , ρ_α^{com} , u_α and $\rho_\alpha u_\alpha$. In the new integrated model, this is accounted for by defining the loss of the density ($\psi \rho_\alpha^{com}$) and the corresponding loss of the flow ($\psi \rho_\alpha^{com} u^e$) at X_{Exit} . Following multi-lane macroscopic fluid dynamic partial differential equations (Equations 4.4, 4.5 and 4.6) propose an integrated model that defines this behavior and reflect the effect of communication on mobility. Equations 4.4 and 4.5 are deduced from Equations 3.1 and 3.2, respectively.

Density Equation:

$$\begin{aligned}
\partial_t(\rho_\alpha) + \partial_x(\rho_\alpha u_\alpha) &= \left(\frac{1}{T_{\alpha-1}^L} \rho_{\alpha-1} - \frac{1}{T_\alpha^R} \rho_\alpha\right)(1 - \delta_{\alpha,1}) \\
&\quad + \left(\frac{1}{T_{\alpha+1}^R} \rho_{\alpha+1} - \frac{1}{T_\alpha^L} \rho_\alpha\right)(1 - \delta_{\alpha,N}) \\
&\quad - \delta_{x, X_{Exit}} [\psi \rho_\alpha^{com} + \rho_\alpha^{Exit}]
\end{aligned} \tag{4.4}$$

Flow Equation:

$$\begin{aligned}
\partial_t(\rho_\alpha u_\alpha) + \partial_x(p^e(\rho_\alpha) + \rho_\alpha u_\alpha^2) + \partial_x(A^e(\rho_\alpha)) &= \\
&\quad \left(\frac{1}{T_{\alpha-1}^L} \rho_{\alpha-1} u_{\alpha-1} - \frac{1}{T_\alpha^R} \rho_\alpha u_\alpha\right)(1 - \delta_{\alpha,1}) \\
&\quad + \left(\frac{1}{T_{\alpha+1}^R} \rho_{\alpha+1} u_{\alpha+1} - \frac{1}{T_\alpha^L} \rho_\alpha u_\alpha\right)(1 - \delta_{\alpha,N}) \\
&\quad + \frac{1}{T^e(\rho_\alpha)} \rho_\alpha [u^e(\rho_\alpha) - u_\alpha] \\
&\quad - \delta_{x, X_{Exit}} [\psi \rho_\alpha^{com} u^e(\rho_\alpha) + \rho_\alpha^{Exit} u^e(\rho_\alpha)]
\end{aligned} \tag{4.5}$$

Finally, we also need a new equation (Equation 4.6) for representing the fact that the density of CECs that exit is withdrawn from the flow that continues beyond the X_{Exit} . This drop in the density of CECs propagates down the freeway with time. The reduction in ρ_α^{com} defines the loss in number of CECs on the freeway and the subsequent reduction in the network connectivity. Equation 4.6 is similar to Equation 3.1, as ρ_α^{com} is a fraction of ρ_α , and its nature is intuitively similar to that of ρ_α .

CEC Density Equation:

$$\begin{aligned}
\partial_t(\rho_\alpha^{com}) + \partial_x(\rho_\alpha^{com} u_\alpha) &= \left(\frac{1}{T_{\alpha-1}^L} \rho_{\alpha-1}^{com} - \frac{1}{T_\alpha^R} \rho_\alpha^{com}\right)(1 - \delta_{\alpha,1}) \\
&\quad + \left(\frac{1}{T_{\alpha+1}^R} \rho_{\alpha+1}^{com} - \frac{1}{T_\alpha^L} \rho_\alpha^{com}\right)(1 - \delta_{\alpha,N}) \\
&\quad - \delta_{x, X_{Exit}} [\psi \rho_\alpha^{com} + \rho_\alpha^{com Exit}]
\end{aligned} \tag{4.6}$$

Following additional parameters (other than what is explained in Section 3.1.1) model the dynamics of these fundamental quantities,

ρ_α^{Exit} : Density of cars that are pre-destined to exit

$\rho_\alpha^{comExit}$: $f_\alpha^{com} \rho_\alpha^{Exit}$, Density of CECs that are pre-destined to exit

Note that the Kronecker Delta ensures that the new interaction (exiting) can only occur at the X_{Exit} .

Remark 1.: The cumulative fluid dynamic equations representing an integrated model for a single-lane freeway are presented by Equations 4.7, 4.8 and 4.9. Such an interpretation for a single-lane freeway is consistent with [5].

Density Equation:

$$\partial_t(\rho) + \partial_x(\rho u) = (-1)\delta_{x, X_{Exit}}[\psi \rho^{com} + \rho^{Exit}] \quad (4.7)$$

Flow Equation:

$$\begin{aligned} \partial_t(\rho u) + \partial_x(p^e(\rho) + \rho u^2) + \partial_x(A^e(\rho)) = \\ \frac{1}{T^e(\rho)} \rho [u^e(\rho) - u] \\ - \delta_{x, X_{Exit}}[\psi \rho^{com} u^e(\rho) + \rho^{Exit} u^e(\rho)] \end{aligned} \quad (4.8)$$

CEC Density Equation:

$$\partial_t(\rho^{com}) + \partial_x(\rho^{com} u) = (-1)\delta_{x, X_{Exit}}[\psi \rho^{com} + \rho^{comExit}] \quad (4.9)$$

Chapter 5

Numerical Investigations

5.1 The Freeway Scenario

For numerical investigations, we have considered an inhomogeneous traffic flow situation on a three-lane freeway of length L , with a lane closure at position X_{LClose} on the left most lane, and an exit at position X_{Exit} such that, $X_{LClose} > X_{Exit}$. In this case, X_{LClose} poses a bottleneck that causes traffic congestion on the freeway.

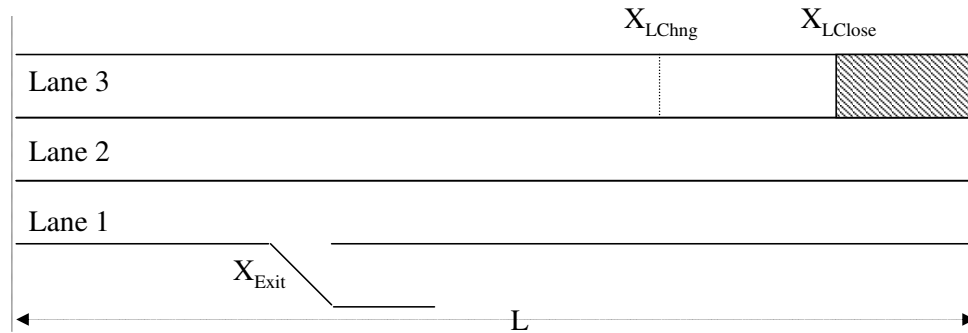


Figure 5.1: The Freeway Cross Section

X_{LChng} is the position from where a strong increase in the lane changing operations from lane 3 to lane 2 happens.

5.2 Macroscopic Solution

In this chapter, the integrated fluid dynamic model and network algorithms proposed in Chapter 4, are investigated on the freeway cross-section presented in Section 5.1. These fluid-dynamic equations belong to a system of hyperbolic conservation laws[22], and numerical methods are able to provide approximate solutions for these with realistic initial and boundary conditions. We solve the fluid dynamic equations using the LaxWendroff's[17] finite-difference method which provides a stable solution for the fluid-dynamic partial differential equations. The LaxWendroff's method is a 3-point scheme, where the solution at x , depends on the data at $x + \Delta x$ and $x - \Delta x$ where, $\Delta x \rightarrow 0$. The model equations are solved in MATLAB.

The LaxWendroff's Finite Difference Method

For illustration, we present below the LaxWendroff's finite-difference representation (Equation 5.1) of the partial differential density equation (Equation 4.4) where, $\Delta x, \Delta t \rightarrow 0$.

$$\begin{aligned}
& \frac{\rho_\alpha(x, t) - (1/2)(\rho_\alpha(x - \Delta x, t - \Delta t) + \rho_\alpha(x + \Delta x, t - \Delta t))}{\Delta t} \\
& + \frac{\rho_\alpha u_\alpha(x + \Delta x, t - \Delta t) - \rho_\alpha u_\alpha(x - \Delta x, t - \Delta t)}{2\Delta x} = \\
& \quad \left(\frac{1}{T_{\alpha-1}^L(x - \Delta x, t - \Delta t)} \rho_{\alpha-1}(x - \Delta x, t - \Delta t) - \right. \\
& \quad \left. \frac{1}{T_\alpha^R(x - \Delta x, t - \Delta t)} \rho_\alpha(x - \Delta x, t - \Delta t) \right) (1 - \delta_{\alpha,1}) \\
& + \left(\frac{1}{T_{\alpha+1}^R(x - \Delta x, t - \Delta t)} \rho_{\alpha+1}(x - \Delta x, t - \Delta t) - \right. \\
& \quad \left. \frac{1}{T_\alpha^L(x - \Delta x, t - \Delta t)} \rho_\alpha(x - \Delta x, t - \Delta t) \right) (1 - \delta_{\alpha,N}) \\
& - \delta_{x, X_{Exit}} [\psi \rho_\alpha^{com}(x - \Delta x, t - \Delta t) + \rho_\alpha^{Exit}(x - \Delta x, t - \Delta t)] \tag{5.1}
\end{aligned}$$

In this finite difference equation, the density $\rho_\alpha(x, t)$ on the lane α , at current position x , and current time t , is determined by the values of macroscopic quantities in its neighborhood ($x + \Delta x$ and $x - \Delta x$) on the same lane and the adjacent lanes, at previous time ($t - \Delta t$).

Due to inhomogeneity at the position of lane closure on the freeway, a special treatment is done in order to account for the fundamental quantities at the position $X_{LClose} - \Delta x$

on the leftmost lane as, for this position the 3-point scheme can not be applied. This is addressed by a 2-point scheme involving the data at position x and $x - \Delta x$. With the heavy traffic inflow on the freeway, the density at $X_{LClose} - \Delta x$ on the leftmost lane increases and the flow at this position reduces. This effect spreads on the freeway as the congestion grows.

The equilibrium coefficients appearing in the fluid dynamic flow equation (Equation 4.5) are obtained by the stationary distributions of the homogeneous cumulative kinetic equation presented in [5] and [6]. With this finite difference numerical solution approach and the equilibrium coefficients, we compute the macroscopic fundamental quantities for the different scenarios and present the results in Sections 5.6 and 5.7. In Sections 5.4 and 5.5, we describe various experimental parameters, and initial and boundary conditions for the macroscopic model.

5.3 Microscopic Simulation

In this thesis, we compare the predictions made by the macroscopic model with the corresponding microscopic simulations. Since in the microscopic simulations, behavior of each individual car is traced, it provides a more realistic representation of the traffic flow that verifies the nature of predictions made by the macroscopic model. In this section, we describe the microscopic rules that serve as the basis for our Java based traffic simulator named μ Sim.

Microscopic Rules

Our simulations are based on the microscopic rules defined by Klar et al.[5], that are presented in Sections 2.3.1 and 3.1.2. Authors have presented rules for lane changing, braking and acceleration operations.

Consider a car C , and its neighbors on the adjacent lanes as shown in the Figure 5.2. For a car C , C^+ and C^- , are the leading and following car on the same lane, C_l^+ and C_l^- , are the leading and following car on the left lane, and, C_r^+ and C_r^- , are the leading and following car on the right lane, respectively. Similarly for a car C^+ , C^{++} and C , are the leading and following car on the same lane, C_l^{++} and C_l^{+-} , are the leading and following

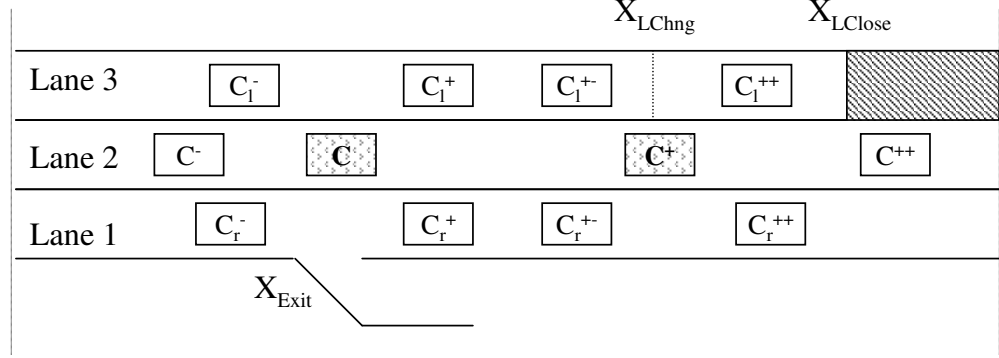


Figure 5.2: Car Notations

car on the left lane, and, C_r^{++} and C_r^{+-} , are the leading and following car on the right lane, respectively.

While deriving the kinetic and fluid dynamic model, authors have put together the lane changing and braking lines and have assumed the sequence of microscopic rules (for a car C) as presented in Algorithm 4.

Algorithm 4 Microscopic Rules for Homogeneous Conditions

```

if Distance between  $C$  and  $C^+$  is less than the braking line then
  if Enough space between  $C$  and  $C_l^+$ , and  $C$  and  $C_l^-$  then
     $C$  will change lane to the left
  else if Enough space between  $C^+$  and  $C_r^{++}$ , and  $C^+$  and  $C_r^{+-}$  then
     $C^+$  will change lane to the right
  else
     $C$  will brake
  end if
else if Distance between  $C$  and  $C^+$  is greater than the braking line then
   $C$  accelerates according to the acceleration rules
end if

```

Algorithm 4 states that, after reaching the braking line, first the driver - will try to change the lane to the left, if this is not possible - the leading car will try to change to the right, and third, if lane changing is not possible at all - the driver will brake. If the braking line is not reached, the driver accelerates according to the acceleration rules. This model assumes that leftmost lanes are the fastest and rightmost are the slowest. Moreover, it also assumes cooperative behavior amongst the drivers. Such sequence of rules applies

to homogeneous conditions. For the inhomogeneous conditions considered in this thesis, we have modified the sequence of rules for the cars in leftmost and the middle lane, between X_{LChng} and X_{LClose} positions. This sequence is presented in Algorithm 5.

Algorithm 5 Microscopic Rules for Inhomogeneous Conditions

```

if Distance between  $C$  and  $C^+$  is less than the braking line then
  if Enough space between  $C$  and  $C_r^+$ , and  $C$  and  $C_r^-$  then
     $C$  will change lane to the right
  else
     $C$  will brake
  end if
else if Distance between  $C$  and  $C^+$  is greater than the braking line then
   $C$  accelerates according to the acceleration rules
end if

```

Hence, after reaching the braking line on the middle and the leftmost lane between X_{LChng} and X_{LClose} , first the driver - will try to change the lane to the right (for his own advantage), if this is not possible - the driver will brake. As a result of these rules, in this region no car from the middle lane changes to the leftmost lane, and the rate of lane change from the leftmost to the middle and from middle to the rightmost lane is increased.

The model presented in [5] does not takes into account the presence of an exit on the freeway. In our investigations, we have assumed that the drivers are able to exit the freeway at X_{Exit} , irrespective of the lane on which they are driving. In the literature[12], similar approach to simulate an exit has been presented.

5.4 Experimental Parameters

The physical units in the numerical computations are consistent with what is presented in [6], and are fixed by setting the unit length x to 1 car length, the maximum velocity w to 1, and the bumper-to-bumper distance H_0 to 1. Thus, the maximum density per lane, $\rho_m = \frac{1}{H_0} = 1$. The unit time t is given by $t = \frac{H_0}{w}$, and is therefore the time needed to travel a distance of one car length with the maximum velocity.

We have experimented with different traffic patterns and driver behaviors on a freeway cross-section of length $L=500$ with $X_{LClose}=460$, $X_{LChng}=450$ and $X_{Exit}=100$. In the remaining section, we describe various experimental parameters for macroscopic and microscopic model.

Macroscopic Model

For a given scenario, the macroscopic model predictions differ on the basis of the boundary conditions (traffic patterns at the inlet) and the initial traffic conditions on the freeway. These conditions are defined by the values of macroscopic fundamental quantities (ρ_α , $\rho_\alpha u_\alpha$ and ρ_α^{com}). In this thesis, we investigate the cases with uniform inflow of traffic on all the lanes. We have experimented with different sets of conditions and have predicted the corresponding traffic states. The initial conditions that have been investigated are:

1. $\rho_\alpha(x, 0) = 0.2$, $\rho_\alpha u_\alpha(x, 0) = 0.1$ and $f_\alpha^{com}(x, 0) = 0$, ($0 < x < L$, $0 < t < T$)
2. $\rho_\alpha(x, 0) = 0.2$, $\rho_\alpha u_\alpha(x, 0) = 0.1$ and $f_\alpha^{com}(x, 0) = 0.1$, ($0 < x < L$, $0 < t < T$)
3. $\rho_\alpha(x, 0) = 0.2$, $\rho_\alpha u_\alpha(x, 0) = 0.1$ and $f_\alpha^{com}(x, 0) = 0.5$, ($0 < x < L$, $0 < t < T$)
4. $\rho_\alpha(x, 0) = 0.2$, $\rho_\alpha u_\alpha(x, 0) = 0.1$ and $f_\alpha^{com}(x, 0) = 0.8$, ($0 < x < L$, $0 < t < T$)

The following boundary conditions hold for each of these initial conditions:

$$\rho_\alpha(0, t) = \rho_\alpha(0, 0), \rho_\alpha u_\alpha(0, t) = \rho_\alpha u_\alpha(0, 0), f_\alpha^{com}(0, t) = f_\alpha^{com}(0, 0), (0 < t < T)$$

Here, T represents the time until which the solutions are computed. In order to closely study the effect of communication on the traffic mobility, we have set $\rho_\alpha^{Exit} = \rho_\alpha^{comExit} = 0$ so that, cars exit the freeway only in response to the *CWMsg*.

Another parameter that affects the traffic operations is the threshold velocity ($u_{threshold}$). If the average velocity on the freeway drops below this threshold, it is declared congested. In our investigations, $u_{threshold} = 0.2$. The transmission range (R) is set to 20 car lengths.

In general, spontaneous lane changing which is not caused by another car also has to be taken into account. For simplicity, this type of lane changing has not been considered in the model[5]. However, particularly for inhomogeneous situations like the one treated in this chapter, it is important to include this kind of lane changing. We have set the spontaneous lane changing rate to 0.005[6]. Moreover, in front of the lane drop an additional strong increase of the lane changing frequency to the right is included on the lane 3. The size of this lane changing area is $X_{LClose} - X_{LCong} = 10$ and the increase in lane changing frequency is $\frac{0.05}{X_{LClose} - X_{LCong}}$. In this region, the lane changing frequency to the left on the lane 2 is set to zero.

Driver behavior (ψ) determines the fraction of ρ_α^{com} that exits the freeway when the *CWMsg* is received, and therefore affects the way in which the congestion grows and

resolves. The ψ is dependent on Φ , scaling factor q and, constants a and c , as shown in Equations 4.2 and 4.3. In our numerical investigations, $q \in \{0, 10, 10000\}$ representing, *Carefree* ($q=0$), *Typical* ($q=10$) and *Panicky* ($q=10000$) driver behaviors. Moreover, we have considered $\{\Phi=1, a=2, c=4\}$ and $\{\Phi=0.5, a=100000, c=3\}$ as shown in Figure 4.1. The different driver behaviors are explained below:

1. *Carefree* behavior($q=0$): In this behavior, drivers ignore the *CWMsg* and therefore do not exit ($\psi = 0$), irrespective of *SoC*.
2. *Typical* behavior($q=10$): In this behavior, the fraction of drivers that exit ($\psi \neq 0$) increases with *SoC*. The variation of this fraction is based on the Equation 4.3.
3. *Panicky* behavior($q=10,000$): In this behavior Φ fraction of ρ_α^{com} ($\psi = \Phi$) exits the freeway in response to the *CWMsg*, irrespective of *SoC*.

Microscopic Model

In the microscopic simulations to define the acceleration, braking and lane changing rules, we have used the reaction thresholds as provided in [6]. Using this model, we have simulated a random inflow of cars at the inlet in such a way that $\rho_\alpha u_\alpha$, ρ_α and ρ_α^{com} are uniform on all the lanes over a given period of time. This way, microscopic initial and boundary conditions that are consistent with the corresponding macroscopic conditions are achieved. Section 5.5 gives a detailed description of generating initial and boundary conditions at the microscopic level. In the microscopic simulations, we implement the similar communication algorithms that are proposed in Section 4.1. When the velocity of a CEC drops below $u_{threshold}$, it generates a *CWMsg* which is forwarded to the target CECs. As each individual car is traced at this level, algorithms compute the precise locations of $Cong_d^{head}$ and $Cong_d^{tail}$. Therefore, the need of defining $Cong_a$ is eliminated for microscopic level simulations. CECs inside the traffic congestion communicate with each other to determine the *SoC*. This information is forwarded through the *CWMsg* to the target CECs. The propagation up to the target vehicles happens if there is network connectivity between X_{Exit} and $Cong_d^{tail}$. The connectivity is guaranteed if either, the first CEC after the X_{Exit} , is within R distance of the X_{Exit} and is connected to $Cong_d^{tail}$ or, if it is itself the $Cong_d^{tail}$. Similar to that in the macroscopic model, cars exit the freeway only in response to the *CWMsg*

and are not predestined to take the exit to reach their destinations. Other experimental parameters like, ψ and $u_{threshold}$, are similar to those in the macroscopic model.

5.5 Generating Initial and Boundary Conditions

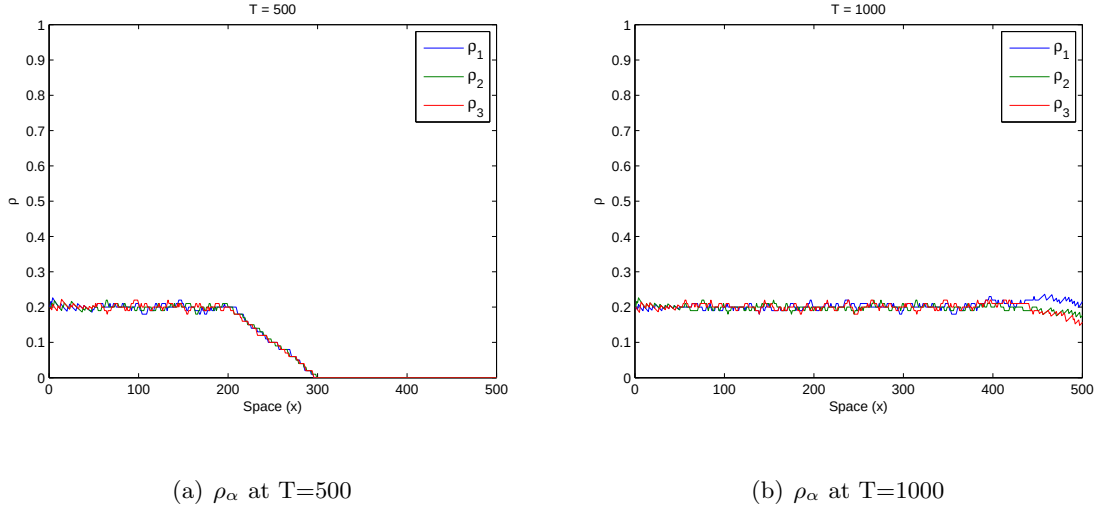


Figure 5.3: Attaining Microscopic Equilibrium ρ_α

For the macroscopic solutions and the μ Sim simulations, we assume that initially the traffic on the freeway is at equilibrium and after this, a lane closure is introduced on the leftmost lane. For the macroscopic solutions, these initial conditions are obtained by initializing the quantities to corresponding values, as described in Section 5.4.

For μ Sim, similar initial conditions are obtained by simulating an equilibrium traffic inflow on an empty freeway, until the average density and the flow on all the lanes and at all the positions, attain similar equilibrium state as at the inlet. In order to attain initial density ρ_α and corresponding equilibrium flow $\rho_\alpha u_\alpha$, $10\rho_\alpha$ cars each with u_α velocity, are randomly injected in every $\frac{10}{u_\alpha}$ time interval on each lane. Also, the CECs are injected randomly in such a way that ρ_α^{com} remains uniform over time, and is similar to the corresponding initial values for the macroscopic solution. After $\frac{L}{u_\alpha}$ time, the average density and the flow on all the lanes attains ρ_α and $\rho_\alpha u_\alpha$, respectively. When this initial equilibrium state is reached, a lane closure on the left most lane is introduced. Figures 5.3 and 5.4,

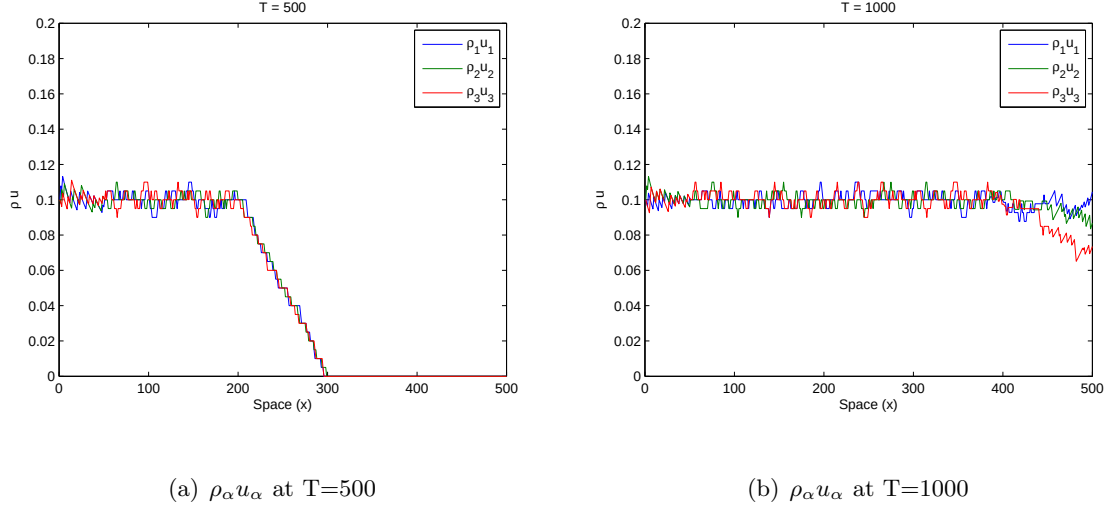


Figure 5.4: Attaining Microscopic Equilibrium $\rho_\alpha u_\alpha$

show the densities and flows for an initially empty freeway stretch of length $L = 500$ for $\rho_\alpha(0, t) = 0.2$ and $\rho_\alpha u_\alpha(0, t) = 0.1$, where $0 \leq t \leq \frac{L}{u_\alpha}$.

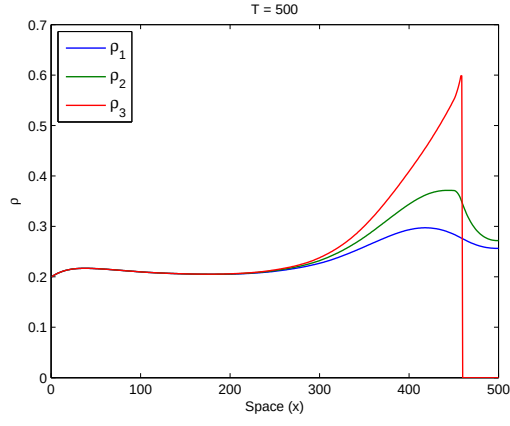
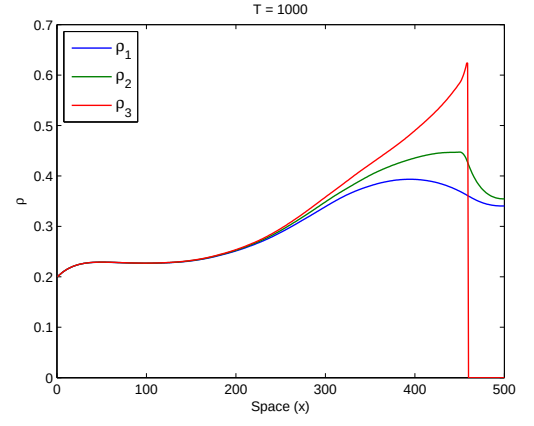
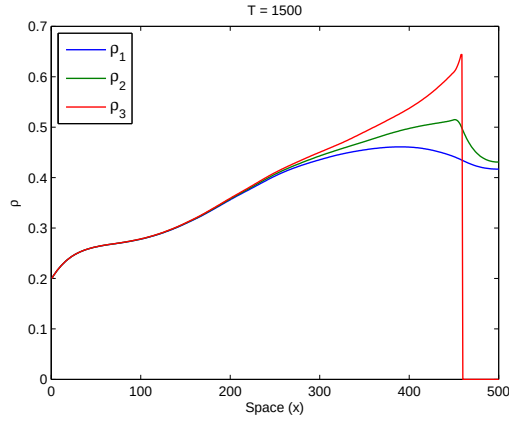
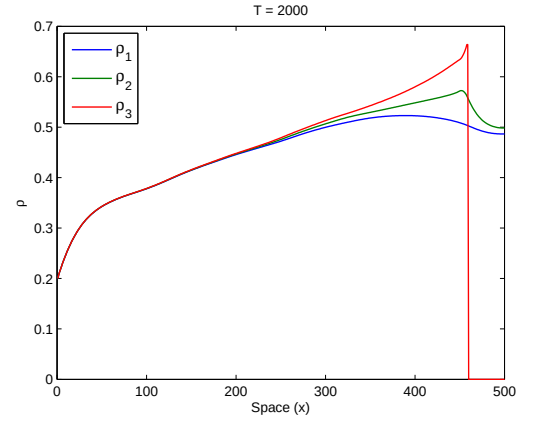
In order to present the results of μSim in a comparable manner with respect to the macroscopic solutions, densities and flows at a position are computed by averaging the values until 50 car lengths in front and behind of that position.

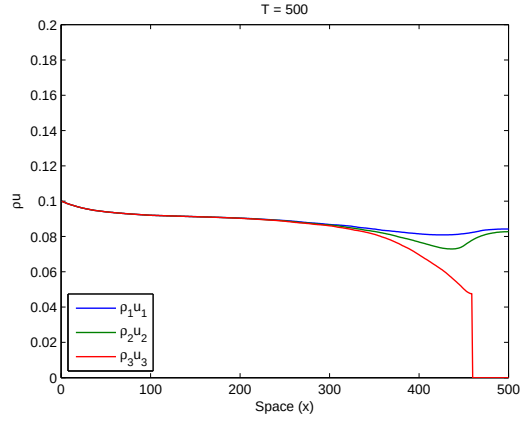
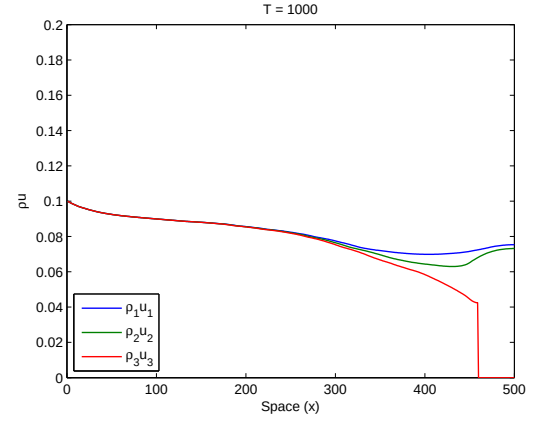
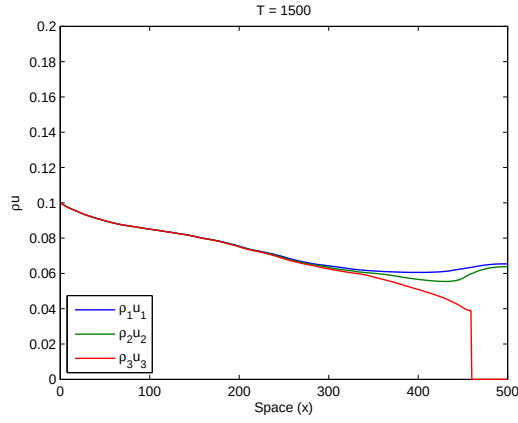
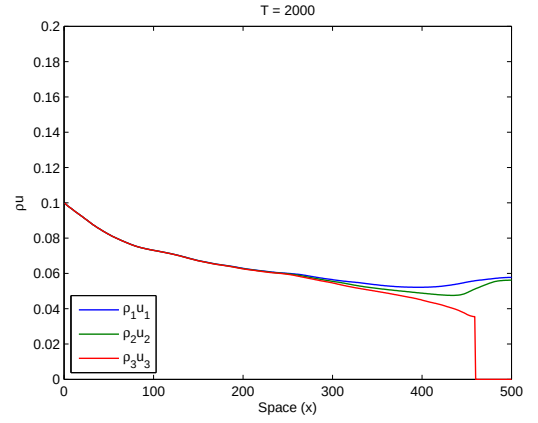
5.6 Comparative Analysis on the basis of Driver Behavior

In this section, we compare the traffic states on the freeway for different driver behaviors. These comparisons are done through the predictions made by the macroscopic solutions and the simulation results by μSim . In this section we only consider the cases where the CWM_{sg} has zero persistence (the CWM_{sg} has a *lifetime* of 1). A comparison based on the CWM_{sg} persistence is presented in Section 5.7.

5.6.1 Carefree Driver Behavior

As defined in Section 5.4, the *Carefree* driver behavior ($q=0$) is a state where drivers ignore the CWM_{sg} , and therefore do not exit the freeway irrespective of the *SoC*. This case is equivalent to $f_\alpha^{com} = 0$, and therefore serves as the base case for comparison

(a) ρ_α at $T=500$ (b) ρ_α at $T=1000$ (c) ρ_α at $T=1500$ (d) ρ_α at $T=2000$ Figure 5.5: Macroscopic ρ_α for *Carefree* Driver Behavior or $f_\alpha^{com}(x, 0) = 0$

(a) $\rho_\alpha u_\alpha$ at T=500(b) $\rho_\alpha u_\alpha$ at T=1000(c) $\rho_\alpha u_\alpha$ at T=1500(d) $\rho_\alpha u_\alpha$ at T=2000Figure 5.6: Macroscopic $\rho_\alpha u_\alpha$ for *Carefree* Driver Behavior or $f_\alpha^{com}(x, 0) = 0$

with other cases with different driver behaviors and f_α^{com} .

Figures 5.5 and 5.6 show the snapshots of the densities and the flows on the freeway at different time instants for the *Carefree* Driver behavior.

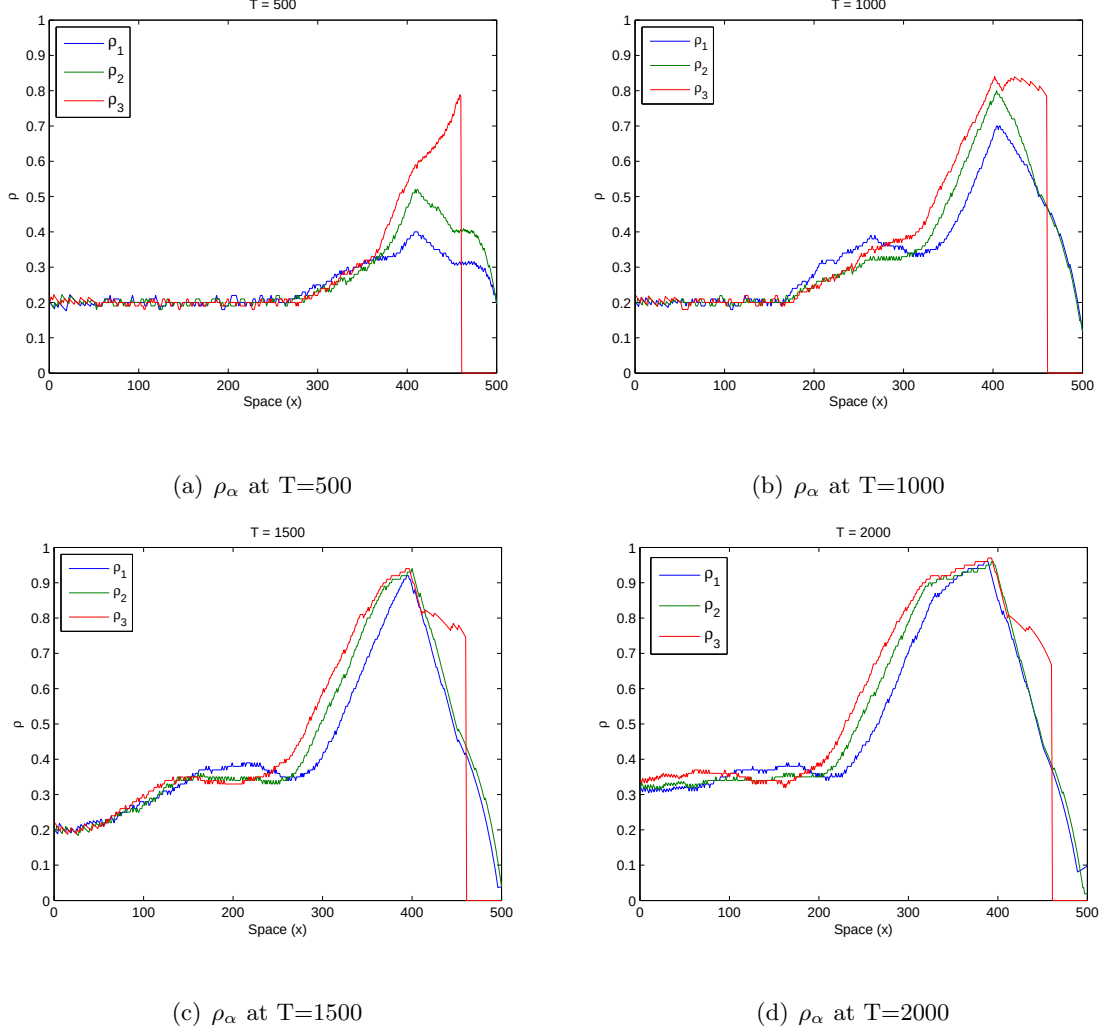
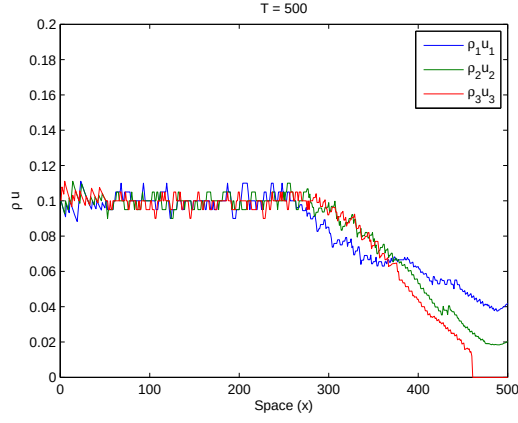
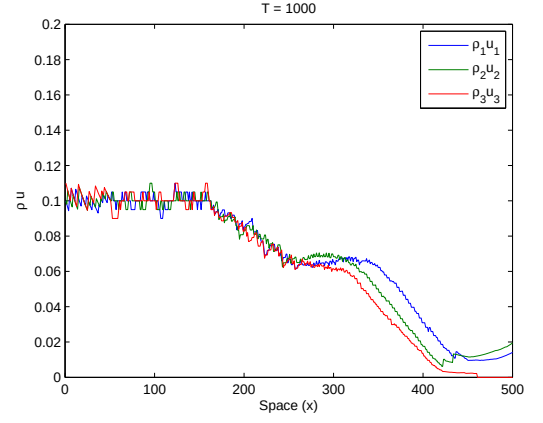
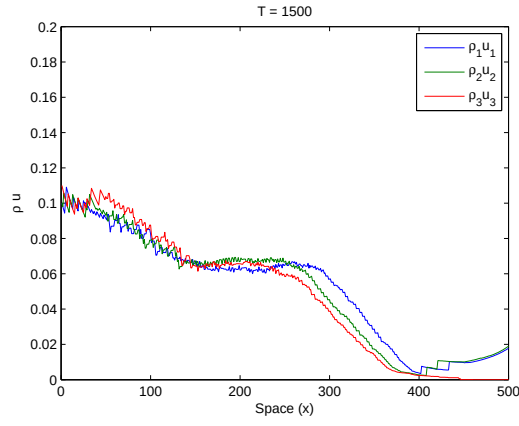
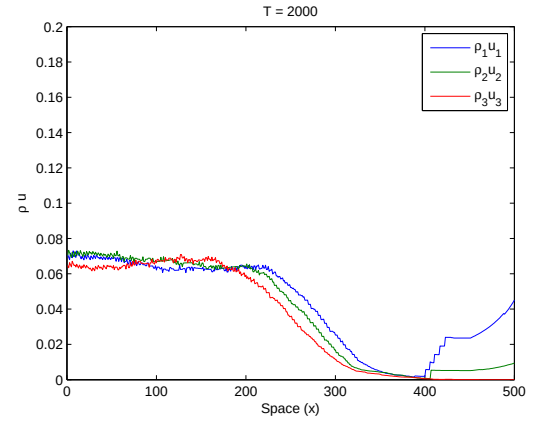


Figure 5.7: Microscopic ρ_α for *Carefree* Driver Behavior or $f_\alpha^{com}(x, 0) = 0$

Initially at $T=0$, the traffic on the freeway is in equilibrium ($\rho_\alpha(x, 0)=0.2$ and $\rho_\alpha u_\alpha(x, 0)=0.1$), and then a lane closure is introduced on lane 3. With the constant inflow of traffic ($\rho_\alpha(0, t)=0.2$ and $\rho_\alpha u_\alpha(0, t)=0.1$) the density increases and the flow decreases near the bottleneck on the lane 3. This increased density causes greater lane changing rates to the right, onto lane 2 and lane 1. This marks the onset of traffic congestion that builds up

(a) $\rho_\alpha u_\alpha$ at $T=500$ (b) $\rho_\alpha u_\alpha$ at $T=1000$ (c) $\rho_\alpha u_\alpha$ at $T=1500$ (d) $\rho_\alpha u_\alpha$ at $T=2000$ Figure 5.8: Microscopic $\rho_\alpha u_\alpha$ for *Carefree* Driver Behavior or $f_\alpha^{com}(x, 0) = 0$

on all the lanes near X_{LClose} . Figures 5.5(a) and 5.6(a) show this increase in density and loss of traffic flow, respectively, on the three lanes at $T=500$ near X_{LClose} . Further down the time, as shown by Figures 5.5 and 5.6, the congestion expands over greater lengths of road.

Similar behavior as predicted by the macroscopic solution, is also shown by the corresponding μSim simulation (Figures 5.7 and 5.8). Due to the lane closure at X_{LClose} , cars in the lane 3 pile up in front of the closure, resulting in the increase in traffic density on lane 3, which gets carried on to lane 2 and lane 1, causing traffic congestion near X_{LClose} , which expands with time.

5.6.2 Typical Driver Behavior

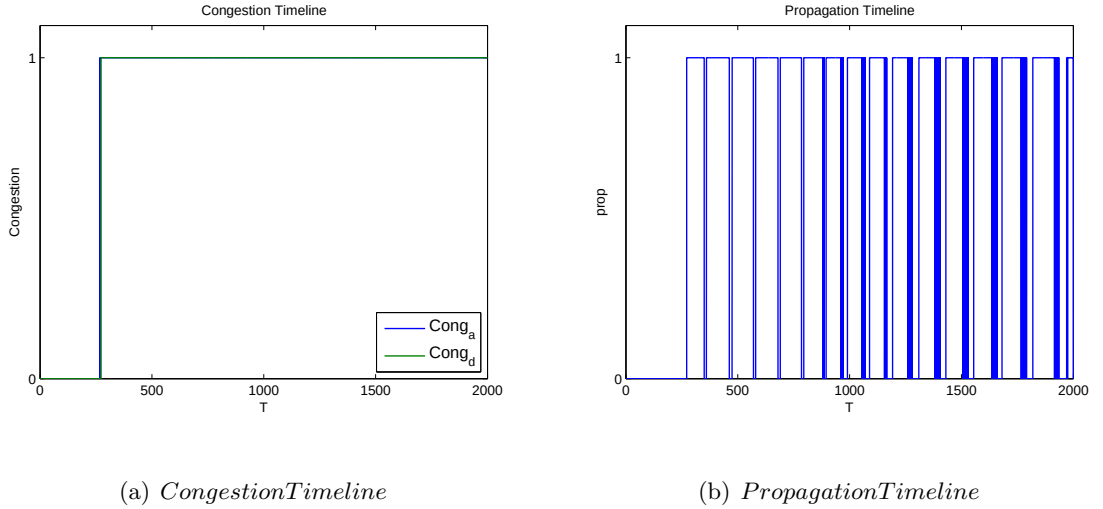


Figure 5.9: Macroscopic Communication Timelines for *Typical* Driver Behavior with Zero Persistence and $f_{\alpha}^{com}(x, 0) = 0.5$

As defined in Section 5.4, in the *Typical* driver behavior state ($q=10$), the fraction of the drivers (ψ) that exit the freeway in response to the $CWMsg$ increases with SoC . The variation of ψ with SoC is presented in Section 4.2. In this section, we consider the cases with $\{\Phi=1, a=2, c=4\}$ (Figure 4.1(a)). As compared to the *Carefree* and the *Panicky* driver behaviors, this kind of a behavior is more realistic.

In this section, we investigate the effects of the *Typical* driver behavior on the traffic operations in a scenario with $f_{\alpha}^{com} = 0.5$. In this scenario, as presented in Figure

5.9(a), when the congestion occurs on the freeway ($Cong_a = 1$), it is detected ($Cong_d = 1$) with minimal latency. The latency with which the congestion is detected is inversely proportional to the ρ_α^{com} . Figure A.10(a) shows significantly increased latency in congestion detection when $f_\alpha^{com} = 0.1$.

As inferred from Figure 5.9, after the congestion is detected, the $CWMsg$ is propagated ($prop = 1$) to the target vehicles. In response to the $CWMsg$, ψ fraction of ρ_α^{com} exits the freeway. This leads to decrease in the f_α^{com} near the X_{Exit} and subsequently to network disconnection due to absence of a CEC within R distance of X_{Exit} towards $Cong_{tail}^d$. Due to zero persistent $CWMsg$, when network gets disconnected ($prop=0, \psi=0$), none of the cars exit the freeway. This results in increase in f_α^{com} near X_{Exit} , leading back to a connected network. This phenomenon of transitions between connected and disconnected states, happen very frequently in shorter durations of time and can be seen in Figure 5.9(b). As shown by Figures 5.10 and 5.11, at $T = 500$, less fraction of ρ_α exits the freeway in response to low SoC , leading to negligible drop in f_α^{com} at X_{Exit} (Figure 5.12). With time the SoC and corresponding ψ increases, which causes greater drops in ρ_α and f_α^{com} at X_{Exit} . This effect spreads on the freeway with time. These increased drops in f_α^{com} result in more frequent transitions between the connected and the disconnected network states (Figure 5.9(b)). Figures C.1 and C.2 show the evolution of ρ_α and $\rho_\alpha u_\alpha$, in two dimensions of space and time. From these figures, the frequent rise and fall in the densities and the flows at X_{Exit} arising due to the fluctuating network states can be seen.

In this *Typical* driver behavior scenario, significant reduction in the traffic congestion, as compared to the base case with *Carefree* driver behavior ($f_\alpha^{com}=0$) is achieved. This is because in the former case $\psi\rho_\alpha^{com}(\neq 0)$ density exits the freeway in response to SoC .

Similar to the macroscopic solution, the μSim simulation results also show a similar significant reduction in the traffic densities and increase in the traffic flows (Figures 5.13 and 5.14), as compared to the *Carefree* driver behavior case (Figures 5.7 and 5.8).

Moreover, with increase in f_α^{com} , better network connectivity and traffic conditions are achieved. This can be deduced by comparing the macroscopic predictions and the μSim simulation results for this scenario ($f_\alpha^{com}=0.5$) with the scenarios with $f_\alpha^{com}=0.8$ (Section A.1) and $f_\alpha^{com}=0.1$ (Section A.2).

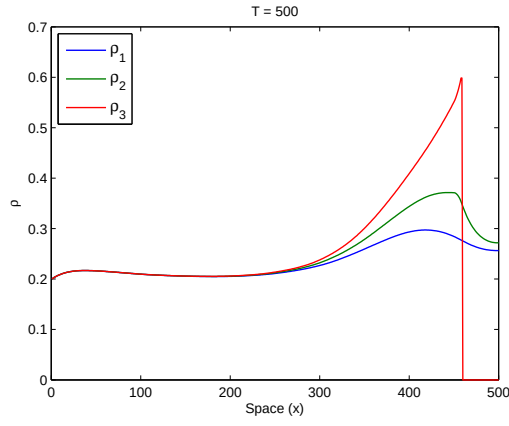
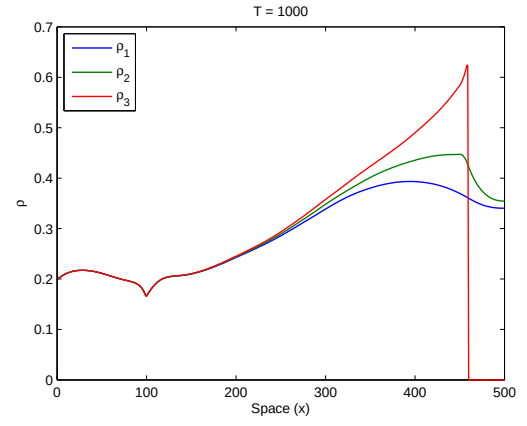
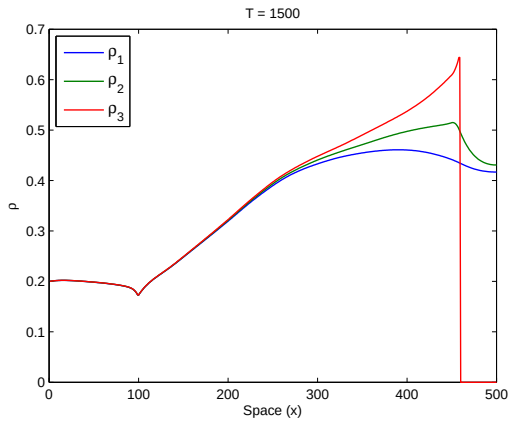
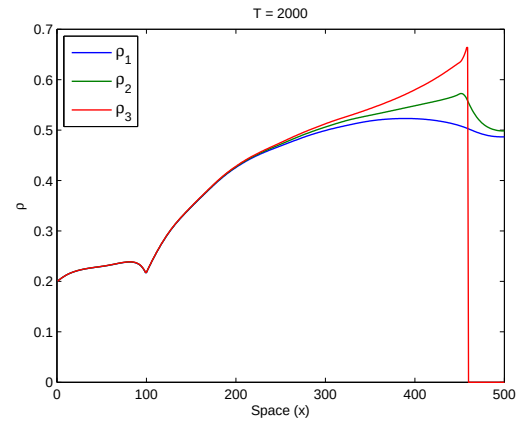
(a) ρ_α at $T=500$ (b) ρ_α at $T=1000$ (c) ρ_α at $T=1500$ (d) ρ_α at $T=2000$

Figure 5.10: Macroscopic ρ_α for *Typical* Driver Behavior with Zero Persistence and $f_\alpha^{com}(x, 0) = 0.5$

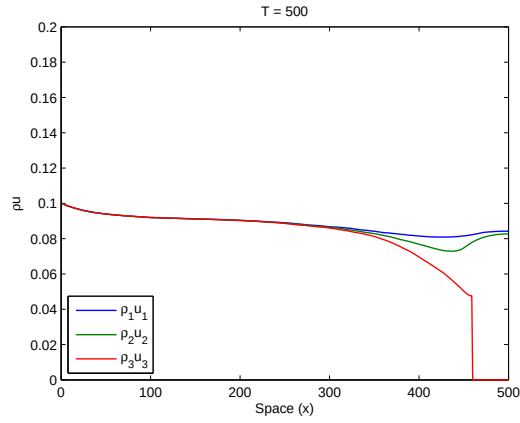
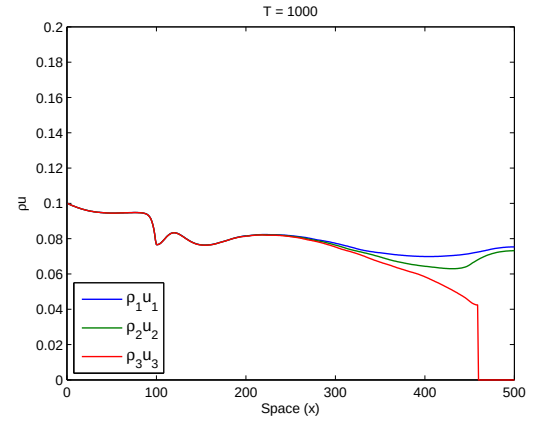
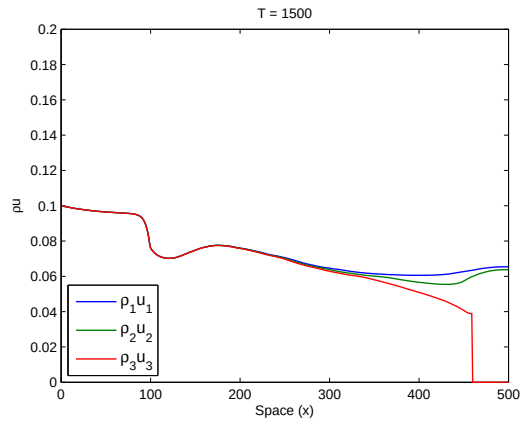
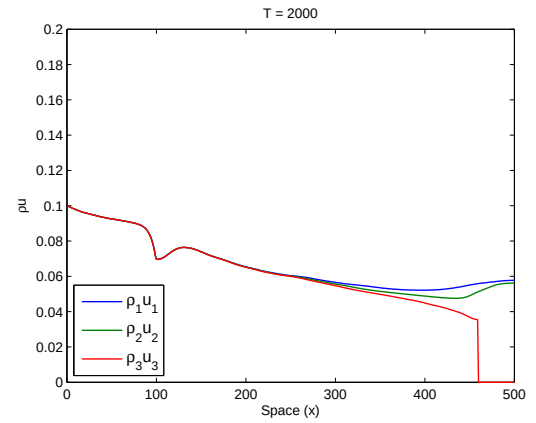
(a) $\rho_\alpha u_\alpha$ at $T=500$ (b) $\rho_\alpha u_\alpha$ at $T=1000$ (c) $\rho_\alpha u_\alpha$ at $T=1500$ (d) $\rho_\alpha u_\alpha$ at $T=2000$

Figure 5.11: Macroscopic $\rho_\alpha u_\alpha$ for *Typical* Driver Behavior with Zero Persistence and $f_\alpha^{com}(x, 0) = 0.5$

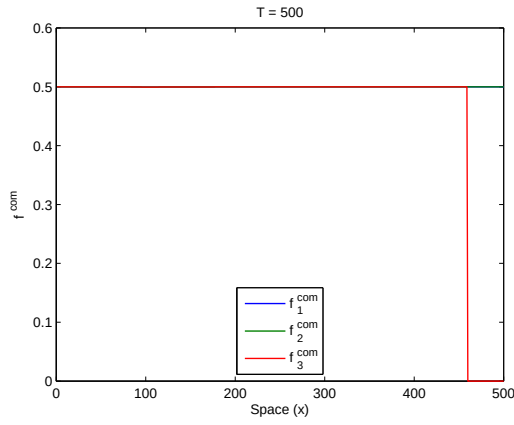
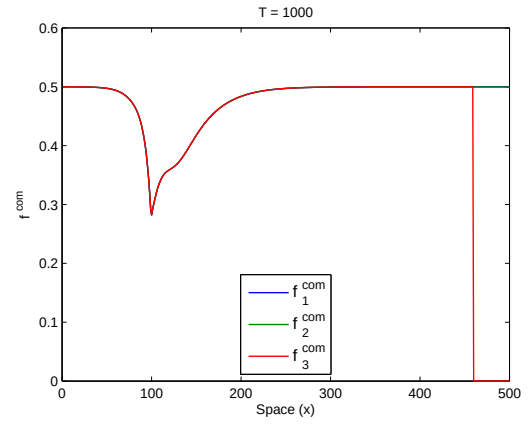
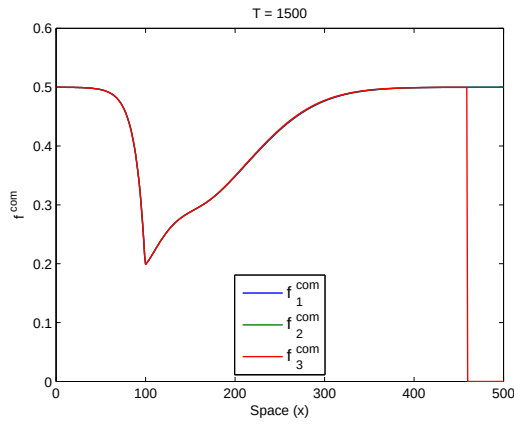
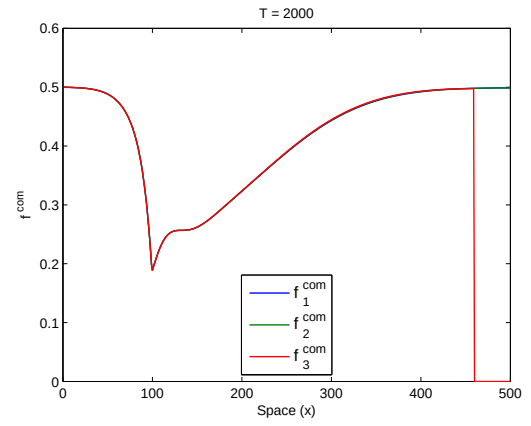
(a) $f_{\alpha}^{com}(x, t)$ at $T=500$ (b) $f_{\alpha}^{com}(x, t)$ at $T=1000$ (c) $f_{\alpha}^{com}(x, t)$ at $T=1500$ (d) $f_{\alpha}^{com}(x, t)$ at $T=2000$

Figure 5.12: Macroscopic $f_{\alpha}^{com}(x, t)$ for *Typical* Driver Behavior with Zero Persistence and $f_{\alpha}^{com}(x, 0) = 0.5$

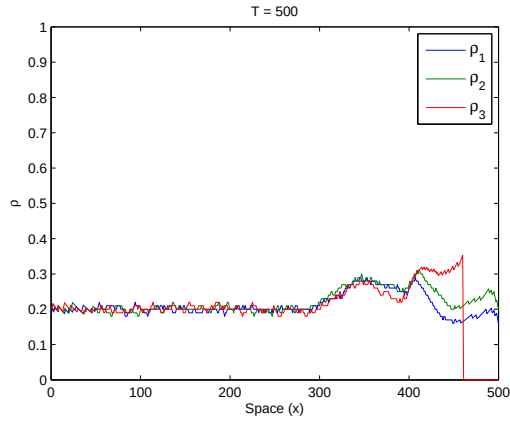
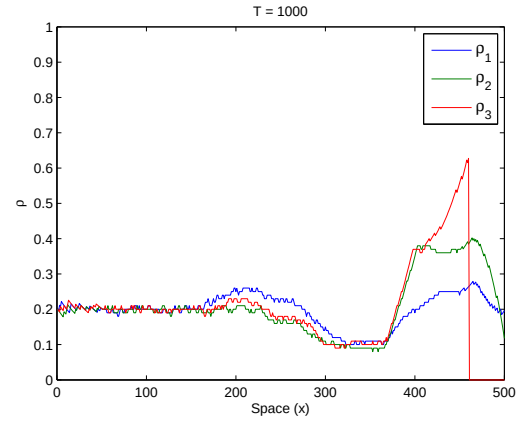
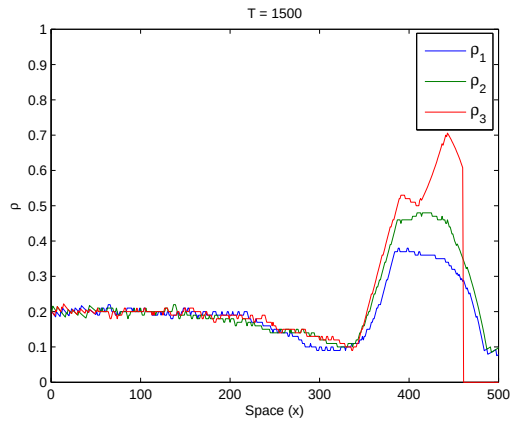
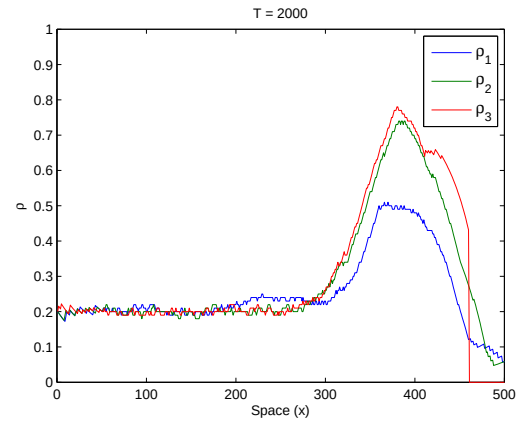
(a) ρ_α at T=500(b) ρ_α at T=1000(c) ρ_α at T=1500(d) ρ_α at T=2000

Figure 5.13: Microscopic ρ_α for *Typical* Driver Behavior with Zero Persistence and $f_\alpha^{com}(x, 0) = 0.5$

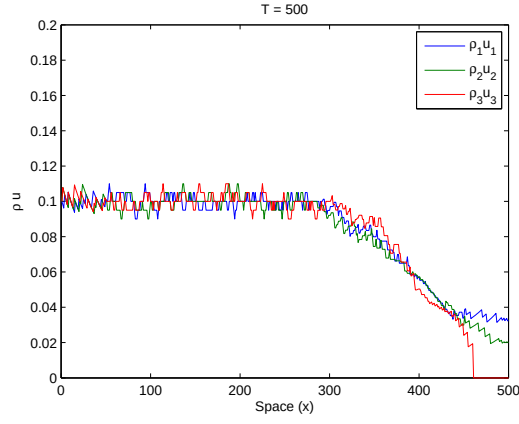
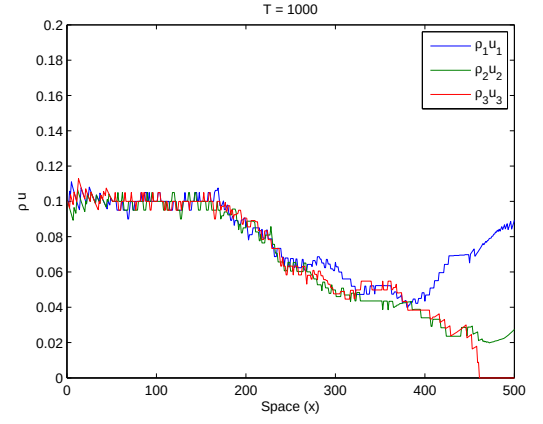
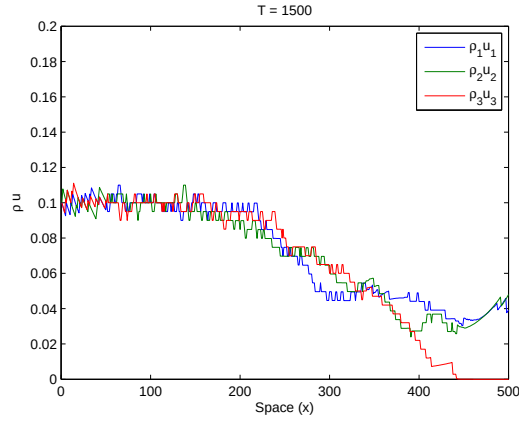
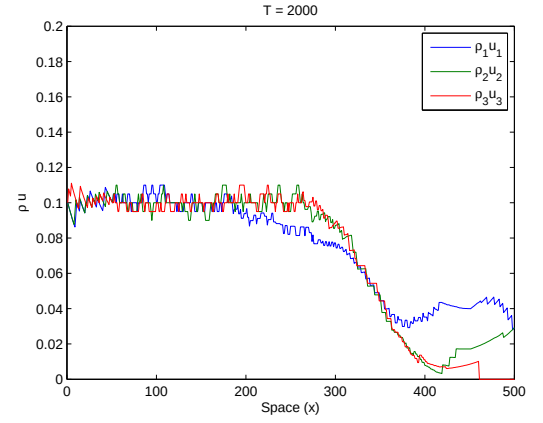
(a) $\rho_\alpha u_\alpha$ at T=500(b) $\rho_\alpha u_\alpha$ at T=1000(c) $\rho_\alpha u_\alpha$ at T=1500(d) $\rho_\alpha u_\alpha$ at T=2000

Figure 5.14: Microscopic $\rho_\alpha u_\alpha$ for *Typical* Driver Behavior with Zero Persistence and $f_\alpha^{com}(x, 0) = 0.5$

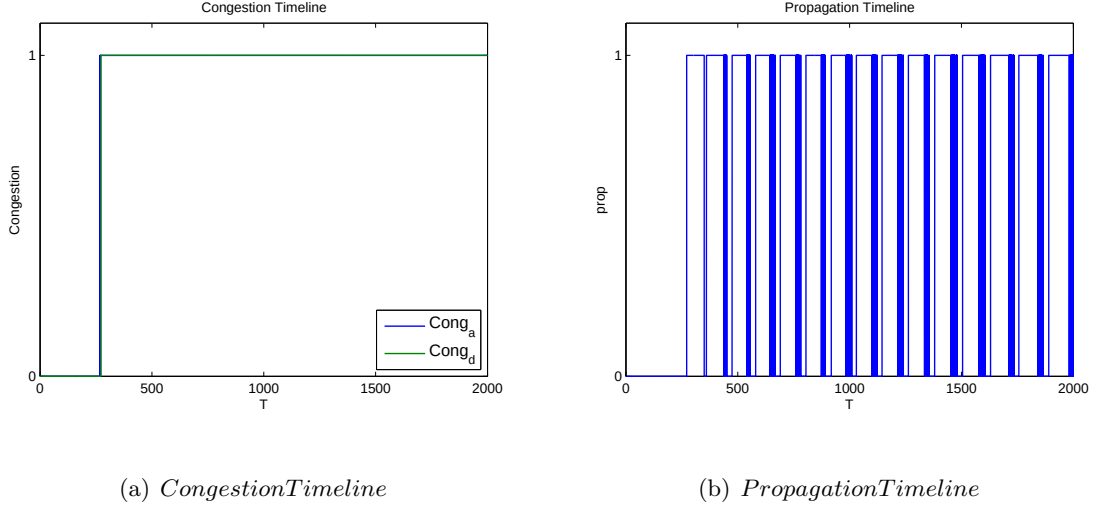


Figure 5.15: Macroscopic Communication Timelines for *Panicky* Driver Behavior with Zero Persistence and $f_\alpha^{com}(x, 0) = 0.5$

5.6.3 *Panicky* Driver Behavior

As defined in Section 5.4, in the *Panicky* driver behavior state ($q=10,000$) when $Cong_d=1$ and $prop=1$ then, $\psi=\Phi$, irrespective of the *SoC*. Hence, unlike the *Typical* driver behavior, in this case f_α^{com} drops significantly at X_{Exit} even for low *SoC*. In this section, we investigate the effect of *Panicky* driver behavior on the traffic operations in a scenario where $f_\alpha^{com}=0.5$ and $\{\Phi=1, a=2, c=4\}$ (Figure 4.1(a)).

As shown by Figure 5.18, in *Panicky* driver behavior state, f_α^{com} drops to lower values as early as $T=500$. Similar drop does not happen in the corresponding case with the *Typical* driver behavior as, the value of ψ for the corresponding *SoC* is smaller in the later case. Due to such significant drops in f_α^{com} at X_{Exit} for lower *SoC*, the frequent transitions between the connected and the disconnected network states (Figure 5.15(b)) begins earlier than in the corresponding case with the *Typical* driver behavior (Figure 5.9(b)). Due to these increased frequent transitions, the gain due to greater ψ is nullified, and the overall traffic densities and flows on the freeway (Figures 5.16 and 5.17) remain comparable to the corresponding quantities in the *Typical* driver behavior case (Figures 5.10 and 5.11).

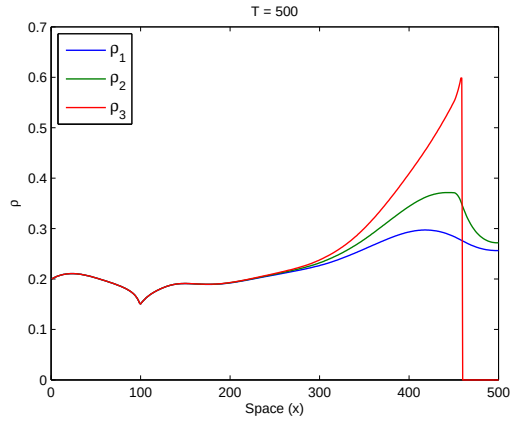
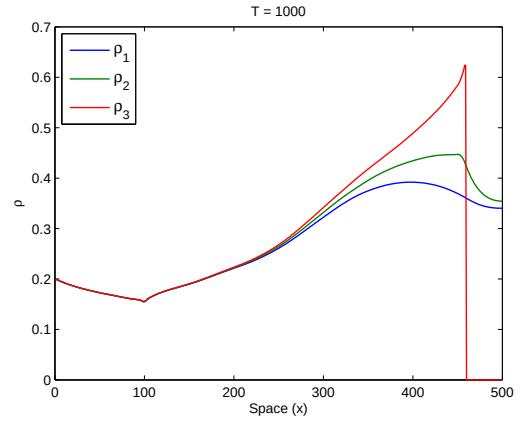
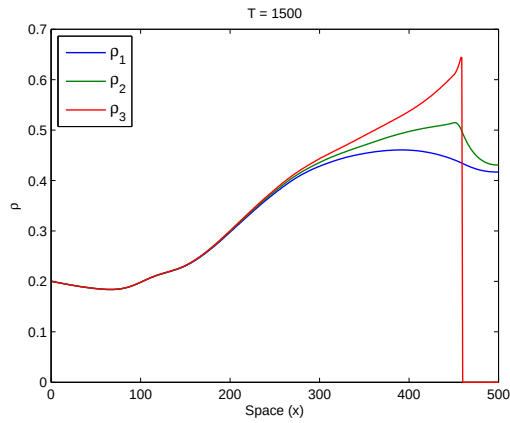
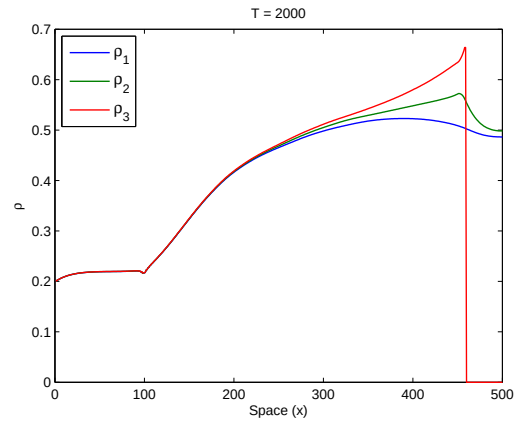
(a) ρ_α at $T=500$ (b) ρ_α at $T=1000$ (c) ρ_α at $T=1500$ (d) ρ_α at $T=2000$

Figure 5.16: Macroscopic ρ_α for *Panicky* Driver Behavior with Zero Persistence and $f_\alpha^{com}(x, 0) = 0.5$

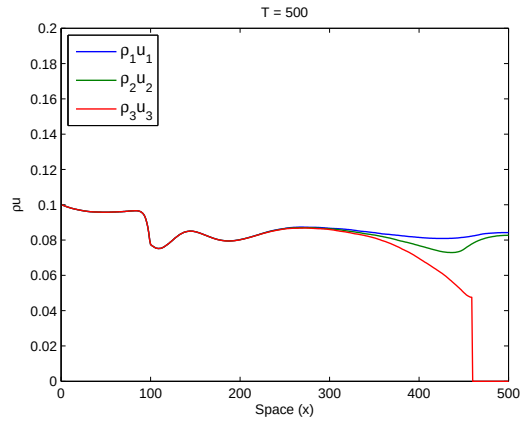
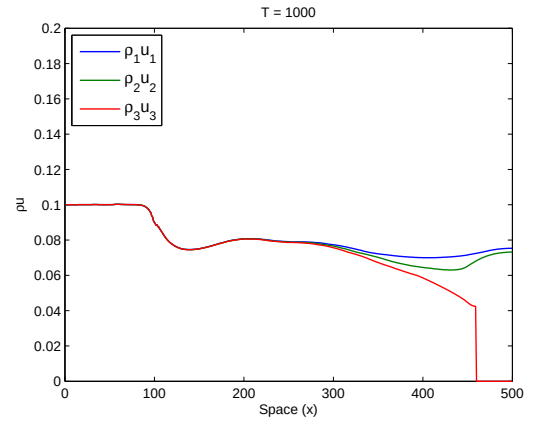
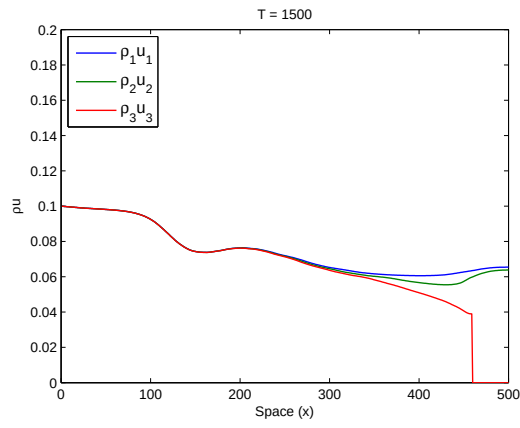
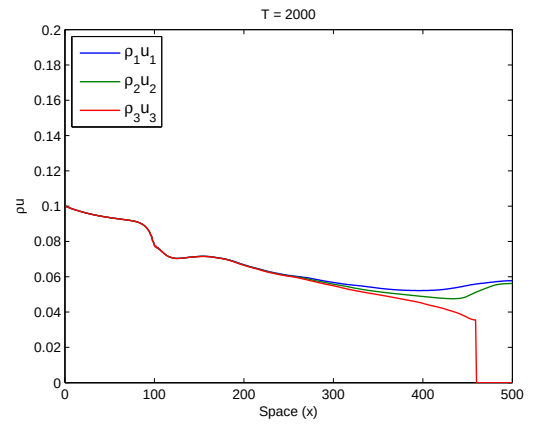
(a) $\rho_\alpha u_\alpha$ at T=500(b) $\rho_\alpha u_\alpha$ at T=1000(c) $\rho_\alpha u_\alpha$ at T=1500(d) $\rho_\alpha u_\alpha$ at T=2000

Figure 5.17: Macroscopic $\rho_\alpha u_\alpha$ for *Panicky* Driver Behavior with Zero Persistence and $f_\alpha^{com}(x, 0) = 0.5$

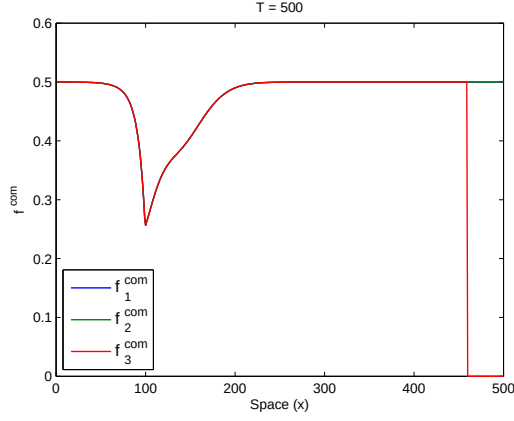
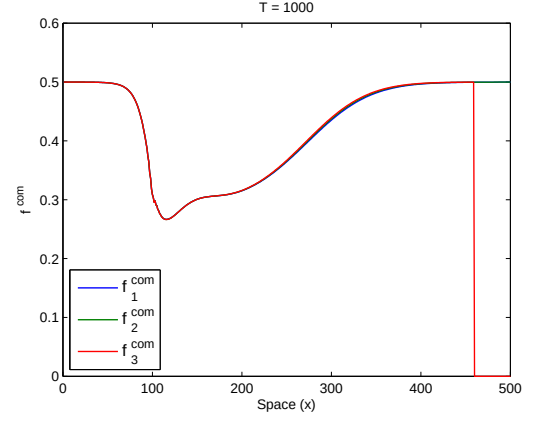
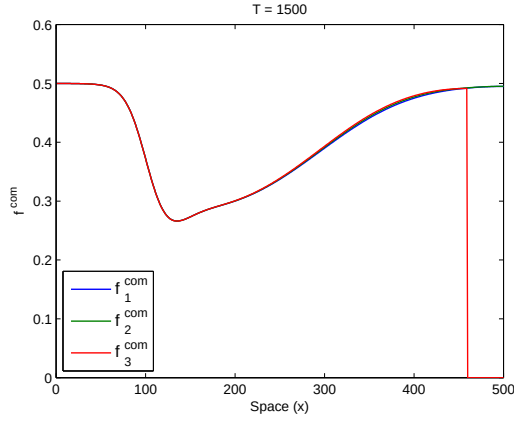
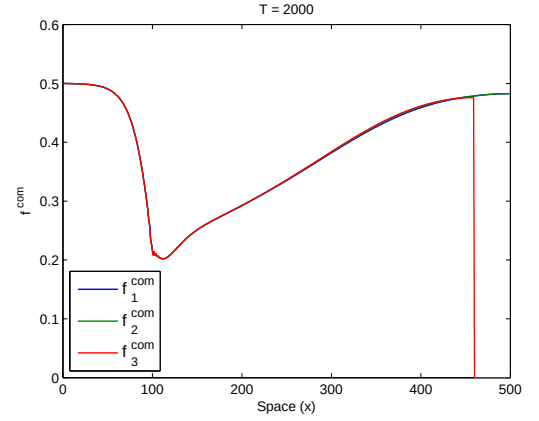
(a) $f_{\alpha}^{com}(x, t)$ at $T=500$ (b) $f_{\alpha}^{com}(x, t)$ at $T=1000$ (c) $f_{\alpha}^{com}(x, t)$ at $T=1500$ (d) $f_{\alpha}^{com}(x, t)$ at $T=2000$

Figure 5.18: Macroscopic $f_{\alpha}^{com}(x, t)$ for *Panicky* Driver Behavior with Zero Persistence and $f_{\alpha}^{com}(x, 0) = 0.5$

Figures 5.19 and 5.20 show the results of the μ Sim simulation for this case. These results show a similar traffic behavior as shown by the μ Sim simulation for the corresponding *Typical* driver behavior case (Figures 5.13 and 5.14). The difference between the results of these two cases lie in the distribution of the densities across the lanes which is due to the randomness in the traffic flow. However, the aggregate densities and flows on the freeway remain comparable. Hence, the μ Sim results confirm that improvements in the traffic conditions that are achieved by high values of ψ (irrespective of *SoC*) are nullified by the resultant increase of fluctuations in the network connectivity.

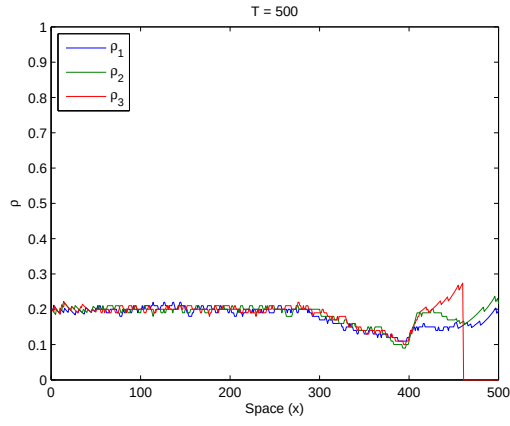
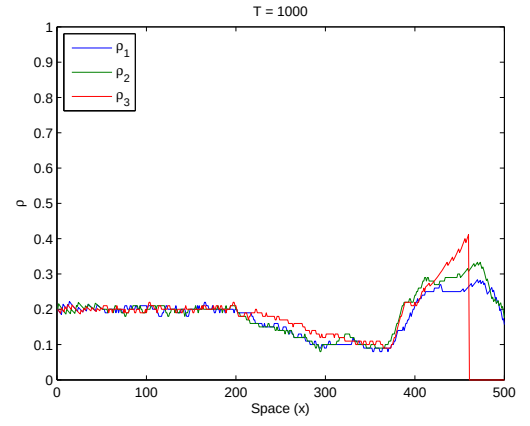
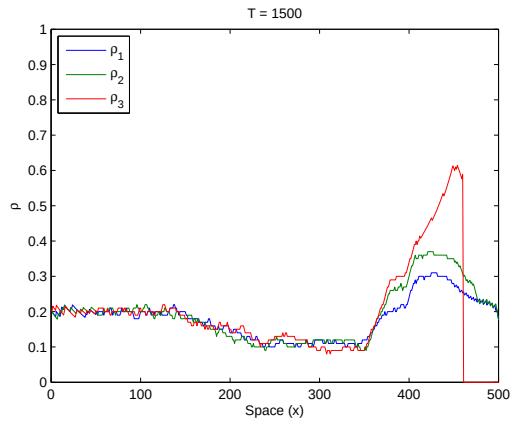
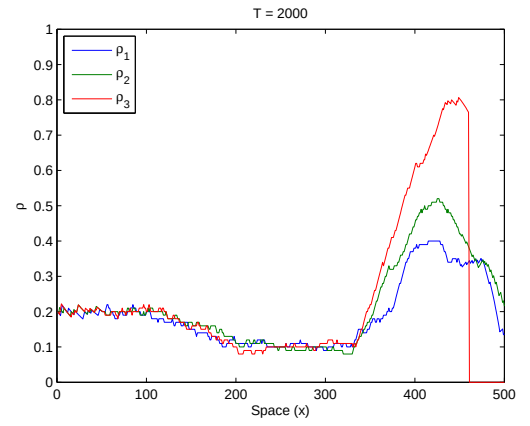
(a) ρ_α at $T=500$ (b) ρ_α at $T=1000$ (c) ρ_α at $T=1500$ (d) ρ_α at $T=2000$

Figure 5.19: Microscopic ρ_α for *Panicky* Driver Behavior with Zero Persistence and $f_\alpha^{com}(x, 0) = 0.5$

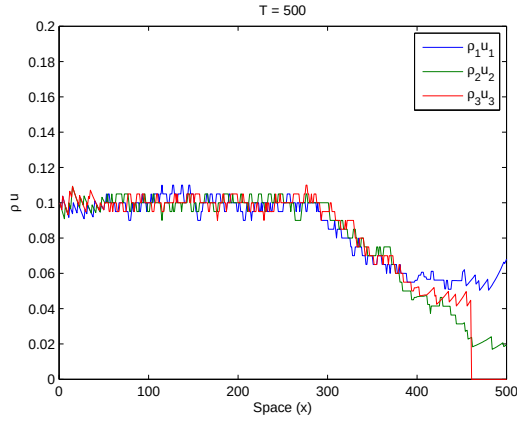
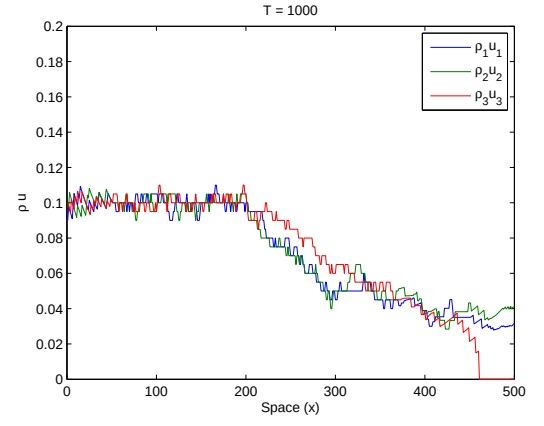
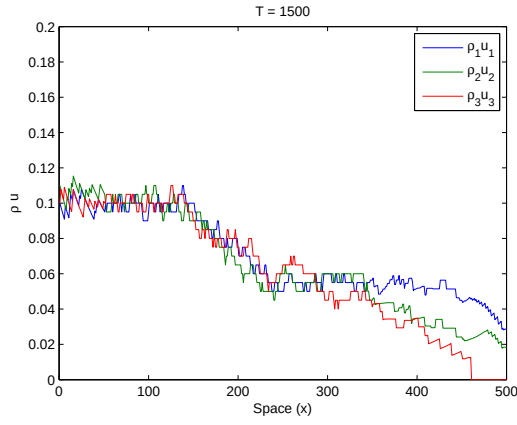
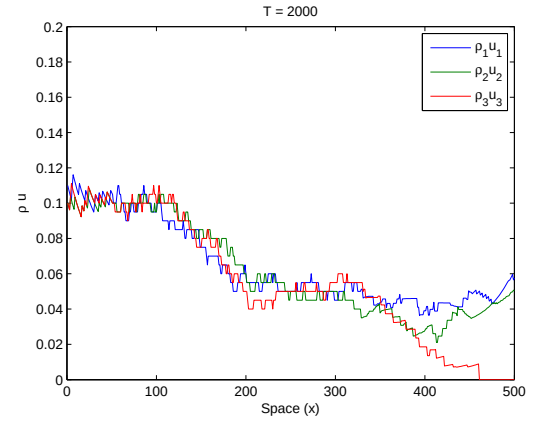
(a) $\rho_\alpha u_\alpha$ at T=500(b) $\rho_\alpha u_\alpha$ at T=1000(c) $\rho_\alpha u_\alpha$ at T=1500(d) $\rho_\alpha u_\alpha$ at T=2000

Figure 5.20: Microscopic $\rho_\alpha u_\alpha$ for *Panicky* Driver Behavior with Zero Persistence and $f_\alpha^{com}(x, 0) = 0.5$

By comparing the macroscopic solutions and the μ Sim simulation results for the cases with $f_{\alpha}^{com} = 0.8$ (Sections A.1 and A.3) and $f_{\alpha}^{com} = 0.1$ (Sections A.2 and A.4), we conclude that the similarities in the traffic conditions for the cases with the *Typical* driver behavior and the corresponding cases with the *Panicky* driver behavior, are independent of f_{α}^{com} . For cases with the *Panicky* driver behavior, with increase in f_{α}^{com} better network connectivity and traffic conditions are achieved. This can be seen by comparing the macroscopic solutions and μ Sim simulation results for this scenario ($f_{\alpha}^{com} = 0.5$), with the scenarios with $f_{\alpha}^{com} = 0.8$ (Section A.3) and $f_{\alpha}^{com} = 0.1$ (Section A.4). This trend is similar to the cases with the *Typical* driver behavior.

5.7 Comparative Analysis on the basis of *CWMsg* Persistence

5.7.1 *CWMsg* with Zero Persistence

In Section 5.6 above, we investigated the scenarios with the *CWMsg* having zero persistence. In these scenarios the *CWMsg* had a *lifetime*=1 and hence, the *CWMsg* expired the very time step it was received by a CEC. In Section 5.7.2 below, we compare the traffic states achieved in these scenarios (with zero persistent *CWMsg*) with the scenarios with non-zero persistent *CWMsg*.

5.7.2 *CWMsg* with Non-Zero Persistence

In this section, we investigate the scenarios where the *CWMsg* has a *lifetime*>1. The dissimilarity in the cases with zero persistence and non-zero persistence arises from the underlying difference in the traffic behavior in the two cases. When the target CECs receive the *CWMsg*, ψ fraction of them exit the freeway depending on the *SoC*. In the scenarios with the *CWMsg* having zero persistence, this phenomenon happens until the network gets disconnected due to reduced ρ_{α}^{com} near X_{Exit} . Hence, when the network gets disconnected, there is no loss in the ρ_{α}^{com} at X_{Exit} until the network connectivity is re-established. With the persistent *CWMsg*, $\psi\rho_{\alpha}^{com}$ density continues to exit the freeway even after the network gets disconnected until, the *lifetime* of the last received *CWMsg* expires.

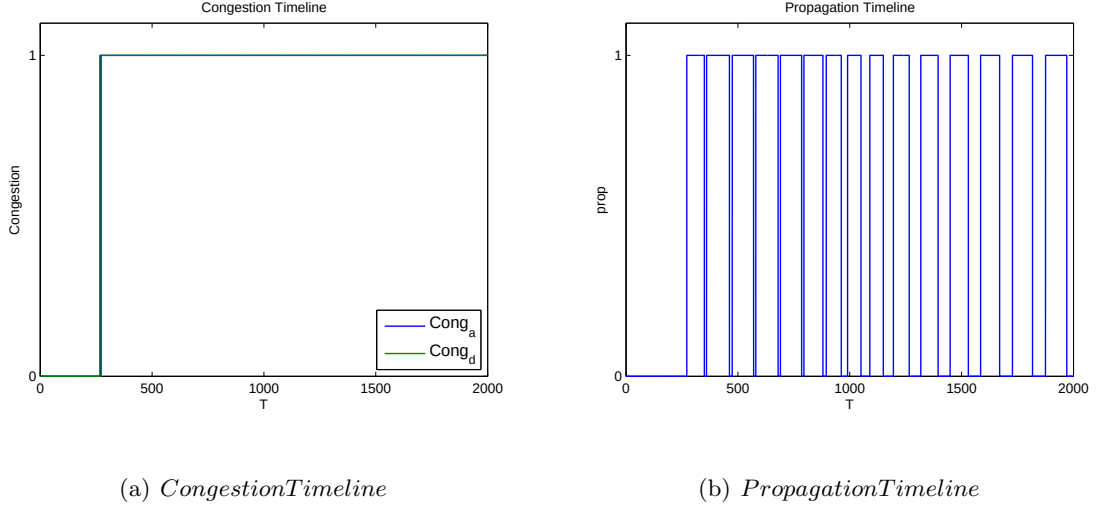


Figure 5.21: Macroscopic Communication Timelines for *Typical* Driver Behavior with Non-Zero Persistence and $f_\alpha^{com}(x,0) = 0.5$

This results in additional loss of f_α^{com} at the X_{Exit} . In our experiments, we have considered a *lifetime* of 50 time units for the $CWMsg$. In rest of the section, we investigate a scenario of the *Typical* driver behavior with the persistent $CWMsg$, $f_\alpha^{com}=0.5$ and $\{\Phi=1, a=2, c=4\}$ (Figure 4.1(a)). We compare the traffic states in this scenario with the corresponding scenario with the non-persistent $CWMsg$.

In the cases with the persistent $CWMsg$, transitions between the connected and the disconnected network states are less frequent as compared to the corresponding cases with the non-persistent $CWMsg$. This can be deduced by comparing the propagation lifetimes for the persistent case (Figure 5.21(b)) with the corresponding non-persistent case (Figure 5.9(b)). Such a dissimilarity is because in the former case, f_α^{com} at X_{Exit} drops even after the network gets disconnected. This additional drop subsequently causes longer durations of disconnected network and therefore the transitions between the network states are less frequent. This can also be seen by comparing the densities and the flows at X_{Exit} in two dimensions of space and time for this case (Figures C.3 and C.4) with the corresponding case with zero persistence (Figures C.1 and C.2).

Due to this phenomenon, the drop in f_α^{com} at X_{Exit} (Figure 5.22), is more severe as compared to the corresponding non-persistent case (Figure 5.12). Figure B.10 shows the drawback of these additional drops for cases with low f_α^{com} ($f_\alpha^{com} = 0.1$). In this case, due to low ρ_α^{com} near the bottleneck the congestion gets undetected ($Cong_d=0$) at $T =$

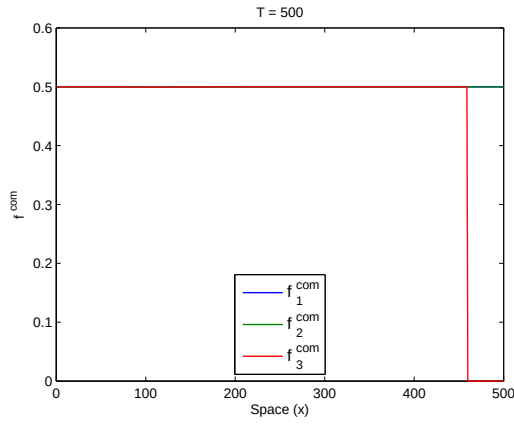
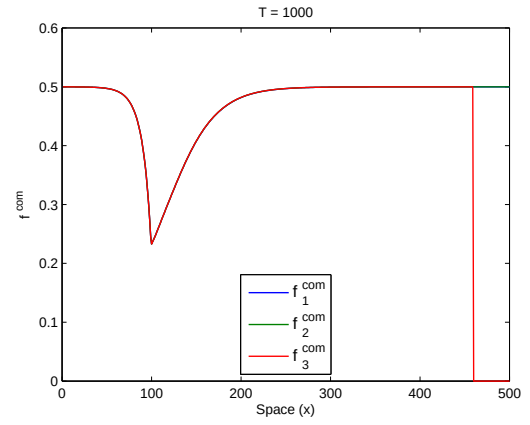
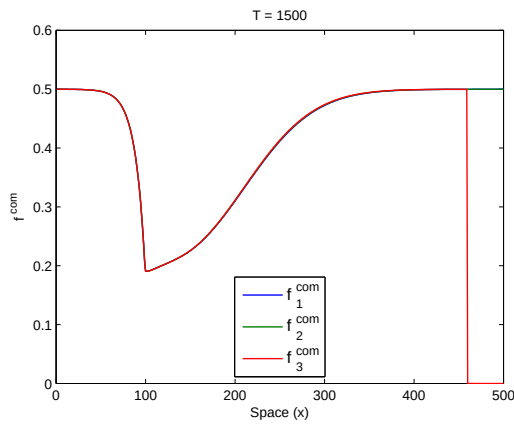
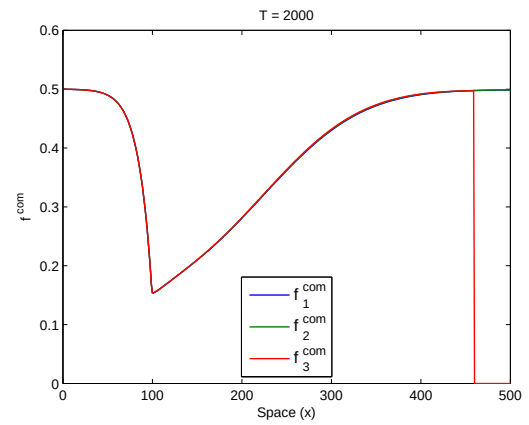
(a) $f_{\alpha}^{com}(x, t)$ at $T=500$ (b) $f_{\alpha}^{com}(x, t)$ at $T=1000$ (c) $f_{\alpha}^{com}(x, t)$ at $T=1500$ (d) $f_{\alpha}^{com}(x, t)$ at $T=2000$

Figure 5.22: Macroscopic $f_{\alpha}^{com}(x, t)$ for *Typical* Driver Behavior with Non-Zero Persistence and $f_{\alpha}^{com}(x, 0) = 0.5$

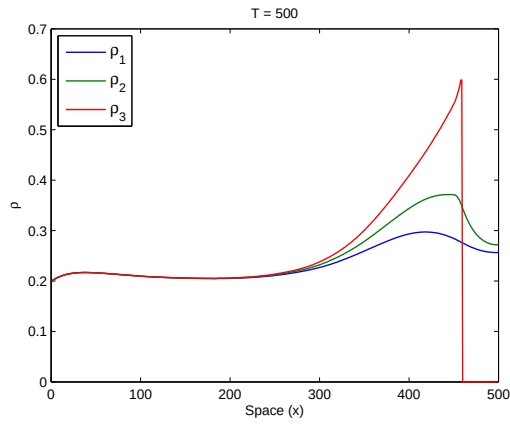
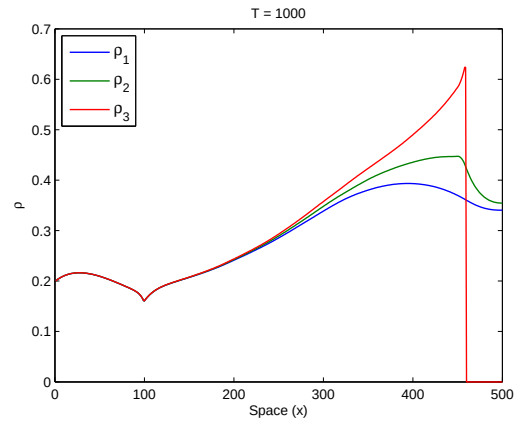
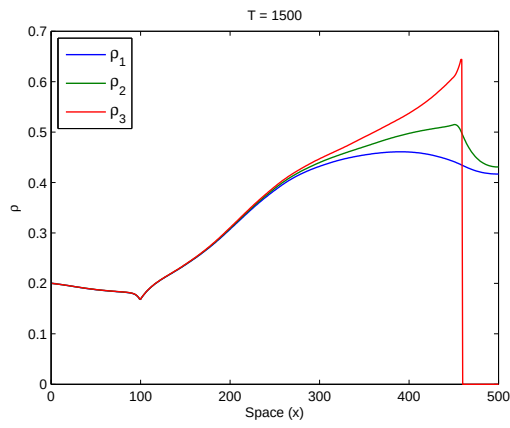
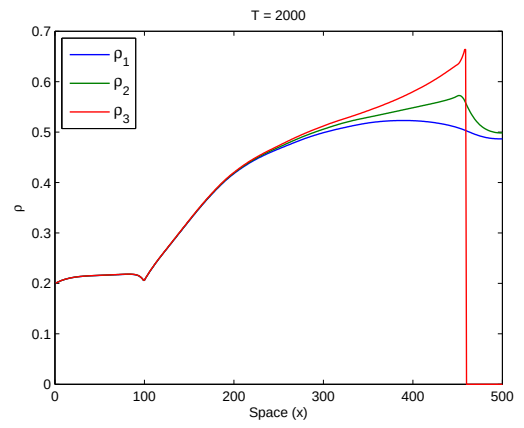
(a) ρ_α at $T=500$ (b) ρ_α at $T=1000$ (c) ρ_α at $T=1500$ (d) ρ_α at $T=2000$

Figure 5.23: Macroscopic ρ_α for *Typical* Driver Behavior with Non-Zero Persistence and $f_\alpha^{com}(x, 0) = 0.5$

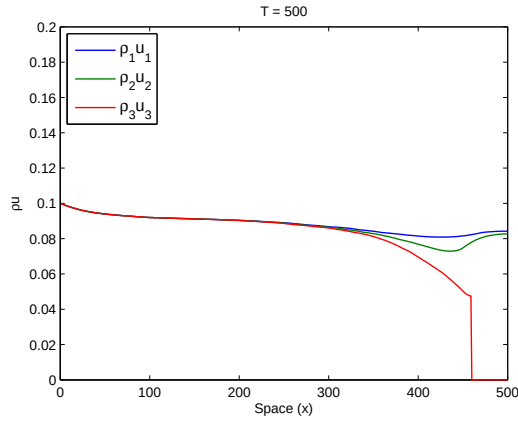
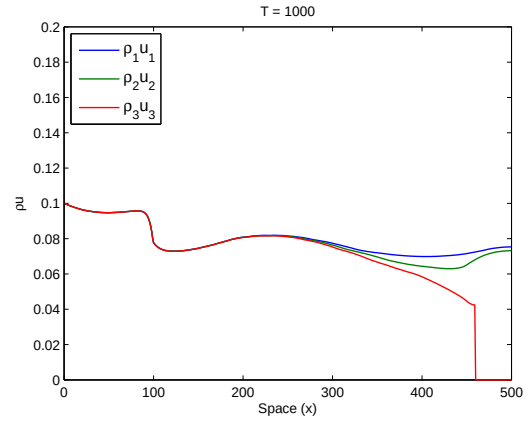
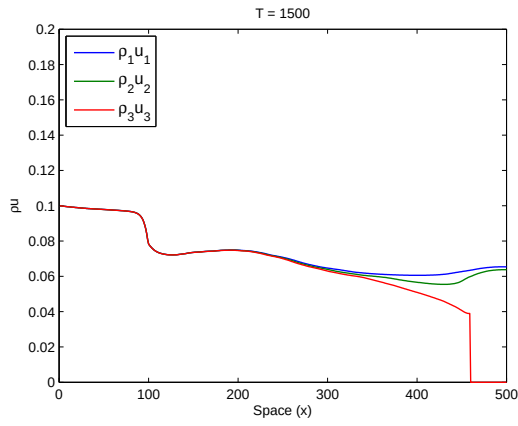
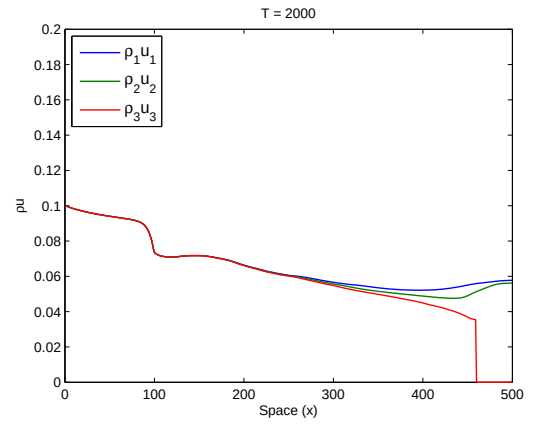
(a) $\rho_\alpha u_\alpha$ at $T=500$ (b) $\rho_\alpha u_\alpha$ at $T=1000$ (c) $\rho_\alpha u_\alpha$ at $T=1500$ (d) $\rho_\alpha u_\alpha$ at $T=2000$

Figure 5.24: Macroscopic $\rho_\alpha u_\alpha$ for *Typical* Driver Behavior with Non-Zero Persistence and $f_\alpha^{com}(x, 0) = 0.5$

1975. Similar event is not seen in the corresponding case with the zero persistent *CWMsg* (Figure A.10).

As shown by Figures 5.23 and 5.24, the densities and the flows on the freeway for the persistent *CWMsg*, are comparable to the densities and the flows for the corresponding non-persistent case (Figures 5.10 and 5.11). Hence, the improvement in the traffic conditions by extending the time over which $\psi\rho_\alpha^{com}$ density exits the freeway, is nullified by the subsequent increased durations of the disconnected network states.

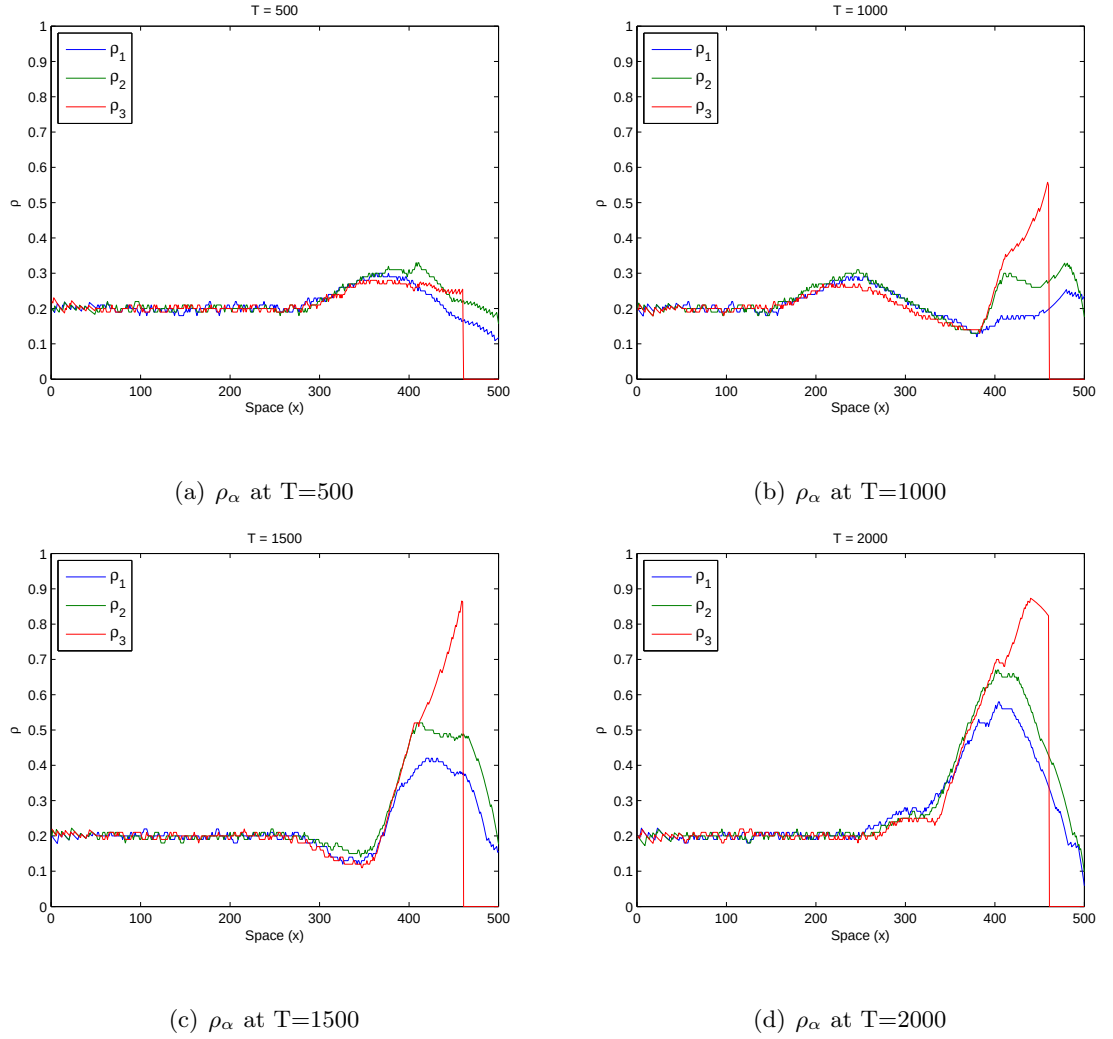


Figure 5.25: Microscopic ρ_α for *Typical* Driver Behavior with Non-Zero Persistence and $f_\alpha^{com}(x, 0) = 0.5$

The microscopic traffic densities and flows for this case (Figures 5.25 and 5.26)

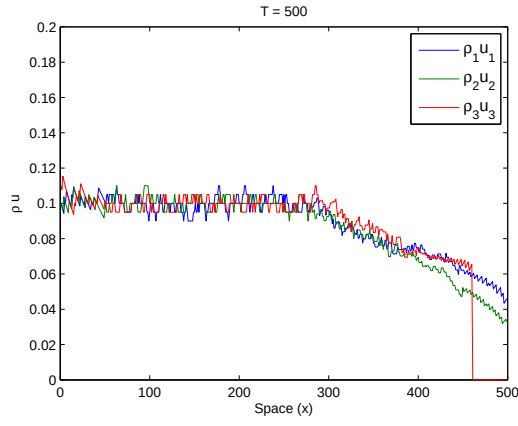
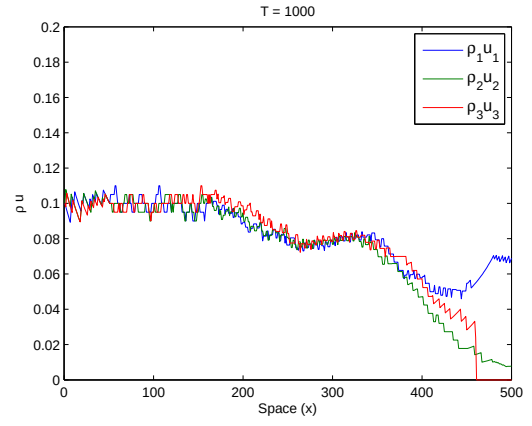
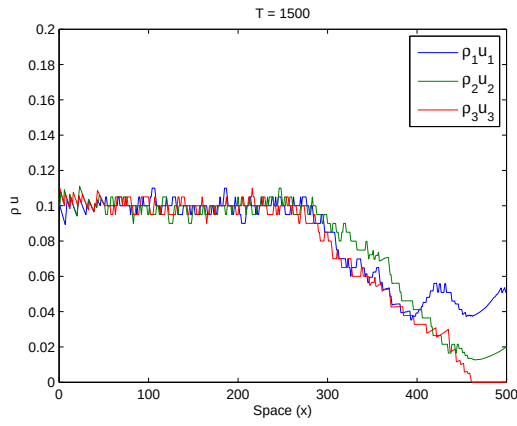
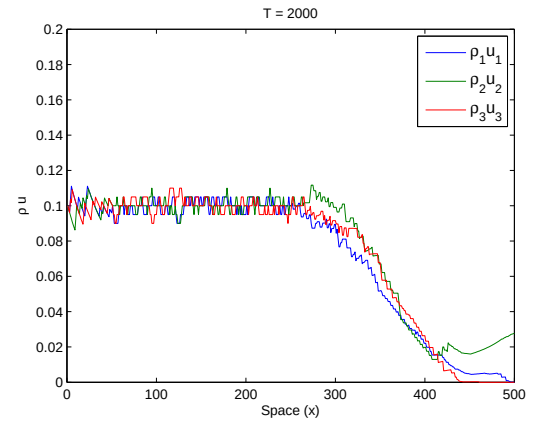
(a) $\rho_\alpha u_\alpha$ at $T=500$ (b) $\rho_\alpha u_\alpha$ at $T=1000$ (c) $\rho_\alpha u_\alpha$ at $T=1500$ (d) $\rho_\alpha u_\alpha$ at $T=2000$

Figure 5.26: Microscopic $\rho_\alpha u_\alpha$ for *Typical* Driver Behavior with Non-Zero Persistence and $f_\alpha^{com}(x, 0) = 0.5$

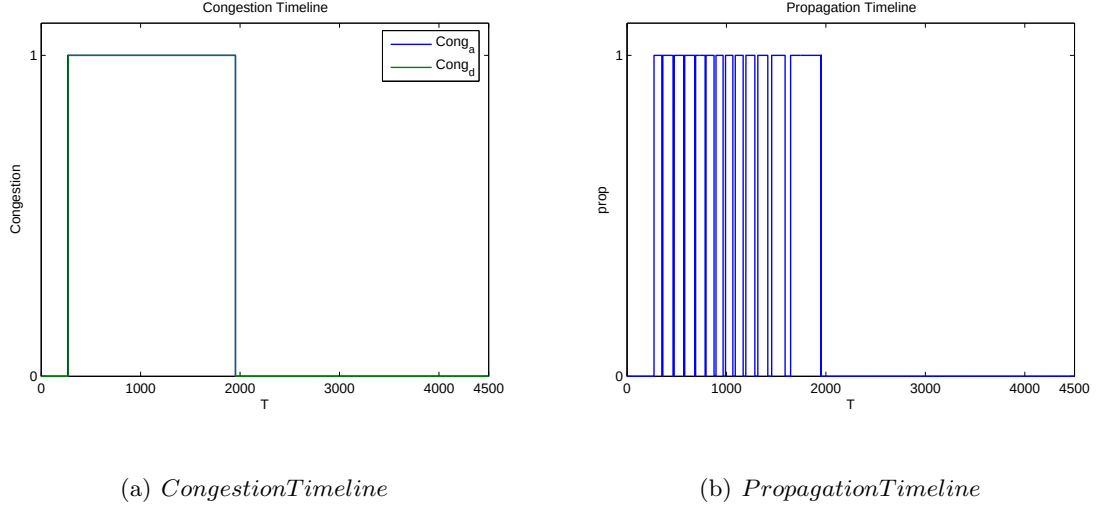


Figure 5.27: Removing the Lane Closure: Macroscopic Communication Timelines for *Typical* Driver Behavior with Non-Zero Persistence and $f_\alpha^{com}(x, 0) = 0.5$

are also similar to the corresponding case with zero persistence (Figures 5.13 and 5.14). This is coherent with the predictions made by the macroscopic model.

These similarities in the traffic conditions for the cases with zero and non-zero persistent *CWMsg* are independent of f_α^{com} . This can be seen by macroscopic solutions and μ Sim simulation results for the cases with the *Typical* driver behavior with, $f_\alpha^{com}=0.8$ (Sections A.1 and B.1) and $f_\alpha^{com}=0.1$ (Sections A.2 and B.2). Moreover, these similarities are also independent of the driver behavior and can also be seen in the cases with the *Panicky* driver behavior (Sections A.3 and B.3).

5.8 Removing the Lane Closure on the Freeway

In this section, we consider two different scenarios to compare the time required for the congestion to resolve when the lane closure is removed from the left most lane. The comparisons are made between the two cases, one with $f_\alpha^{com}=0.5$ and the other with $f_\alpha^{com}=0$. We also present the over all improvement in the traffic conditions (densities and flows) that are achieved when the cars are equipped with communication capabilities. The cases considered in this section are with the *Typical* driver behavior with non-zero persistent *CWMsg* (*lifetime*=50) and $\{\Phi=0.5, a=100000, c=3\}$ (Figure 4.1(b)). For both the cases considered in this section, the lane closure (imposed at $T=0$) is removed at $T=1000$.

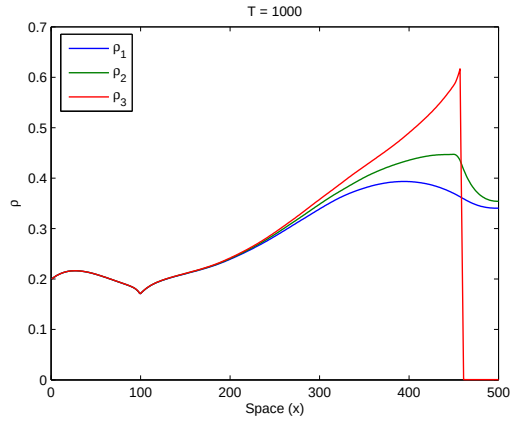
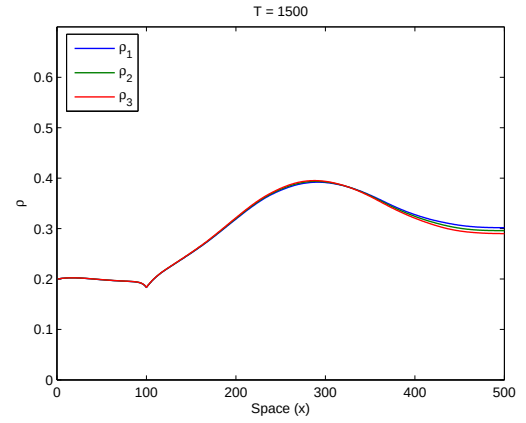
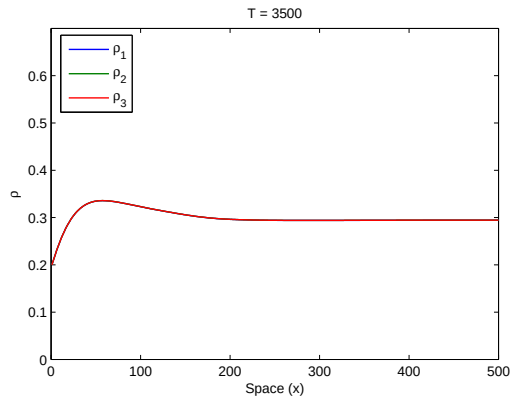
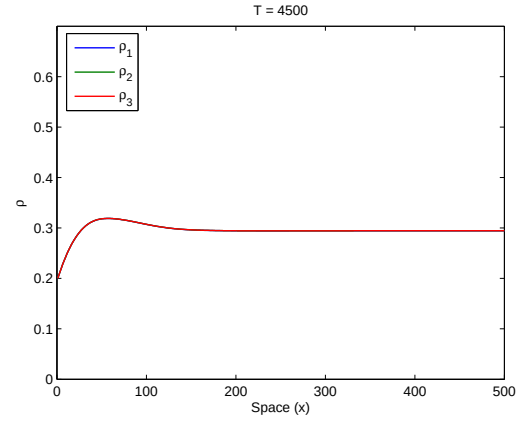
(a) ρ_α at $T=1000$ (b) ρ_α at $T=1500$ (c) ρ_α at $T=3500$ (d) ρ_α at $T=4500$

Figure 5.28: Removing the Lane Closure: Macroscopic ρ_α for *Typical* Driver Behavior with Non-Zero Persistence and $f_\alpha^{com}(x, 0) = 0.5$

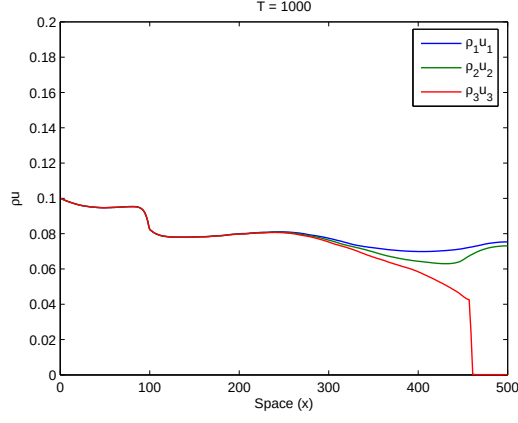
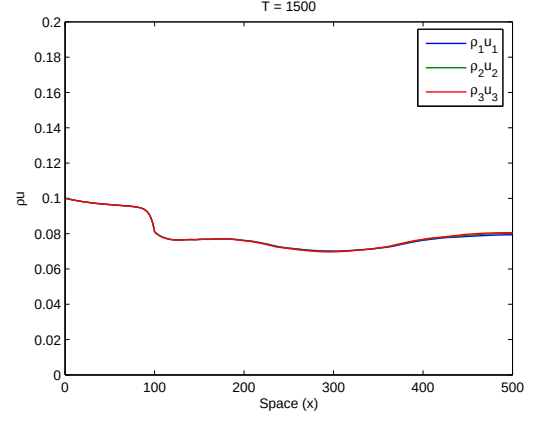
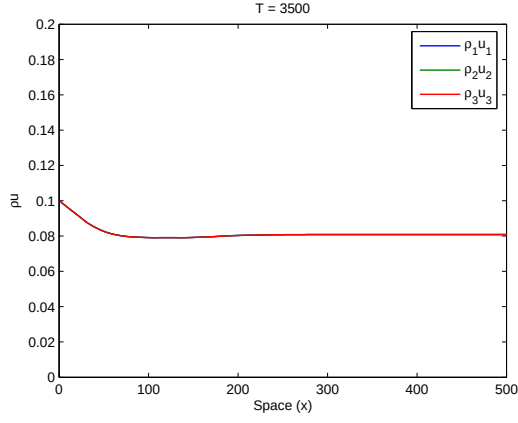
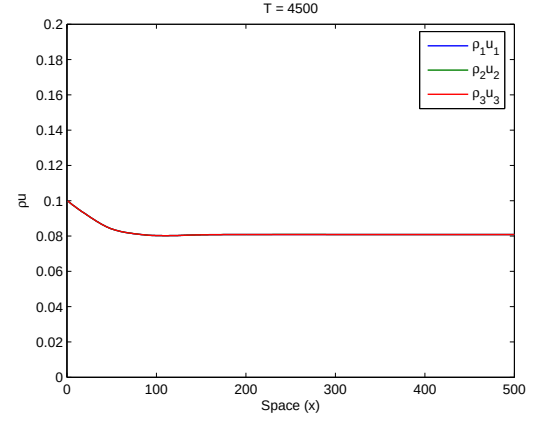
(a) $\rho_\alpha u_\alpha$ at $T=1000$ (b) $\rho_\alpha u_\alpha$ at $T=1500$ (c) $\rho_\alpha u_\alpha$ at $T=3500$ (d) $\rho_\alpha u_\alpha$ at $T=4500$

Figure 5.29: Removing the Lane Closure: Macroscopic $\rho_\alpha u_\alpha$ for *Typical* Driver Behavior with Non-Zero Persistence and $f_\alpha^{com}(x, 0) = 0.5$

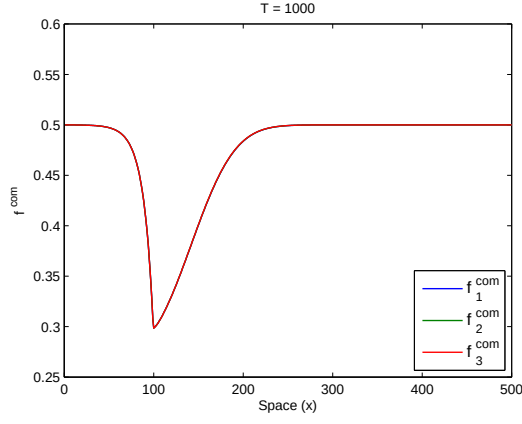
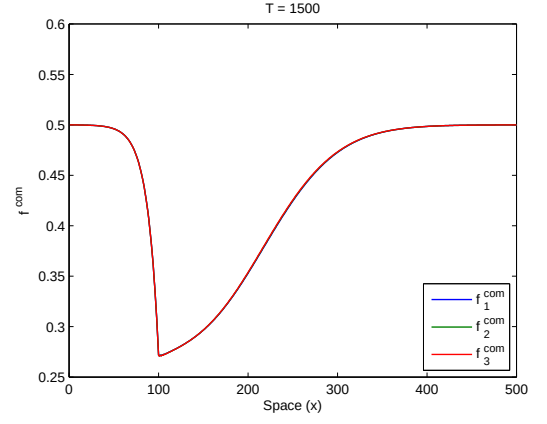
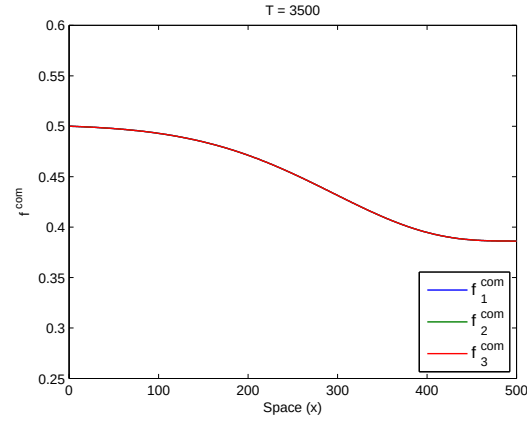
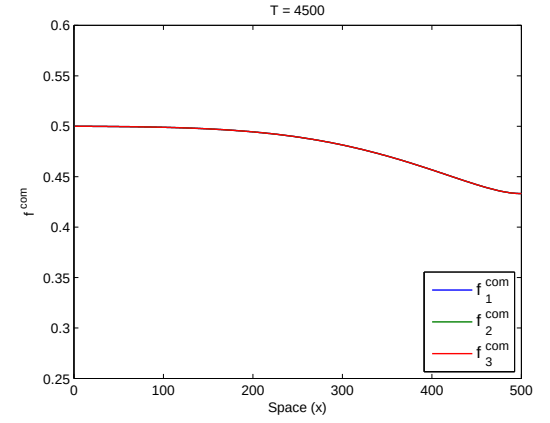
(a) $f_{\alpha}^{com}(x, t)$ at $T=1000$ (b) $f_{\alpha}^{com}(x, t)$ at $T=1500$ (c) $f_{\alpha}^{com}(x, t)$ at $T=3500$ (d) $f_{\alpha}^{com}(x, t)$ at $T=4500$

Figure 5.30: Removing the Lane Closure: Macroscopic $f_{\alpha}^{com}(x, t)$ for *Typical* Driver Behavior with Non-Zero Persistence and $f_{\alpha}^{com}(x, 0) = 0.5$

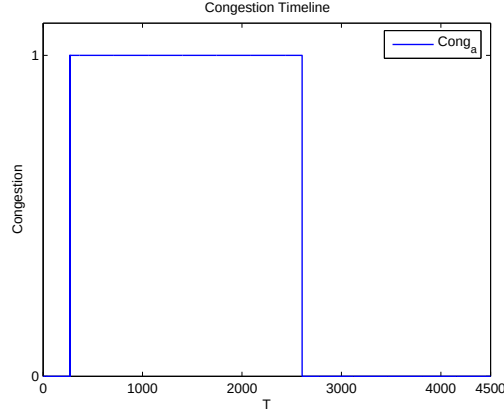
(a) *CongestionTimeline*

Figure 5.31: Removing the Lane Closure: Macroscopic Communication Timelines for *Typical* Driver Behavior with Non-Zero Persistence and $f_\alpha^{com}(x, 0) = 0$

Figure 5.27(a) shows the lifetime of congestion for the case with $f_\alpha^{com}=0.5$. The congestion in this case resolves at $T=1954$. The impact of communication on improving the traffic mobility can be seen by comparing this case with the case with $f_\alpha^{com}=0$ (Figure 5.31(a)). The congestion in the later case resolves at $T=2605$. Figures 5.28 and 5.29 show the densities and the flows, respectively, for the case with $f_\alpha^{com}=0.5$. Figure 5.30 shows the variations in f_α^{com} . Figures 5.32 and 5.33 show the densities and the flows, respectively, for the case with $f_\alpha^{com}=0$. It can be seen that the densities in the case with $f_\alpha^{com}=0.5$ are lesser than that in the case with $f_\alpha^{com}=0$.

Figures 5.34 and 5.35 show the microscopic densities and flows, respectively, for the case with $f_\alpha^{com}=0.5$. Figures 5.36 and 5.37 show the microscopic densities and flows, respectively, for the case with $f_\alpha^{com}=0$. By comparing these figures, it can be concluded that traffic operations are restored to normal much earlier in the case with $f_\alpha^{com}=0.5$, than in the case with $f_\alpha^{com}=0$.

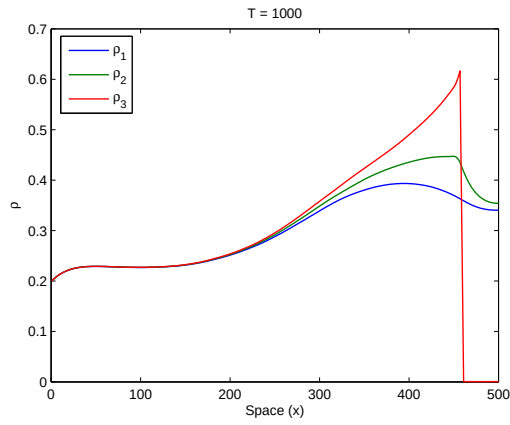
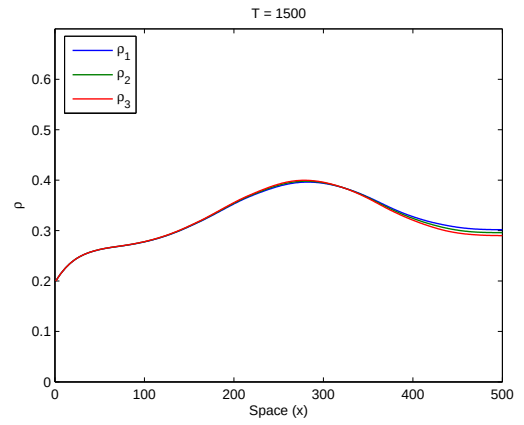
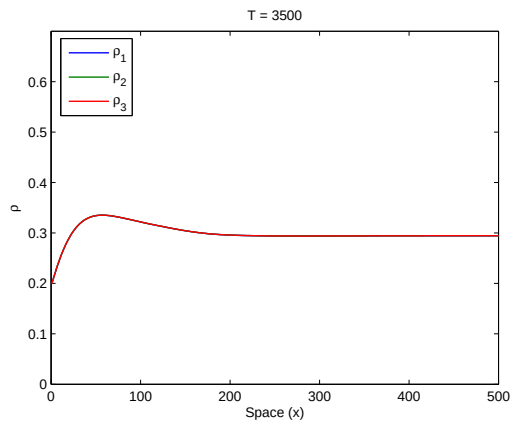
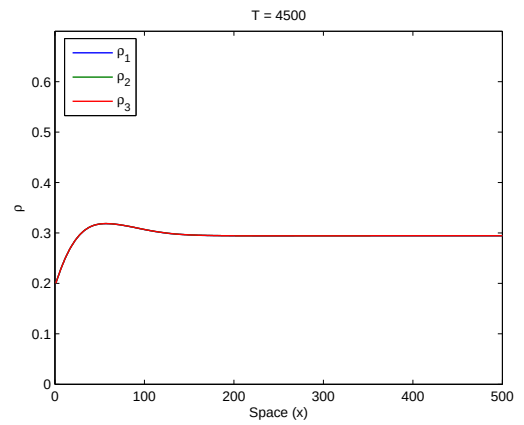
(a) ρ_α at $T=1000$ (b) ρ_α at $T=1500$ (c) ρ_α at $T=3500$ (d) ρ_α at $T=4500$

Figure 5.32: Removing the Lane Closure: Macroscopic ρ_α for *Typical* Driver Behavior with Non-Zero Persistence and $f_\alpha^{com}(x, 0) = 0$

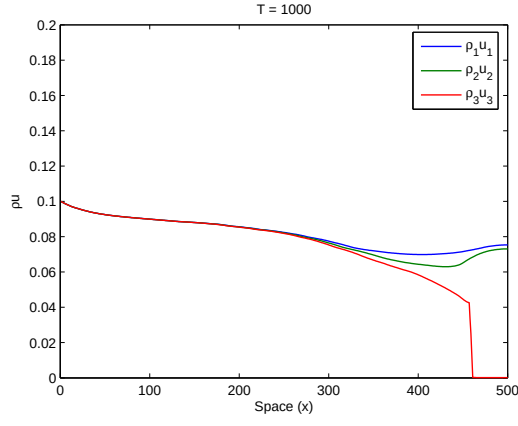
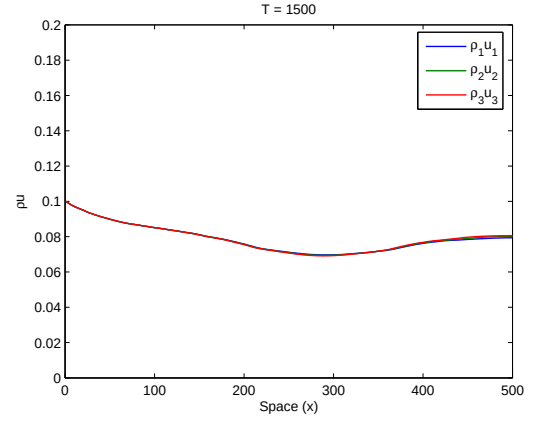
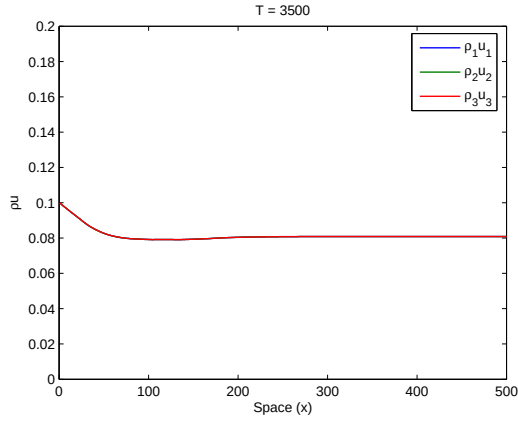
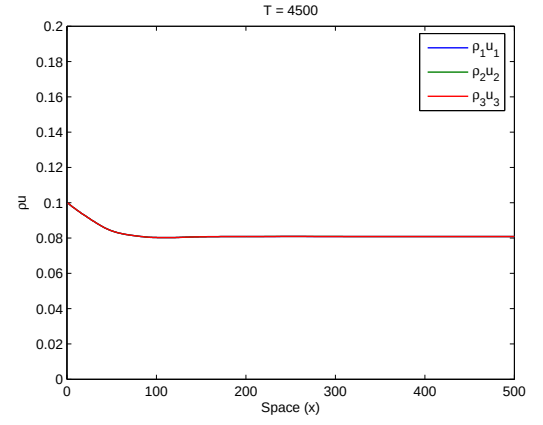
(a) $\rho_\alpha u_\alpha$ at T=1000(b) $\rho_\alpha u_\alpha$ at T=1500(c) $\rho_\alpha u_\alpha$ at T=3500(d) $\rho_\alpha u_\alpha$ at T=4500

Figure 5.33: Removing the Lane Closure: Macroscopic $\rho_\alpha u_\alpha$ for *Typical* Driver Behavior with Non-Zero Persistence and $f_\alpha^{com}(x, 0) = 0$

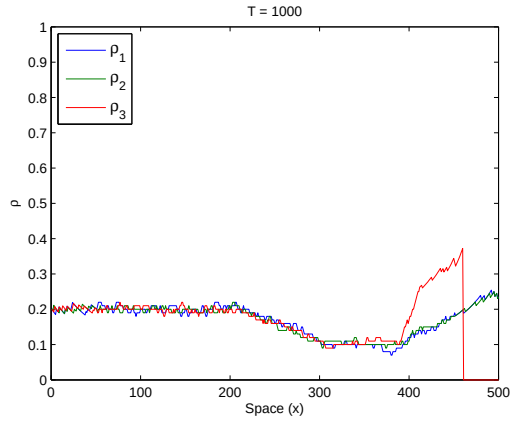
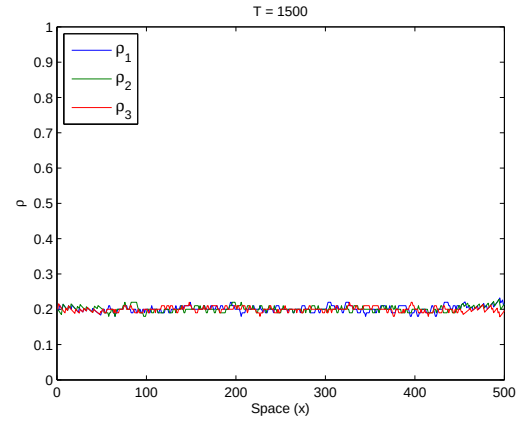
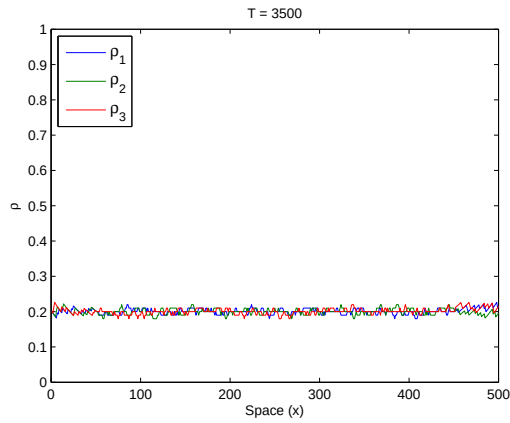
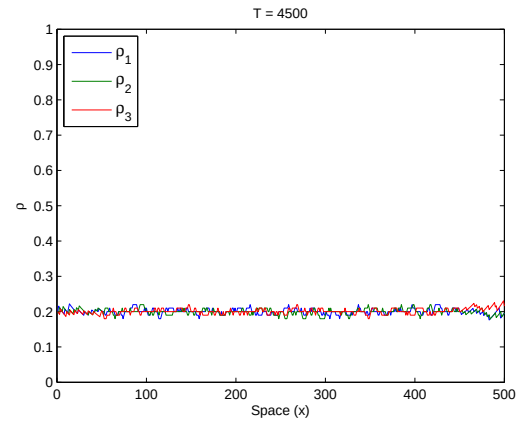
(a) ρ_α at $T=1000$ (b) ρ_α at $T=1500$ (c) ρ_α at $T=3500$ (d) ρ_α at $T=4500$

Figure 5.34: Removing the Lane Closure: Microscopic ρ_α for *Typical* Driver Behavior with Non-Zero Persistence and $f_\alpha^{com}(x, 0) = 0.5$

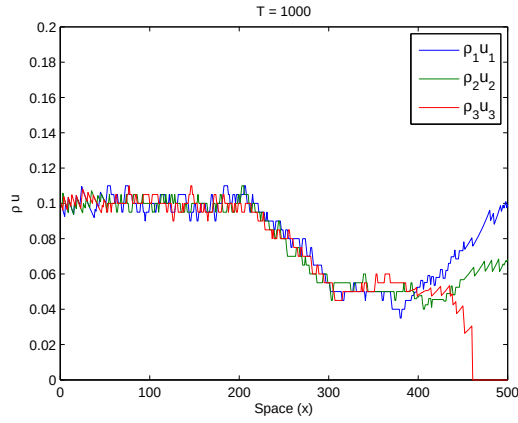
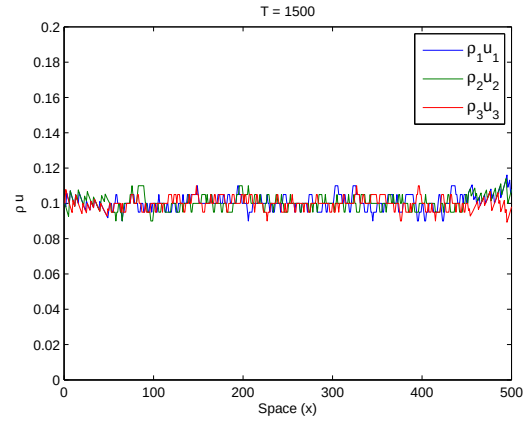
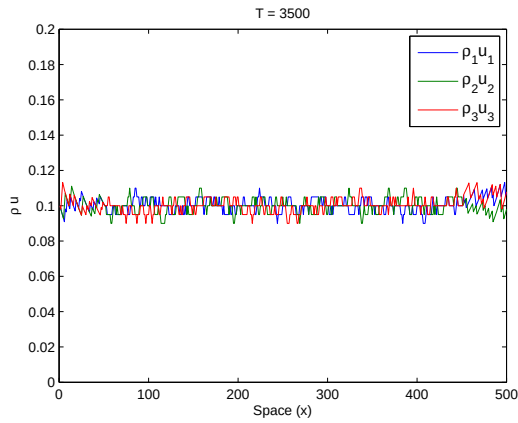
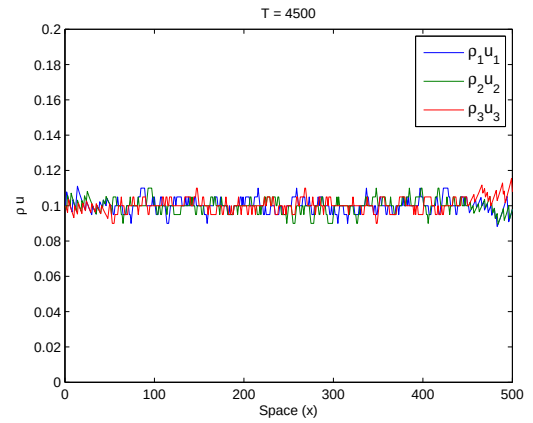
(a) $\rho_\alpha u_\alpha$ at $T=1000$ (b) $\rho_\alpha u_\alpha$ at $T=1500$ (c) $\rho_\alpha u_\alpha$ at $T=3500$ (d) $\rho_\alpha u_\alpha$ at $T=4500$

Figure 5.35: Removing the Lane Closure: Microscopic $\rho_\alpha u_\alpha$ for *Typical* Driver Behavior with Non-Zero Persistence and $f_\alpha^{com}(x, 0) = 0.5$

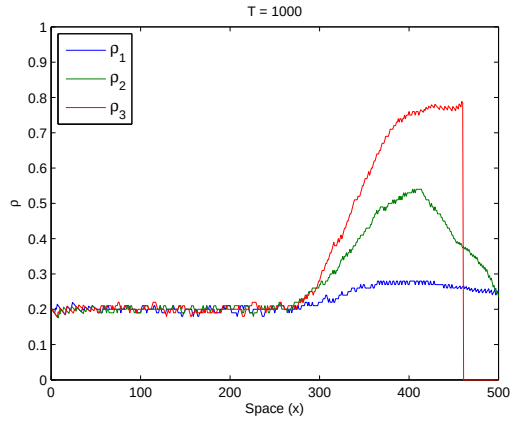
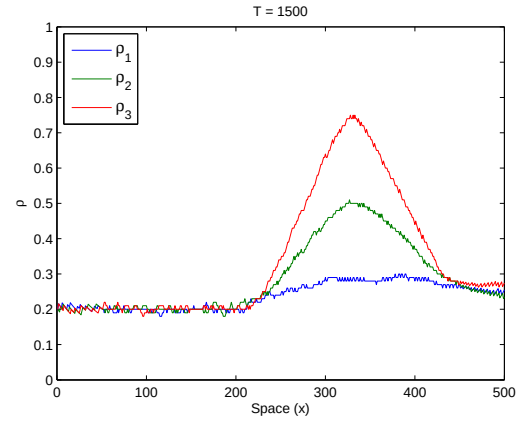
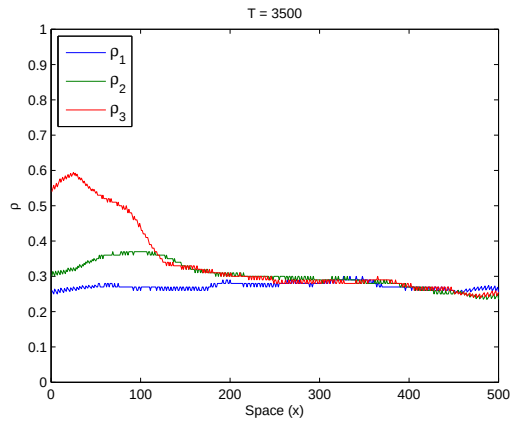
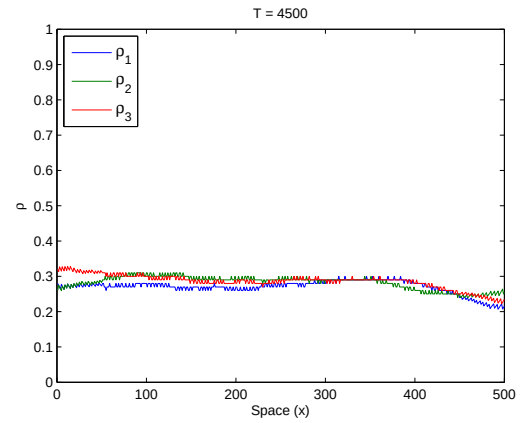
(a) ρ_α at $T=1000$ (b) ρ_α at $T=1500$ (c) ρ_α at $T=3500$ (d) ρ_α at $T=4500$

Figure 5.36: Removing the Lane Closure: Microscopic ρ_α for *Typical* Driver Behavior with Non-Zero Persistence and $f_\alpha^{com}(x, 0) = 0$

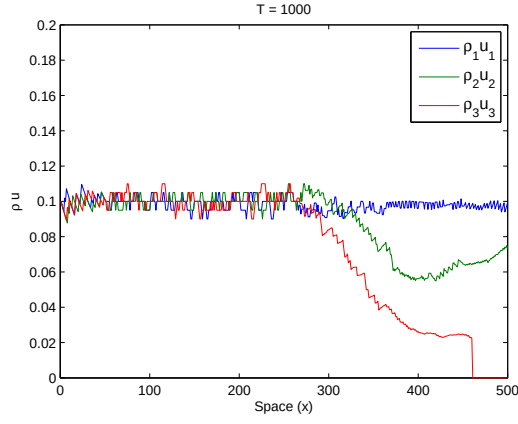
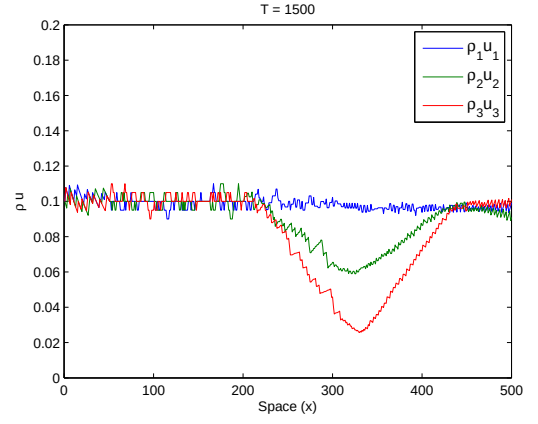
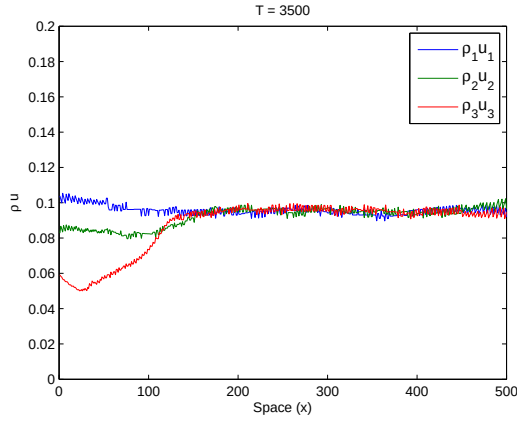
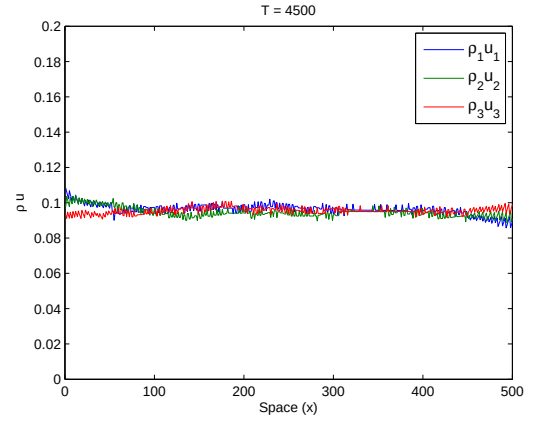
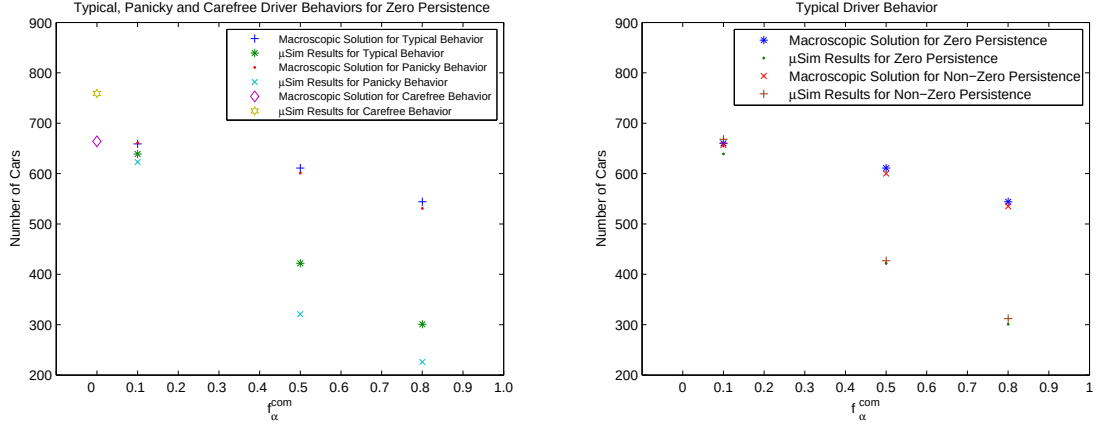
(a) $\rho_\alpha u_\alpha$ at $T=1000$ (b) $\rho_\alpha u_\alpha$ at $T=1500$ (c) $\rho_\alpha u_\alpha$ at $T=3500$ (d) $\rho_\alpha u_\alpha$ at $T=4500$

Figure 5.37: Removing the Lane Closure: Microscopic $\rho_\alpha u_\alpha$ for *Typical* Driver Behavior with Non-Zero Persistence and $f_\alpha^{com}(x, 0) = 0$

5.9 Summary of Investigations and Results

In this chapter we presented the comparative analysis on the basis of driver behavior and $CWMsg$ persistence. Here, we summarize this analysis through Figures 5.38(a) and 5.38(b). For different scenarios considered in this chapter, Figure 5.38 presents the traffic states at $T=2000$ as predicted by the macroscopic solutions and shown by the μSim results. For the macroscopic solutions, these statistics are determined by computing the area under the density curve ($\sum_{\alpha=1}^3 \int_{x=0}^{x=500} \rho_{\alpha} dx$), and for the microscopic model the cars on the freeway are individually traced. From these figures we see that, the nature of the predictions made by the macroscopic model for different scenarios are similar to the nature of simulation results by the μSim . Below we summarize this chapter:



(a) Comparison on the basis of Driver Behavior (b) Comparison on the basis of $CWMsg$ Persistence

Figure 5.38: Summary of Comparative Analysis

- With increase in f_{α}^{com} , the number of cars on the congested freeway stretch decreases both for the macroscopic solutions and the μSim results. This is independent of the driver (*Panicky* or *Typical*) behavior. Moreover, the scenario with the *Carefree* driver behavior ($f_{\alpha}^{com}=0$) has the maximum number of cars on the freeway.
- For the macroscopic solutions, the traffic states for the cases with the *Typical* driver behavior are comparable to the corresponding cases with the *Panicky* driver behavior. The difference in the two cases is more prominent in the μSim results.

- Traffic states on the freeway are similar for the cases with the $CWMsg$ having zero and non-zero persistence.
- After removing the inhomogeneity (lane closure) on the road, the normal (non-congested) traffic conditions are restored faster in the cases with $f_{\alpha}^{com} \neq 0$, than in the cases with $f_{\alpha}^{com} = 0$.

Chapter 6

Conclusion and Future Work

We have proposed a new problem in traffic flow modeling, namely integrated modeling of mobility and communication in vehicular wireless networks. We have argued the motivation for such an integrated approach and have formulated mathematically an integrated macroscopic traffic flow model. This model is based on the partial-differential fluid dynamic equations. We have numerically investigated various traffic scenarios with this model. We have also validated the nature of predictions made by our model by comparing them with the corresponding microscopic (per car based) simulations. To our knowledge, this is the first attempt at an integrated treatment of communication and mobility.

While we believe that our study is an important first step, much useful research remains to be done in this area. In the first place, more study is required in modeling the performance of networking algorithms at different layers and their impact on the overall traffic operations. We expect this to play a defining role for joint consideration of mobility and communication. Moreover, a better representation of the traffic behavior in response to the inhomogeneities like freeway exit, lane closure etc., needs to be modeled in the existing traffic flow models. Also, a thorough numerical investigation on different kinds of road stretches and traffic conditions will provide a better insight towards understanding the effect of communication on traffic mobility.

In conclusion, we have made a beginning on an interesting new problem area in traffic flow modeling. We believe much useful research will be undertaken in this area in the near future.

Bibliography

- [1] Wireless on Wheels. In *MIT Technology Review*, January 2005.
- [2] IEEE 802.11. <http://grouper.ieee.org/groups/802/11/>.
- [3] IEEE 802.11p Task Group. <http://grouper.ieee.org/-groups/scc32/dsrc/index.html>.
- [4] Advanced Cruise—Assist Highway Systems (AHS). <http://www.ahsra.or.jp/>.
- [5] Axel Klar and Raimund Wegener. A Hierarchy of Models for Multilane Vehicular Traffic I: Modeling. In *Society for Industrial and Applied Mathematics*, volume 59, pages 1002–1011, 1999.
- [6] Axel Klar and Raimund Wegener. A Hierarchy of Models for Multilane Vehicular Traffic II: Numerical Investigations. In *Society for Industrial and Applied Mathematics*, volume 59, pages 1002–1011, 1999.
- [7] A. Bachir and A. Benslimane. A Multicast Protocol in Ad Hoc Networks: Inter-Vehicle Geocast. In *The 57th IEEE Semiannual Vehic. Tech. Conf.*, 2003.
- [8] L. Briesemeister. Group Membership and Communication in Highly Mobile Ad Hoc Networks. In *PhD thesis, School of Electrical Engineering and Computer Science, Technical University of Berlin, Germany*, November 2001.
- [9] L. Briesemeister and G. Hommel. Localized Group Membership Service for Ad Hoc Networks. In *Proceedings of the International Conference on Parallel Processing Workshops (ICPPW02), IEEE*, 2002.

- [10] L. Briesmeister and G Hommel. Role-based multicast in highly mobile but sparsely connected ad hoc networks. In *Proc. of the First Annual Workshop on Mobile and Ad Hoc Networking and Computing, MobiHoc'00*, pages 45–40, 2000.
- [11] Car2Car Communication Consortium. <http://www.car-to-car.org/>.
- [12] David Choffnes and Fabian E. Bustamante. STRAW - An Integrated Mobility and Traffic Model for VANETs. In *Proc. of the 10th International Command and Control Research and Technology Symposium (CCRTS)*, volume 62(2), June 2005.
- [13] U.S. Department of Transportation. <http://www.fhwa.dot.gov/policy/final.htm>.
- [14] D. Helbing. Gas-kinetic derivation of Navier-Stokes-like traffic equations. In *Physical Review E*, volume 53, pages 2366–2381, 1996.
- [15] I. Prigogine. A Boltzmann-like Approach to the Statistical Theory of Traffic Flow. In *Herman, R. (ed), Theory of Traffic Flow*, 1961.
- [16] A. Kesting, M. Treiber, and D. Helbing. Game-theoretic approach to lane-changing in microscopic traffic models. In *Submitted to Transportation Research B*, 2006.
- [17] P.D. Lax and B. Wendroff. Systems of conservation laws. In *Commun. Pure Appl. Math.*, volume 13, pages 217–237.
- [18] P. Martin, J. Perrin, B. Hansen, R. Kump, and D. Moore. Incident Detection Algorithm Evaluation. In *Report for Utah Department of Transportation*, March 2001.
- [19] Martin Treiber, Ansgar Hennecke, and Dirk Helbing. Congested traffic states in empirical observations and microscopic simulations. In *PHYSICAL REVIEW E*, volume 62(2), August 2000.
- [20] Panos G. Michalopoulos, Richard D. Jacobson, Craig A. Anderson, and Thomas B. DeBruycker. Automatic Incident Detection Through Video Image Processing. In *Traffic Engineering + Control*, February 1993.
- [21] E. Parkany and C. Xie. A Complete Review of Incident Detection Algorithms and Their Deployment: What Works and What Doesn't. In *Prepared for The New England Transportation Consortium, NETCR37 Project No. 00-7*, February 2005.

- [22] Randall J. LeVque. Systems of conservation laws. In *Numerical Methods for Conservation Laws, Published by Birkhuser*.
- [23] Roberto Baldessari, Andreas Festag, Alfredo Matos, Justino Santos, and Rui Aguiar. Flexible Connectivity Management in Vehicular Communication Networks. In *Proceedings of 3rd International Workshop on Intelligent Transportation(WIT)*, pages 211–216, 2006.
- [24] S.Das, A.Nandan, G.Pau, M. Sananadidi, and M. Gerla. SPAWN: a swarming protocol for vehicular ad-hoc wireless networks. In *Proc. of the first ACM workshop on Vehicular ad hoc networks*, pages 93–94, 2004.
- [25] Serge P. Hoogendoorn. State-of-the-art of Vehicular Traffic Flow Modelling. In *Special Issue on Road Traffic Modelling and Control of the Journal of Systems and Control Engineering, Delft University of Technology*.
- [26] The DSRC Project. <http://www.leearmstrong.com/-dsrc/dsrhomeset.htm>.
- [27] The FleetNet Project. <http://www.fleetnet.de>.
- [28] The PATH Project. <http://www.path.berkeley.edu>.
- [29] Vehicle Information and Communication System Center (VICS). <http://www.vics.or.jp/english/>.
- [30] H. Wu, R. Fujimoto, R. Guensler, and M. Hunter. MDDV: a mobility-centric data dissemination algorithm for vehicular networks. In *Proc. of the first ACM workshop on Vehicular ad hoc networks, VANET'04*, pages 47–56, 2004.

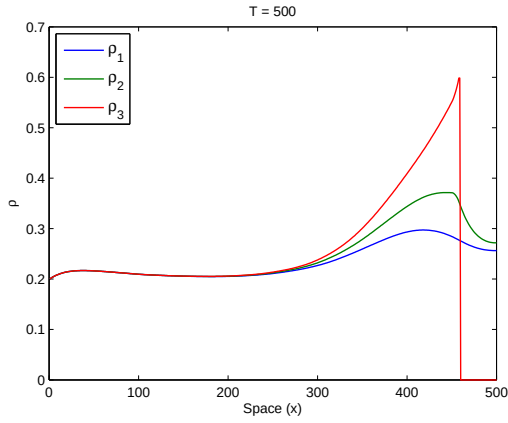
Appendix A

Cases: *CWMsg* with Zero

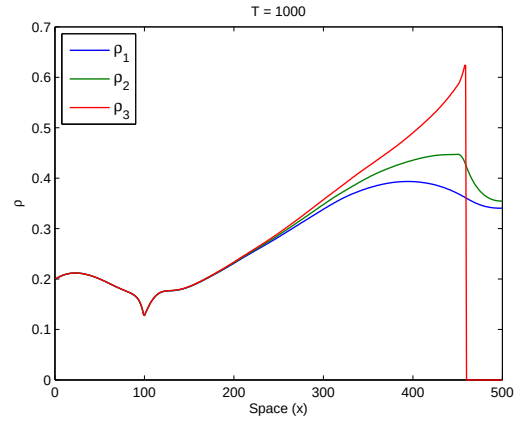
Persistence

A.1 *Typical* Driver Behavior with Zero Persistence and $f_\alpha^{com}(x, 0)$

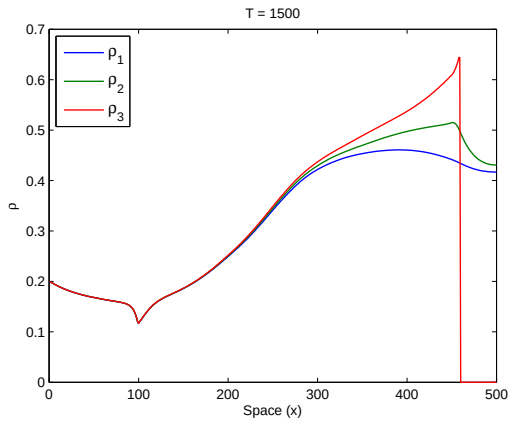
$= 0.8$



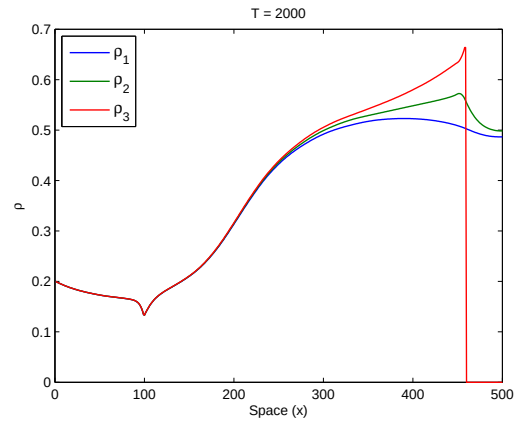
(a) ρ_α at $T=500$



(b) ρ_α at $T=1000$



(c) ρ_α at $T=1500$



(d) ρ_α at $T=2000$

Figure A.1: Macroscopic ρ_α for *Typical* Driver Behavior with Zero Persistence and $f_\alpha^{com}(x, 0) = 0.8$

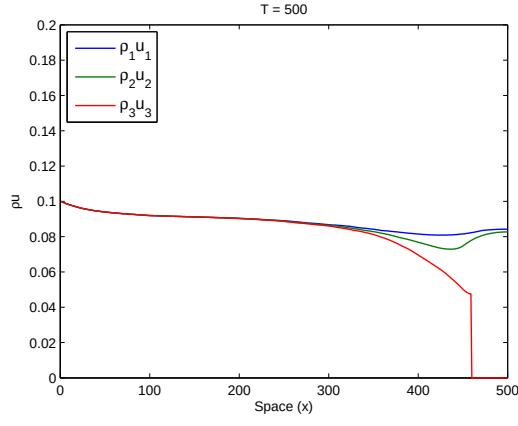
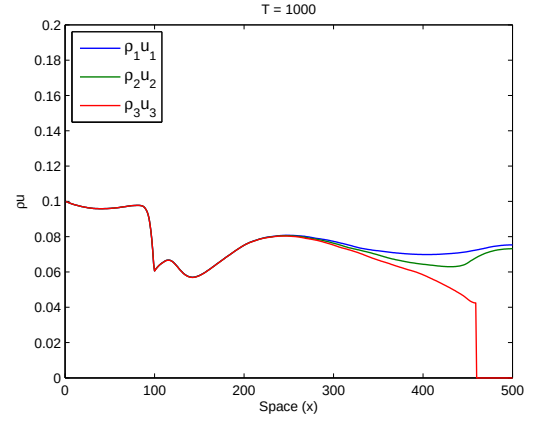
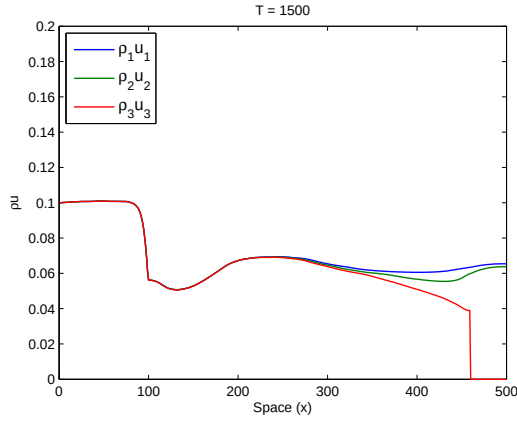
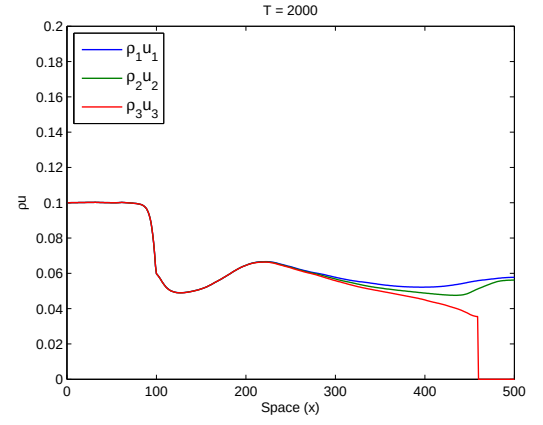
(a) $\rho_\alpha u_\alpha$ at $T=500$ (b) $\rho_\alpha u_\alpha$ at $T=1000$ (c) $\rho_\alpha u_\alpha$ at $T=1500$ (d) $\rho_\alpha u_\alpha$ at $T=2000$

Figure A.2: Macroscopic $\rho_\alpha u_\alpha$ for *Typical* Driver Behavior with Zero Persistence and $f_\alpha^{com}(x, 0) = 0.8$

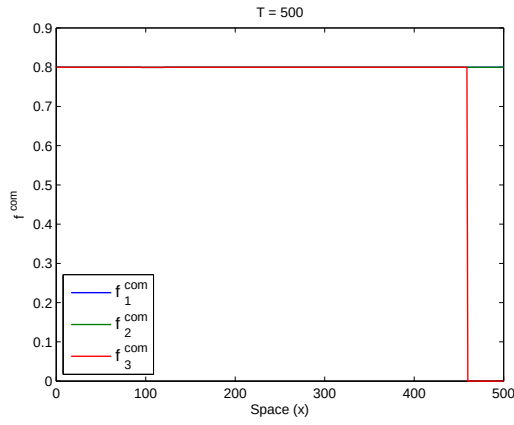
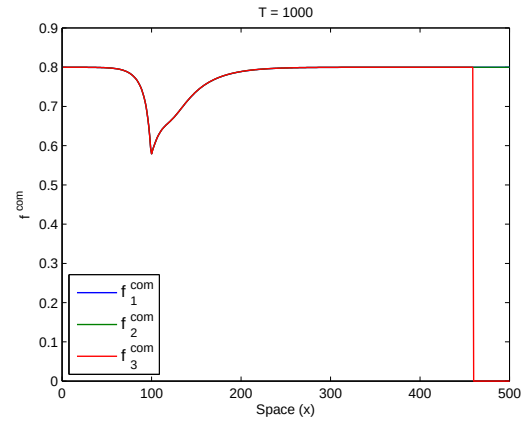
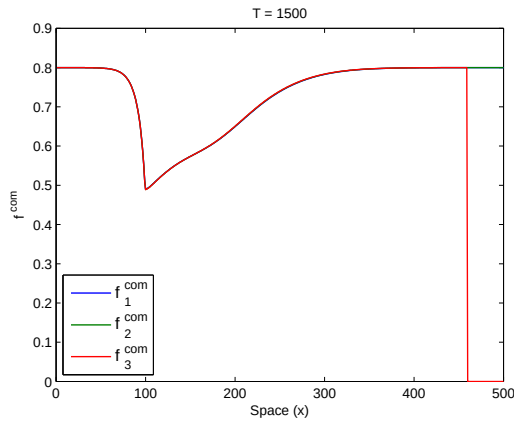
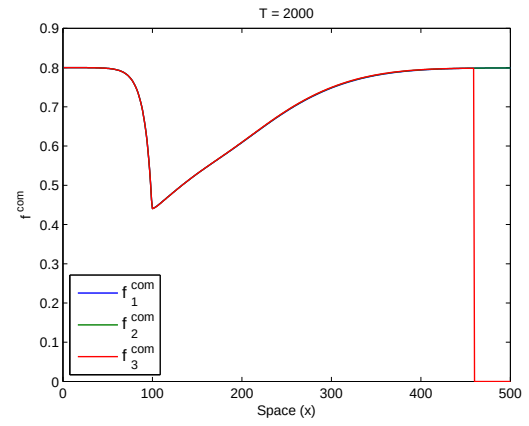
(a) $f_{\alpha}^{com}(x, t)$ at $T=500$ (b) $f_{\alpha}^{com}(x, t)$ at $T=1000$ (c) $f_{\alpha}^{com}(x, t)$ at $T=1500$ (d) $f_{\alpha}^{com}(x, t)$ at $T=2000$

Figure A.3: Macroscopic $f_{\alpha}^{com}(x, t)$ for *Typical* Driver Behavior with Zero Persistence and $f_{\alpha}^{com}(x, 0) = 0.8$

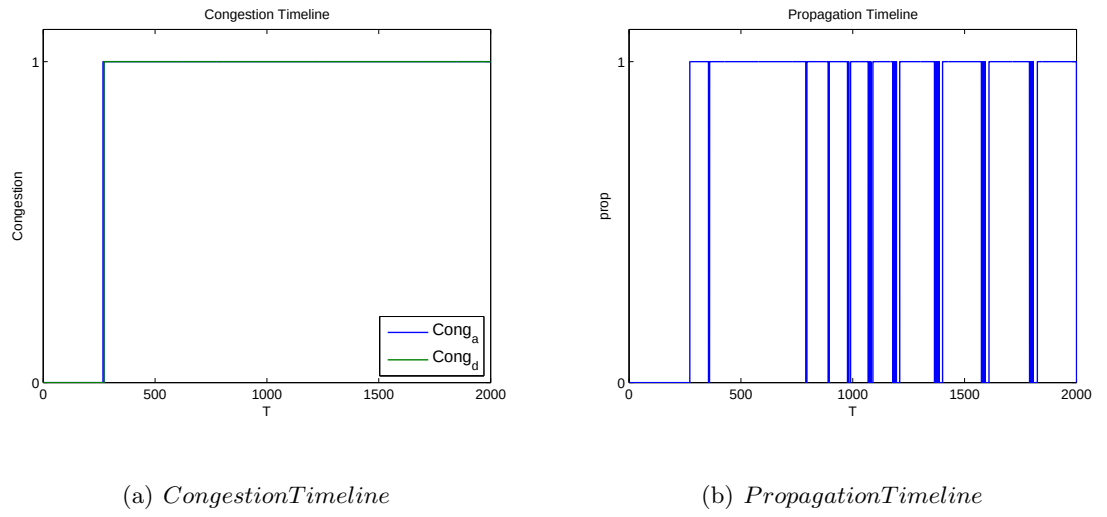


Figure A.4: Macroscopic Communication Timelines for *Typical* Driver Behavior with Zero Persistence and $f_{\alpha}^{com}(x, 0) = 0.8$

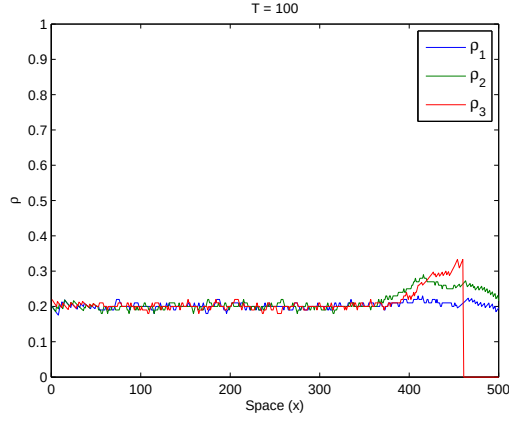
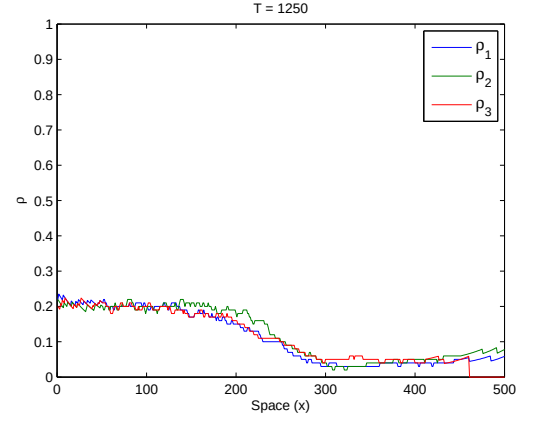
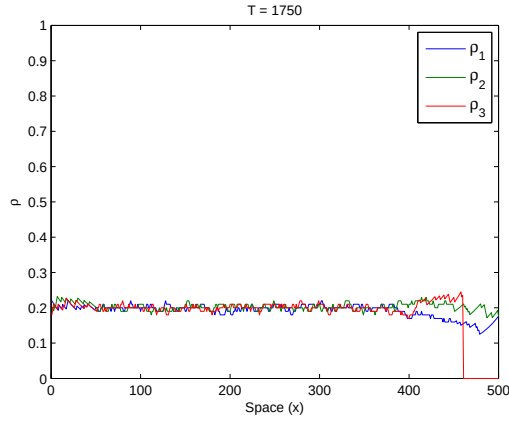
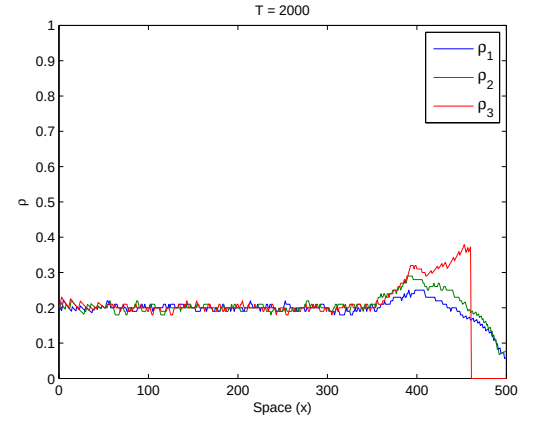
(a) ρ_α at $T=100$ (b) ρ_α at $T=1250$ (c) ρ_α at $T=1750$ (d) ρ_α at $T=2000$

Figure A.5: Microscopic ρ_α for *Typical* Driver Behavior with Zero Persistence and $f_\alpha^{com}(x, 0) = 0.8$

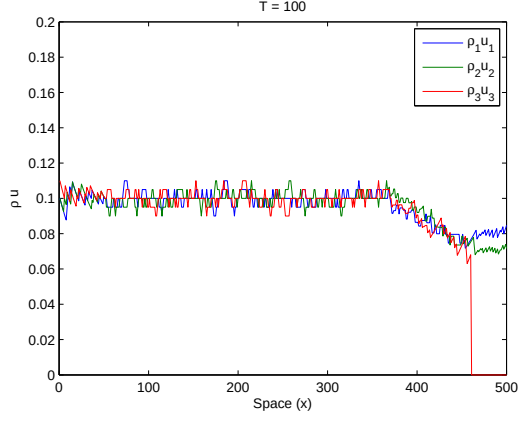
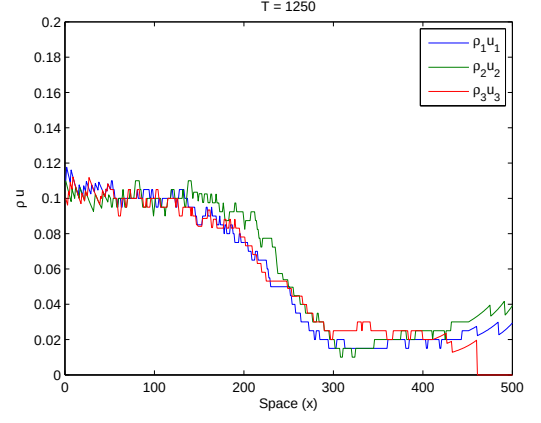
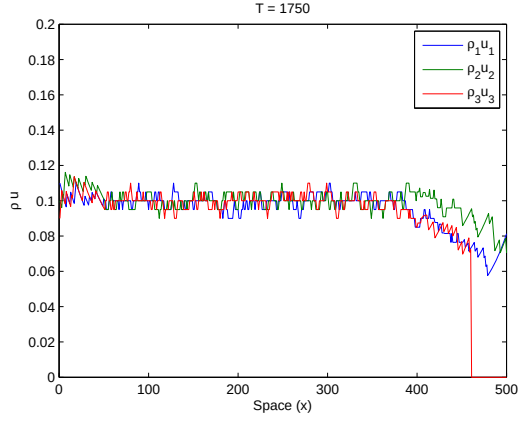
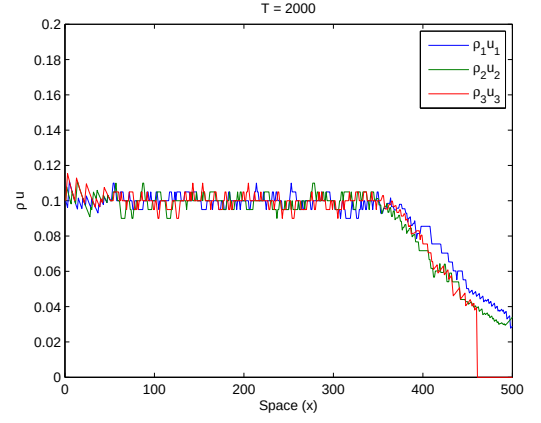
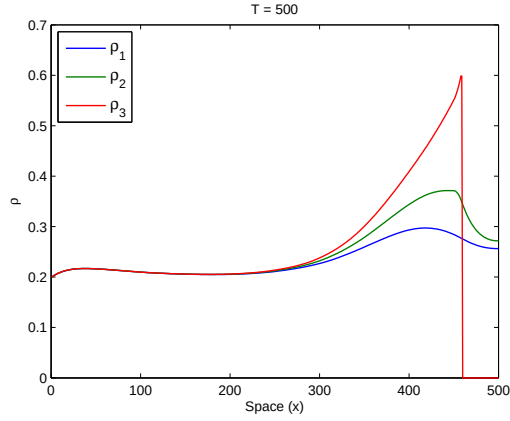
(a) $\rho_\alpha u_\alpha$ at T=100(b) $\rho_\alpha u_\alpha$ at T=1250(c) $\rho_\alpha u_\alpha$ at T=1750(d) $\rho_\alpha u_\alpha$ at T=2000

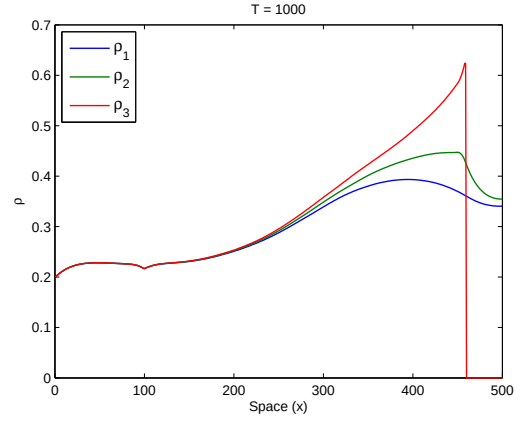
Figure A.6: Microscopic $\rho_\alpha u_\alpha$ for *Typical* Driver Behavior with Zero Persistence and $f_\alpha^{com}(x, 0) = 0.8$

A.2 *Typical* Driver Behavior with Zero Persistence and $f_\alpha^{com}(x, 0)$

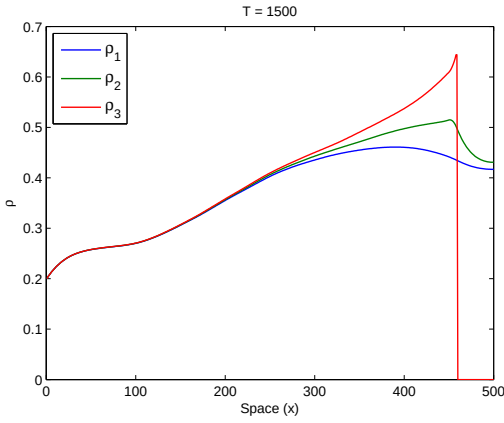
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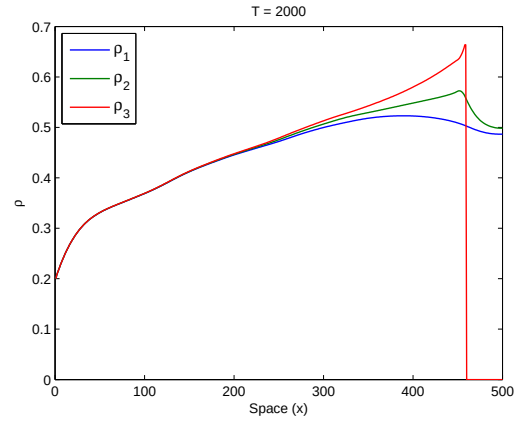
(a) ρ_α at $T=500$



(b) ρ_α at $T=1000$



(c) ρ_α at $T=1500$



(d) ρ_α at $T=2000$

Figure A.7: Macroscopic ρ_α for *Typical* Driver Behavior with Zero Persistence and $f_\alpha^{com}(x, 0) = 0.1$

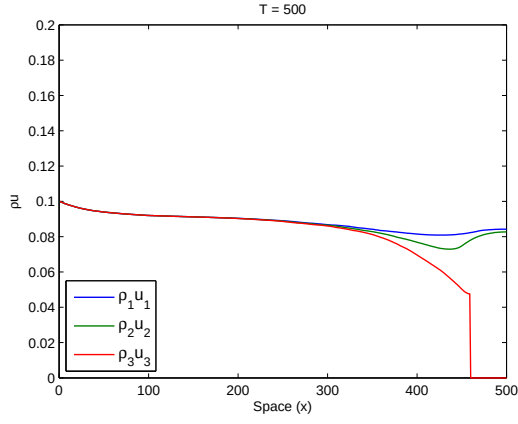
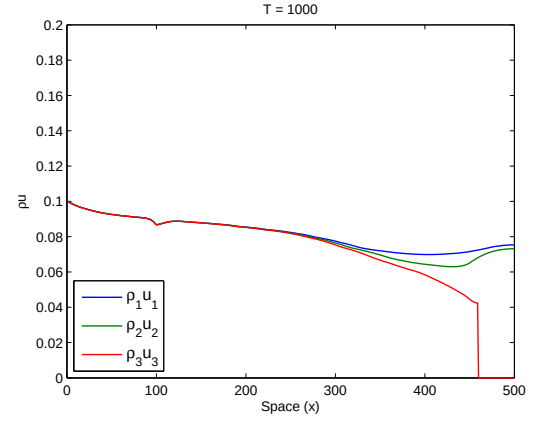
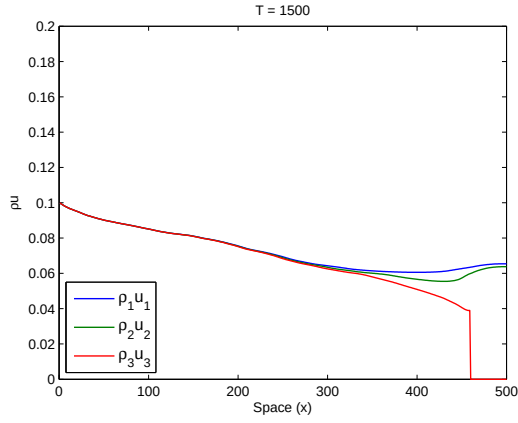
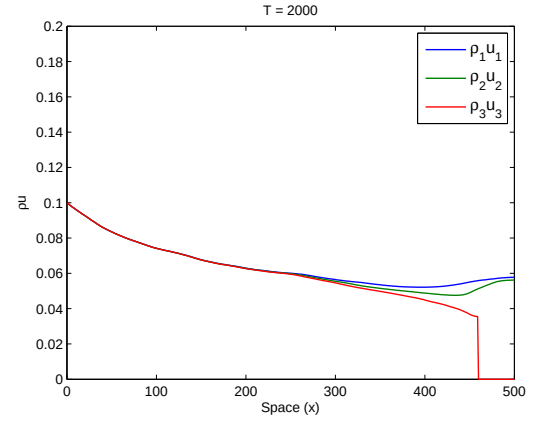
(a) $\rho_\alpha u_\alpha$ at T=500(b) $\rho_\alpha u_\alpha$ at T=1000(c) $\rho_\alpha u_\alpha$ at T=1500(d) $\rho_\alpha u_\alpha$ at T=2000

Figure A.8: Macroscopic $\rho_\alpha u_\alpha$ for *Typical* Driver Behavior with Zero Persistence and $f_\alpha^{com}(x, 0) = 0.1$

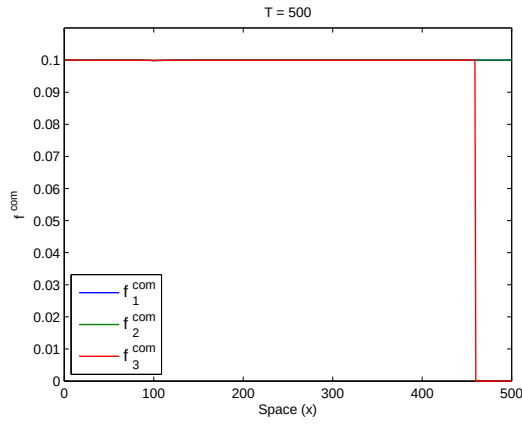
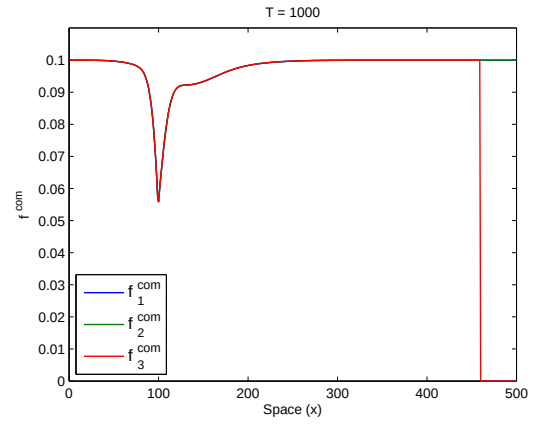
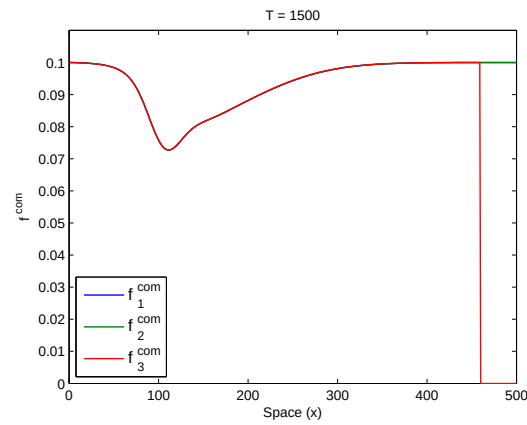
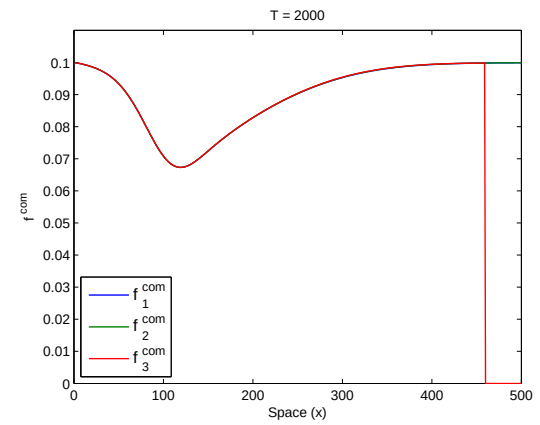
(a) $f_{\alpha}^{com}(x, t)$ at $T=500$ (b) $f_{\alpha}^{com}(x, t)$ at $T=1000$ (c) $f_{\alpha}^{com}(x, t)$ at $T=1500$ (d) $f_{\alpha}^{com}(x, t)$ at $T=2000$

Figure A.9: Macroscopic $f_{\alpha}^{com}(x, t)$ for *Typical* Driver Behavior with Zero Persistence and $f_{\alpha}^{com}(x, 0) = 0.1$

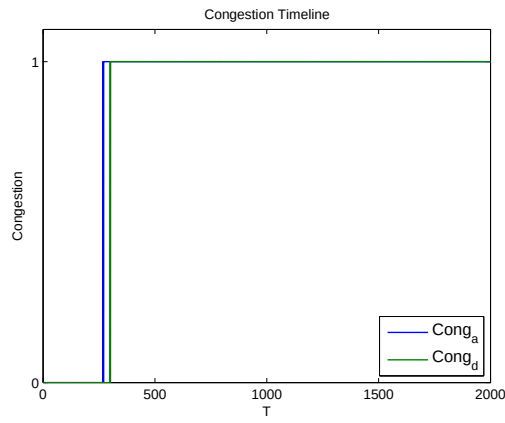
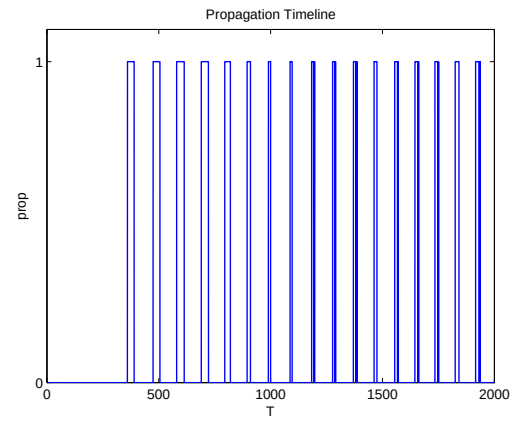
(a) *CongestionTimeline*(b) *PropagationTimeline*

Figure A.10: Macroscopic Communication Timelines for *Typical* Driver Behavior with Zero Persistence and $f_\alpha^{com}(x, 0) = 0.1$

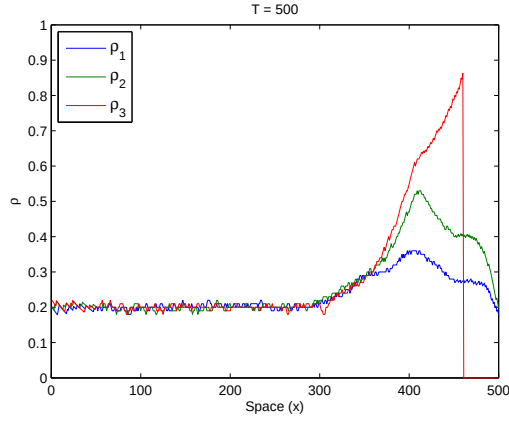
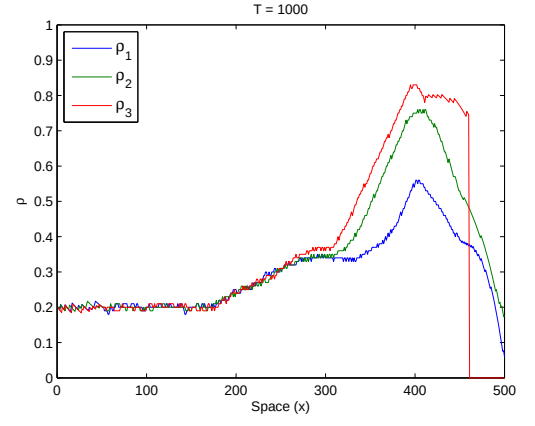
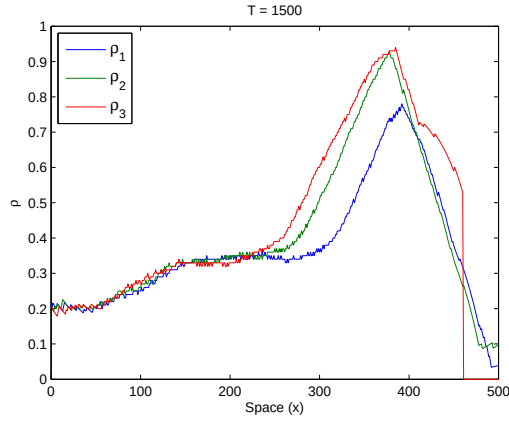
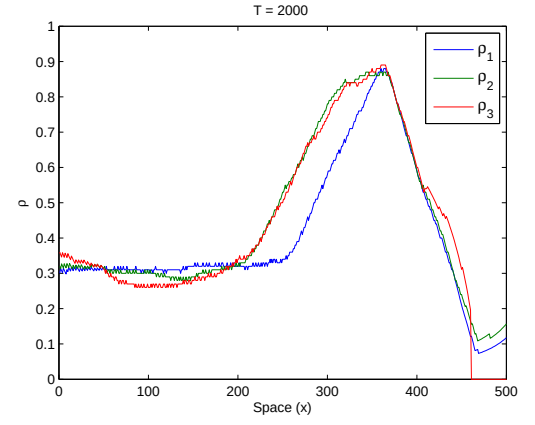
(a) ρ_α at $T=500$ (b) ρ_α at $T=1000$ (c) ρ_α at $T=1500$ (d) ρ_α at $T=2000$

Figure A.11: Microscopic ρ_α for *Typical* Driver Behavior with Zero Persistence and $f_\alpha^{com}(x, 0) = 0.1$

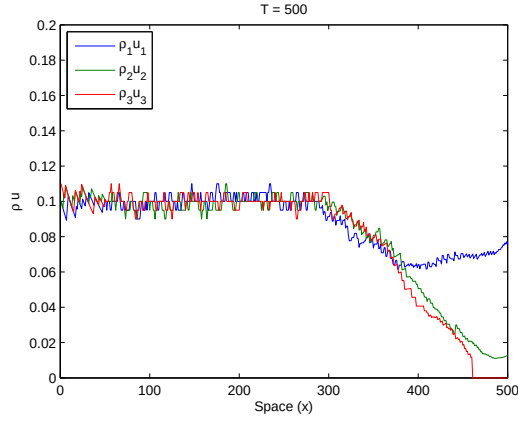
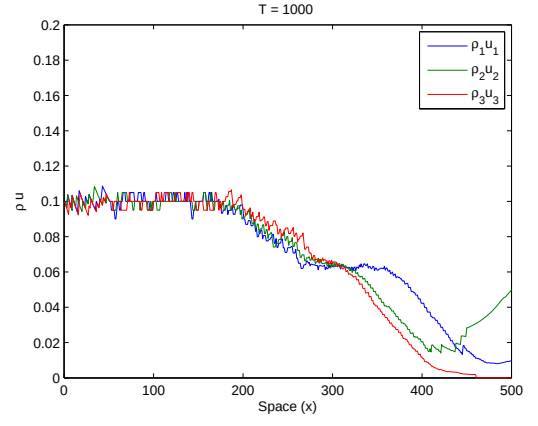
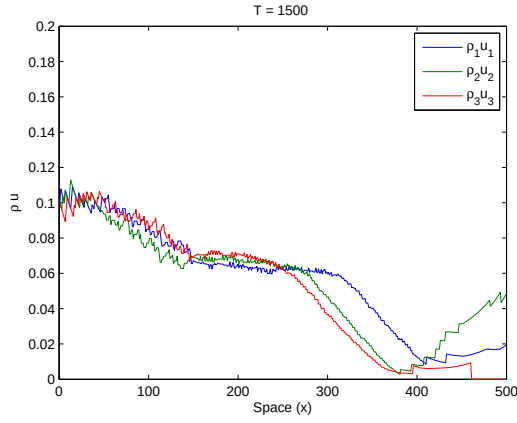
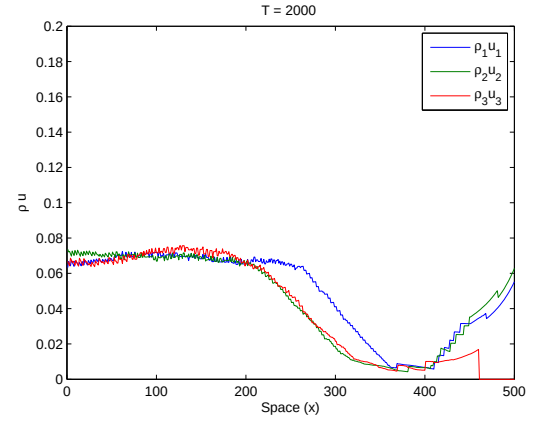
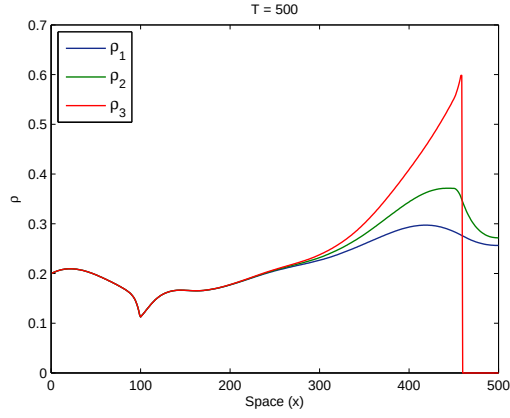
(a) $\rho_\alpha u_\alpha$ at $T=500$ (b) $\rho_\alpha u_\alpha$ at $T=1000$ (c) $\rho_\alpha u_\alpha$ at $T=1500$ (d) $\rho_\alpha u_\alpha$ at $T=2000$

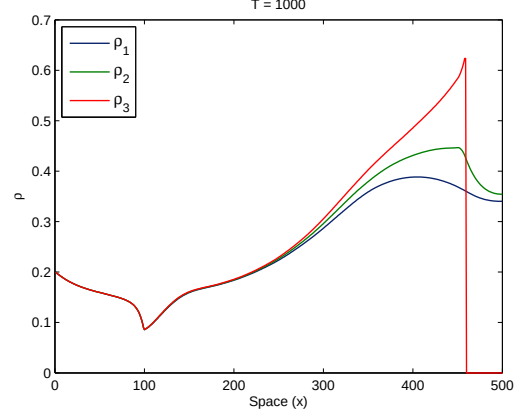
Figure A.12: Microscopic $\rho_\alpha u_\alpha$ for *Typical* Driver Behavior with Zero Persistence and $f_\alpha^{com}(x, 0) = 0.1$

A.3 *Panicky* Driver Behavior with Zero Persistence and $f_\alpha^{com}(x, 0)$

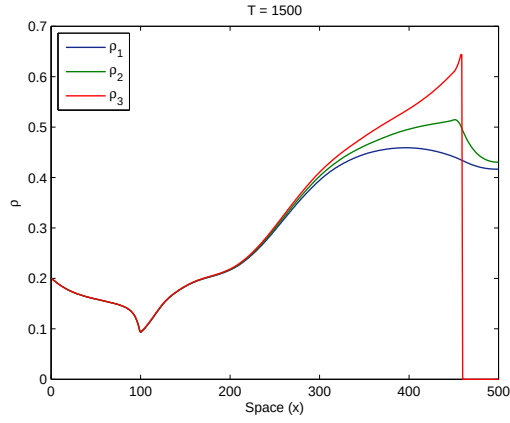
$= 0.8$



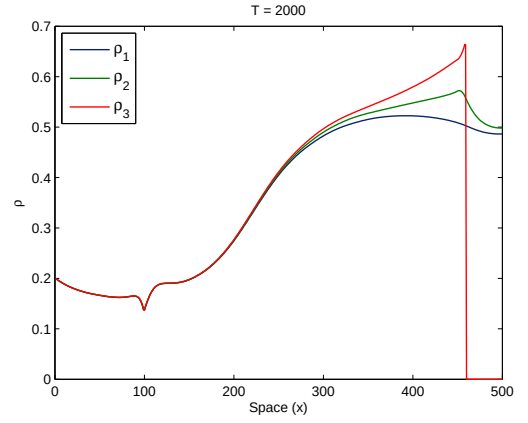
(a) ρ_α at $T=500$



(b) ρ_α at $T=1000$



(c) ρ_α at $T=1500$



(d) ρ_α at $T=2000$

Figure A.13: Macroscopic ρ_α for *Panicky* Driver Behavior with Zero Persistence and $f_\alpha^{com}(x, 0) = 0.8$

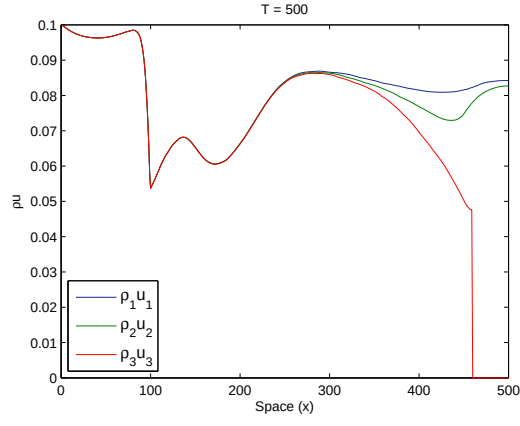
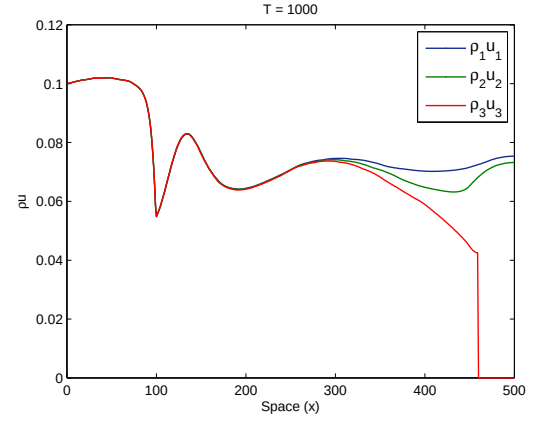
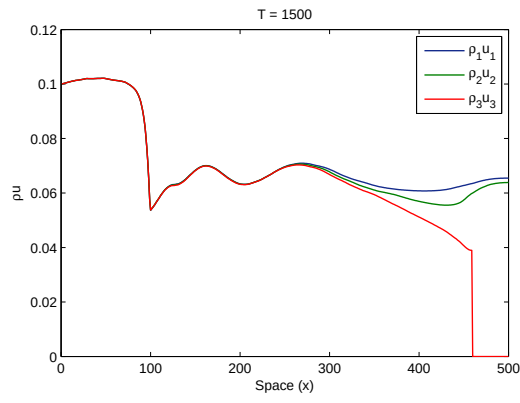
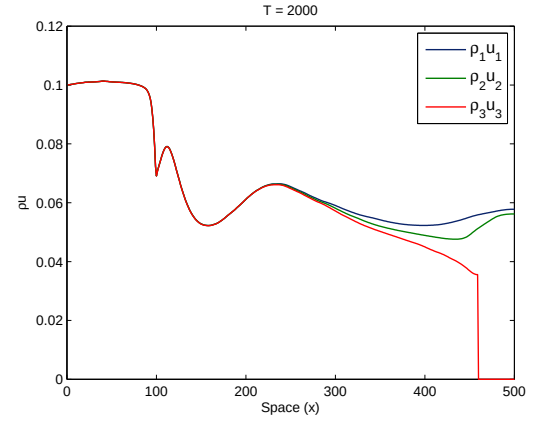
(a) $\rho_\alpha u_\alpha$ at T=500(b) $\rho_\alpha u_\alpha$ at T=1000(c) $\rho_\alpha u_\alpha$ at T=1500(d) $\rho_\alpha u_\alpha$ at T=2000

Figure A.14: Macroscopic $\rho_\alpha u_\alpha$ for *Panicky* Driver Behavior with Zero Persistence and $f_\alpha^{com}(x, 0) = 0.8$

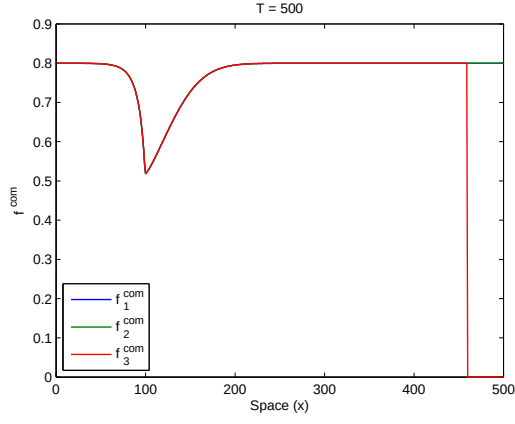
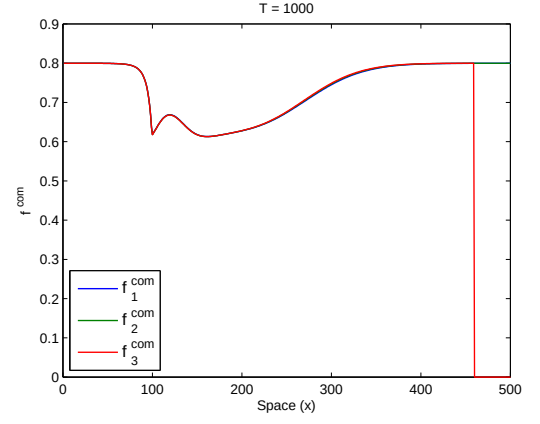
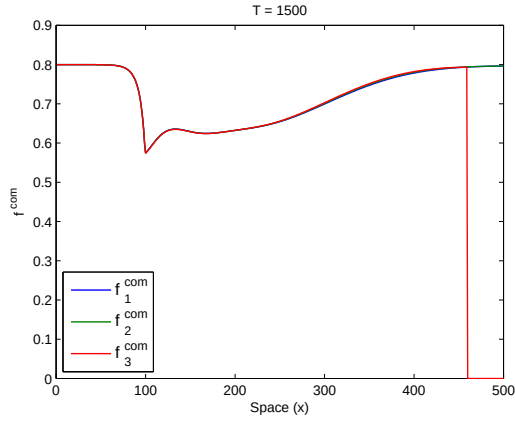
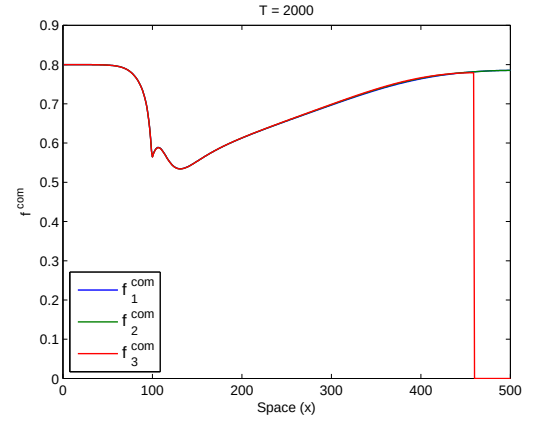
(a) $f_{\alpha}^{com}(x, t)$ at $T=500$ (b) $f_{\alpha}^{com}(x, t)$ at $T=1000$ (c) $f_{\alpha}^{com}(x, t)$ at $T=1500$ (d) $f_{\alpha}^{com}(x, t)$ at $T=2000$

Figure A.15: Macroscopic $f_{\alpha}^{com}(x, t)$ for *Panicky* Driver Behavior with Zero Persistence and $f_{\alpha}^{com}(x, 0) = 0.8$

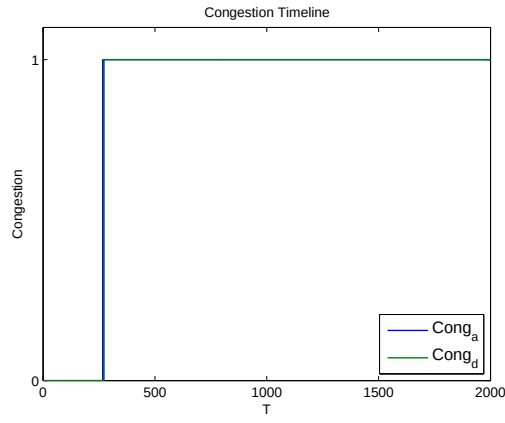
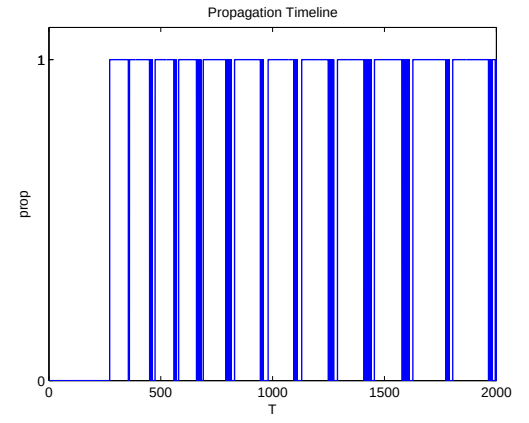
(a) *CongestionTimeline*(b) *PropagationTimeline*

Figure A.16: Macroscopic Communication Timelines for *Panicky* Driver Behavior with Zero Persistence and $f_\alpha^{com}(x, 0) = 0.8$

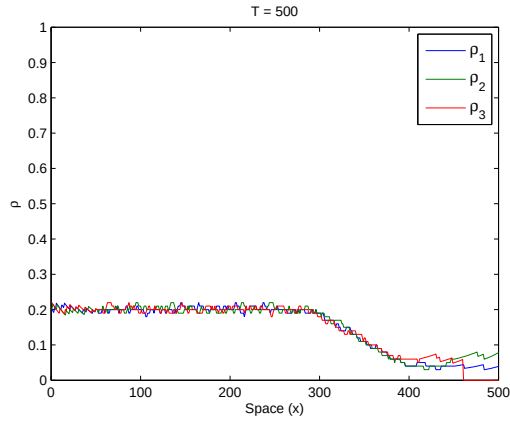
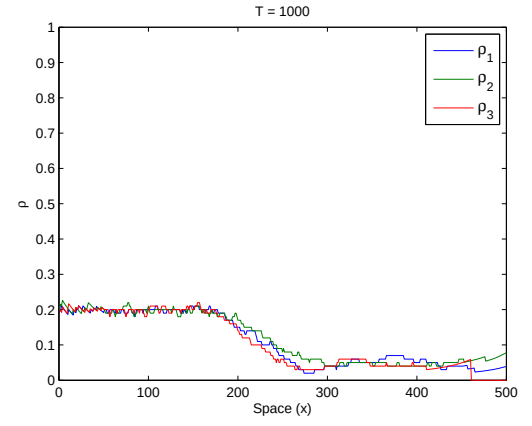
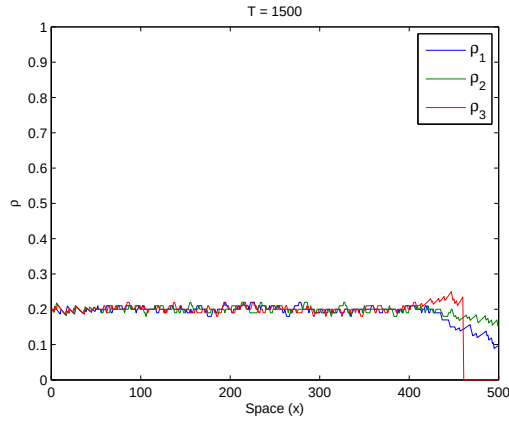
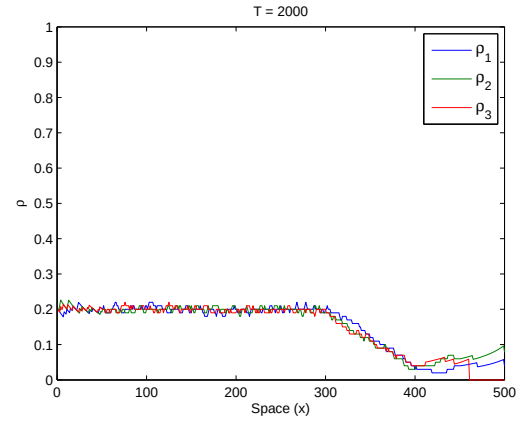
(a) ρ_α at $T=500$ (b) ρ_α at $T=1000$ (c) ρ_α at $T=1500$ (d) ρ_α at $T=2000$

Figure A.17: Microscopic ρ_α for *Panicky* Driver Behavior with Zero Persistence and $f_\alpha^{com}(x,0) = 0.8$

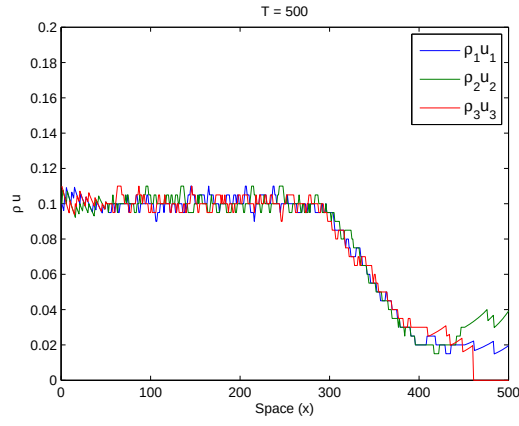
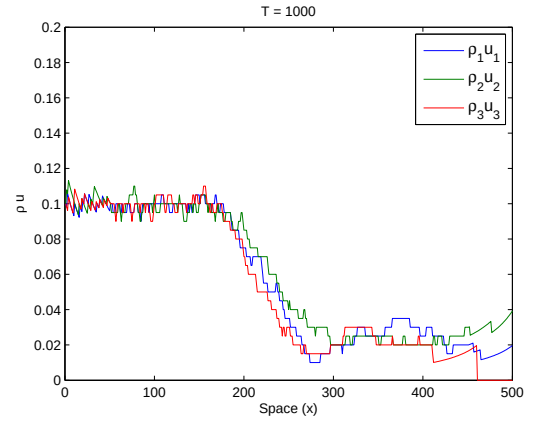
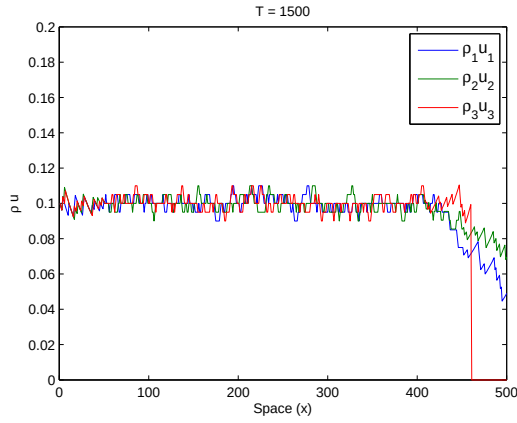
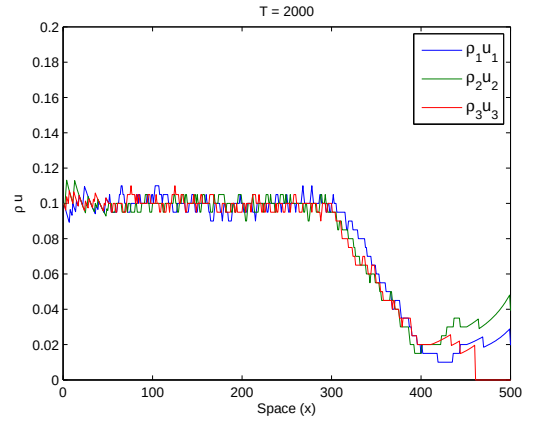
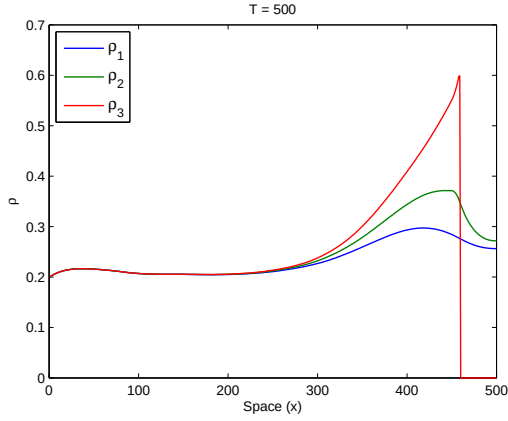
(a) ρ_α at $T=500$ (b) ρ_α at $T=1000$ (c) ρ_α at $T=1500$ (d) ρ_α at $T=2000$

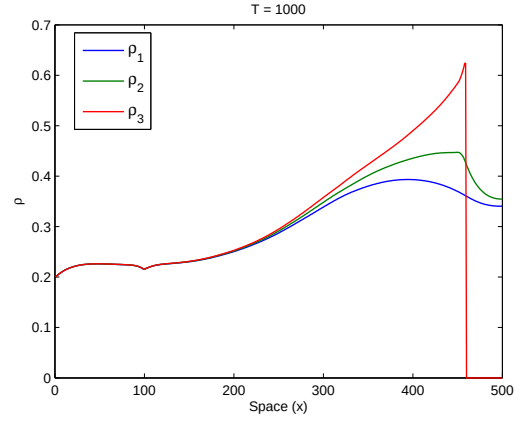
Figure A.18: Microscopic $\rho_\alpha u_\alpha$ for *Panicky* Driver Behavior with Zero Persistence and $f_\alpha^{com}(x,0) = 0.8$

A.4 *Panicky* Driver Behavior with Zero Persistence and $f_\alpha^{com}(x, 0)$

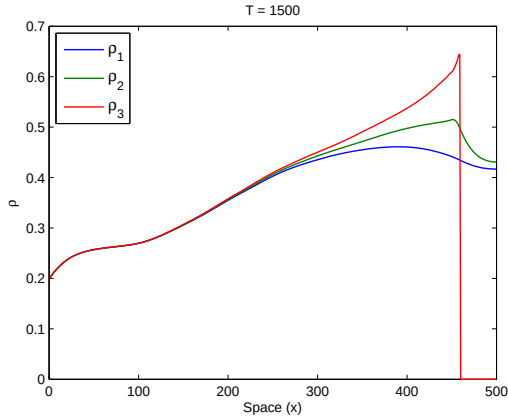
$= 0.1$



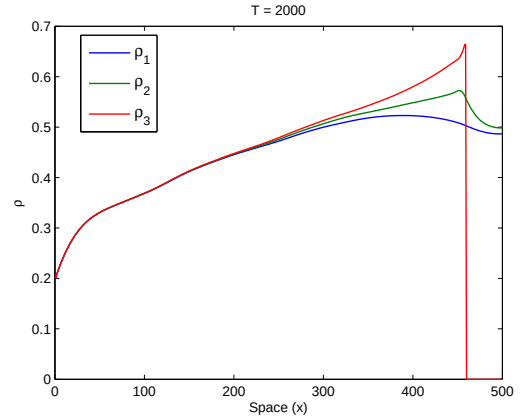
(a) ρ_α at $T=500$



(b) ρ_α at $T=1000$



(c) ρ_α at $T=1500$



(d) ρ_α at $T=2000$

Figure A.19: Macroscopic ρ_α for *Panicky* Driver Behavior with Zero Persistence and $f_\alpha^{com}(x, 0) = 0.1$

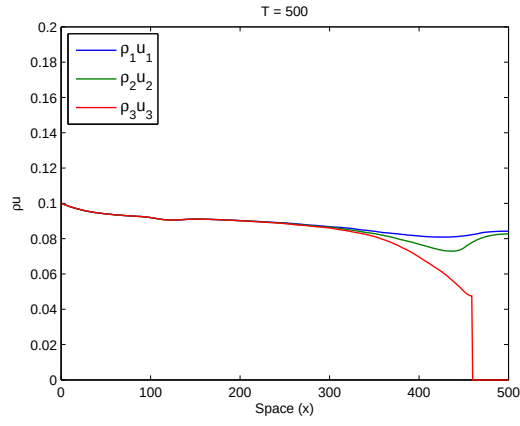
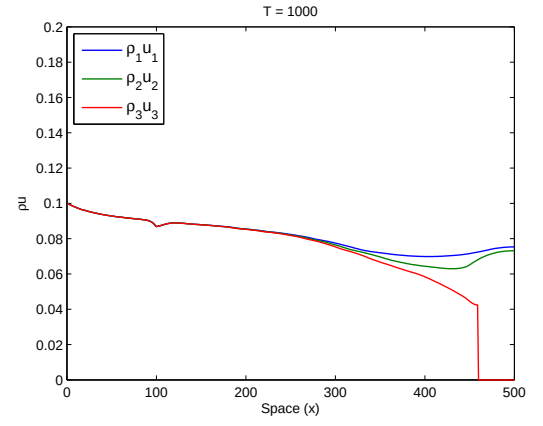
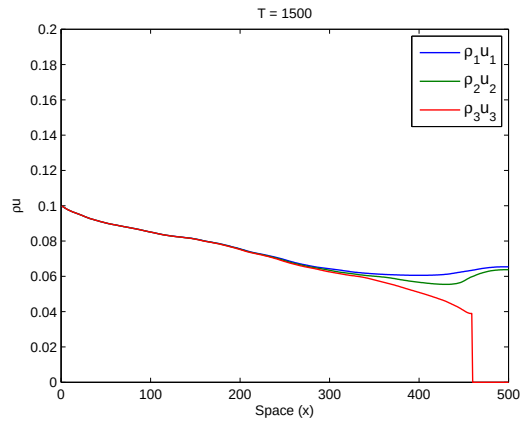
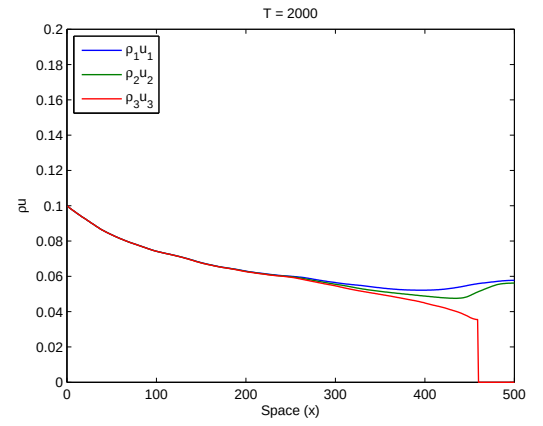
(a) $\rho_\alpha u_\alpha$ at T=500(b) $\rho_\alpha u_\alpha$ at T=1000(c) $\rho_\alpha u_\alpha$ at T=1500(d) $\rho_\alpha u_\alpha$ at T=2000

Figure A.20: Macroscopic $\rho_\alpha u_\alpha$ for *Panicky* Driver Behavior with Zero Persistence and $f_\alpha^{com}(x, 0) = 0.1$

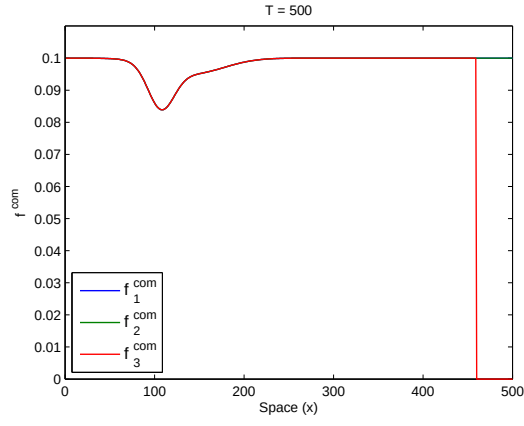
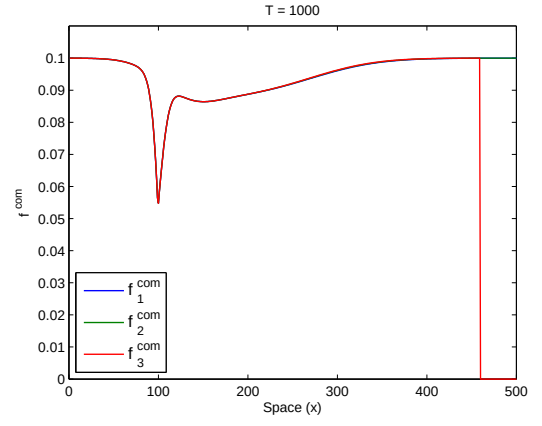
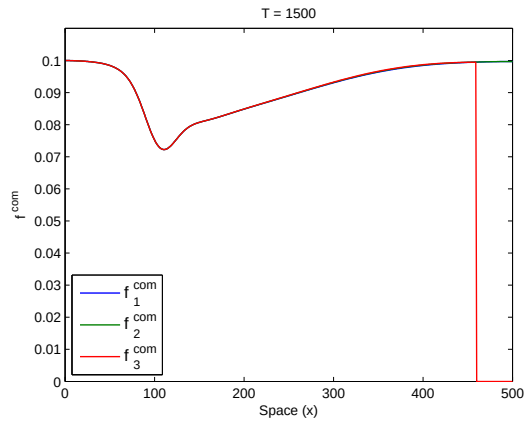
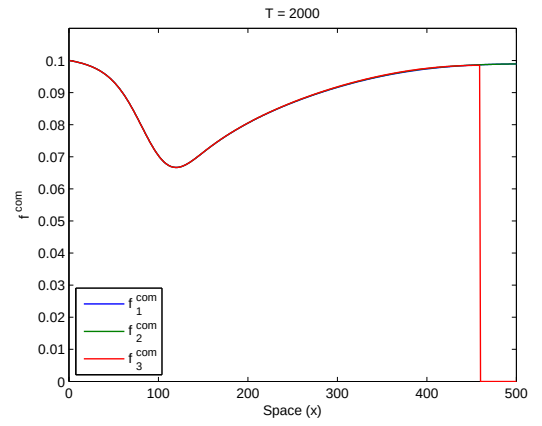
(a) $f_{\alpha}^{com}(x, t)$ at $T=500$ (b) $f_{\alpha}^{com}(x, t)$ at $T=1000$ (c) $f_{\alpha}^{com}(x, t)$ at $T=1500$ (d) $f_{\alpha}^{com}(x, t)$ at $T=2000$

Figure A.21: Macroscopic $f_{\alpha}^{com}(x, t)$ for *Panicky* Driver Behavior with Zero Persistence and $f_{\alpha}^{com}(x, 0) = 0.1$

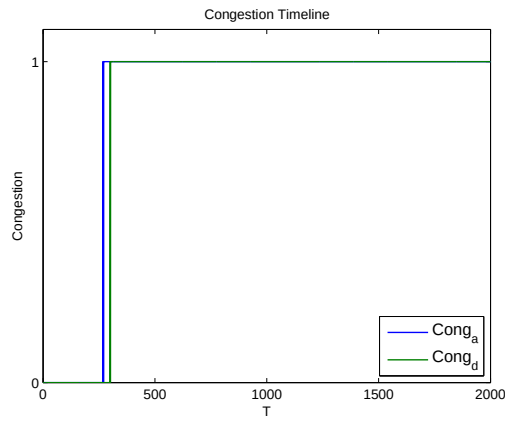
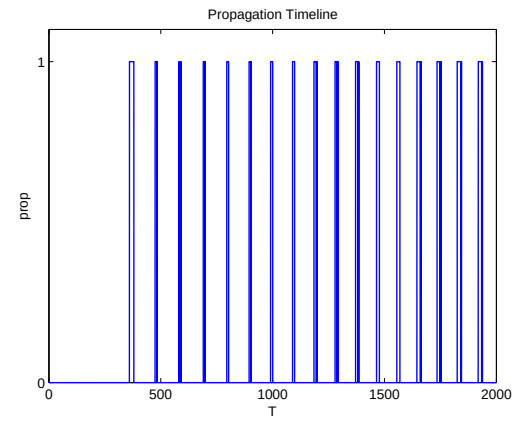
(a) *CongestionTimeline*(b) *PropagationTimeline*

Figure A.22: Macroscopic Communication Timelines for *Panicky* Driver Behavior with Zero Persistence and $f_\alpha^{com}(x, 0) = 0.1$

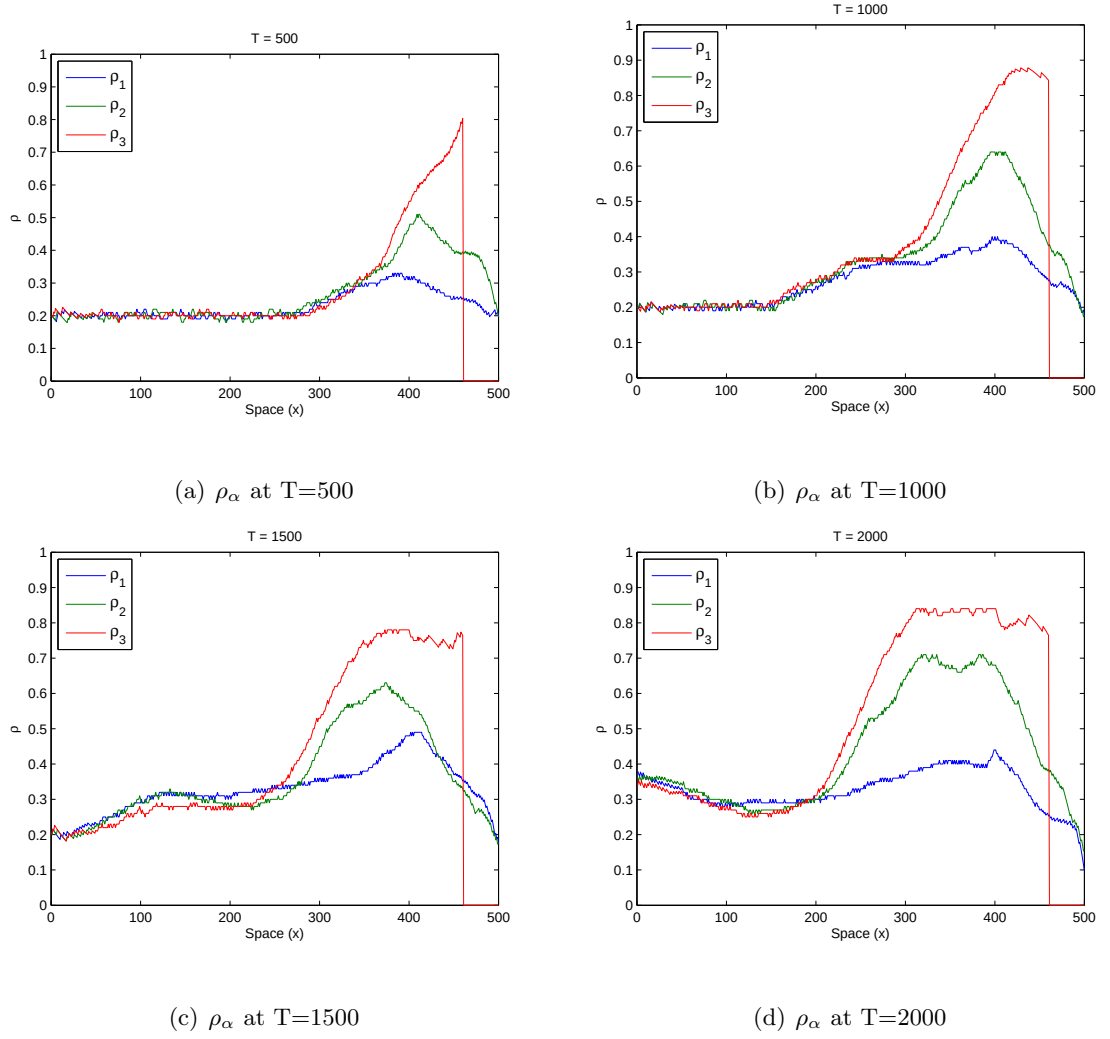


Figure A.23: Microscopic ρ_α for *Panicky* Driver Behavior with Zero Persistence and $f_\alpha^{com}(x, 0) = 0.1$

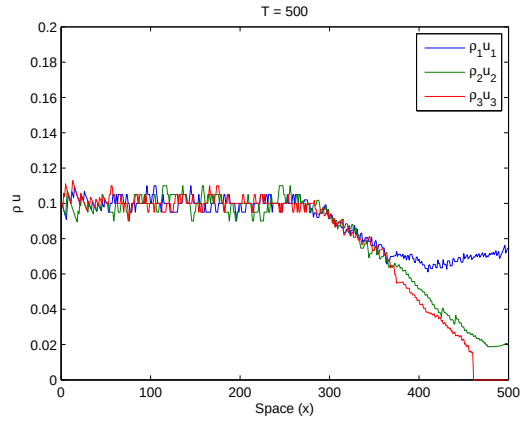
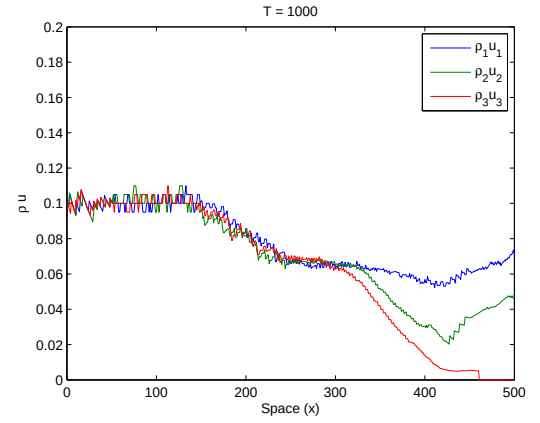
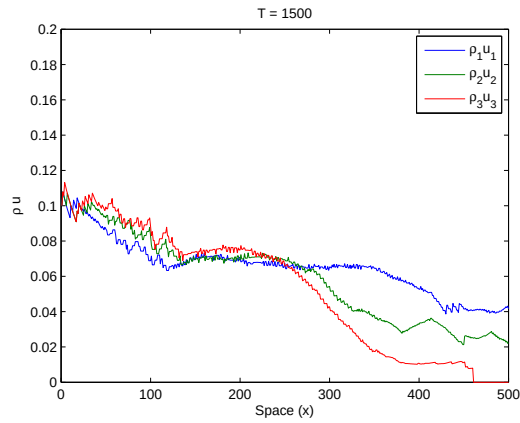
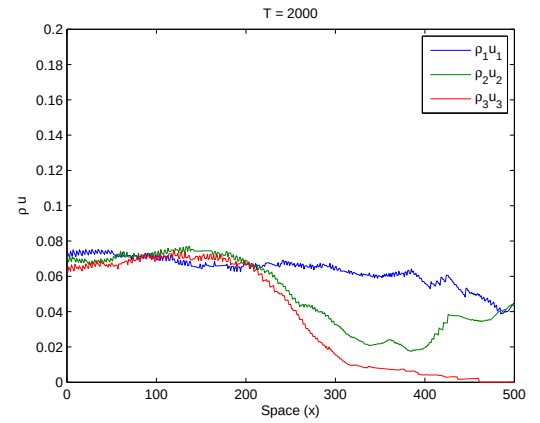
(a) $\rho_\alpha u_\alpha$ at T=500(b) $\rho_\alpha u_\alpha$ at T=1000(c) $\rho_\alpha u_\alpha$ at T=1500(d) $\rho_\alpha u_\alpha$ at T=2000

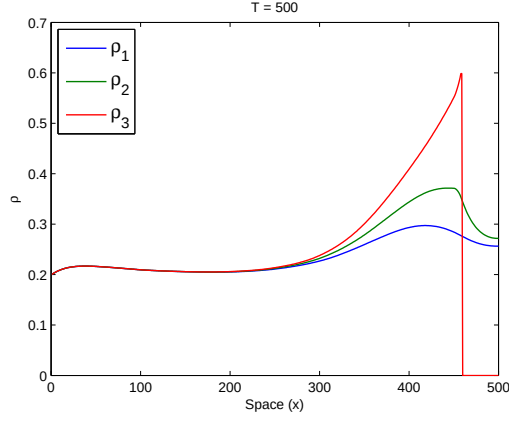
Figure A.24: Microscopic $\rho_\alpha u_\alpha$ for *Panicky* Driver Behavior with Zero Persistence and $f_\alpha^{com}(x, 0) = 0.1$

Appendix B

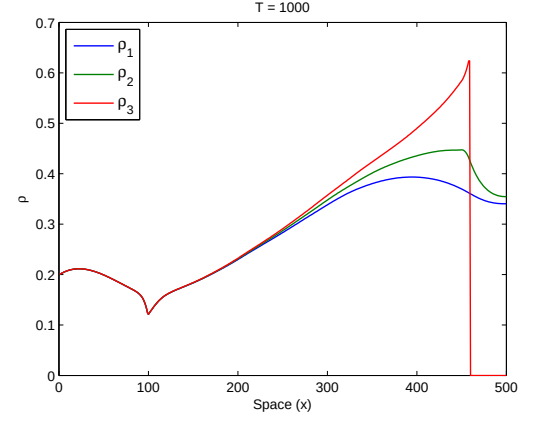
Cases: *CWMsg* with Non-Zero
Persistence

B.1 *Typical* Driver Behavior with Non-Zero Persistence and

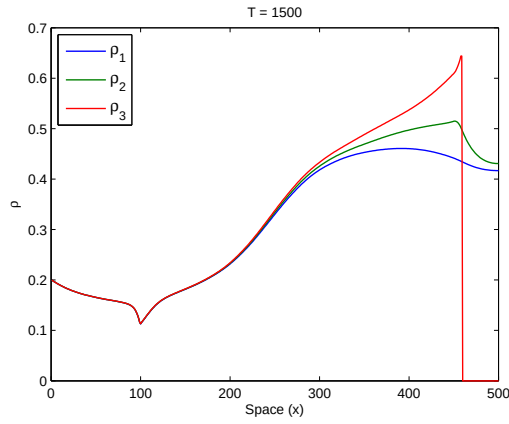
$$f_{\alpha}^{com}(x, 0) = 0.8$$



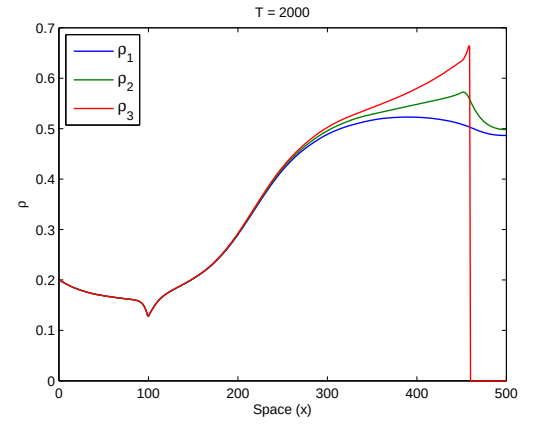
(a) ρ_{α} at $T=500$



(b) ρ_{α} at $T=1000$



(c) ρ_{α} at $T=1500$



(d) ρ_{α} at $T=2000$

Figure B.1: Macroscopic ρ_{α} for *Typical* Driver Behavior with Non-Zero Persistence and $f_{\alpha}^{com}(x, 0) = 0.8$

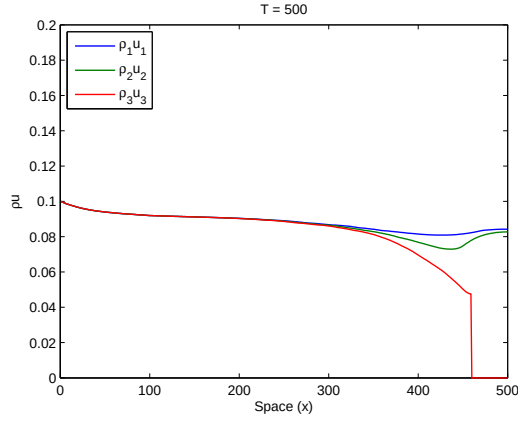
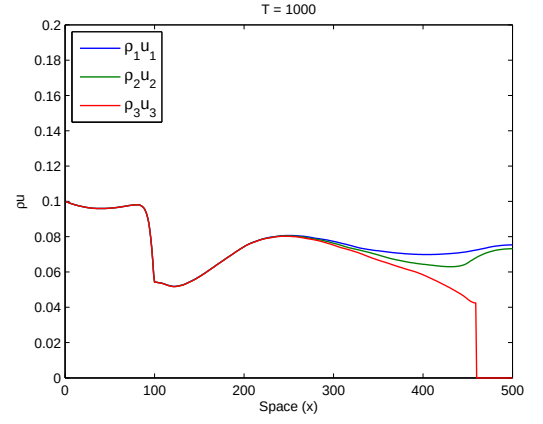
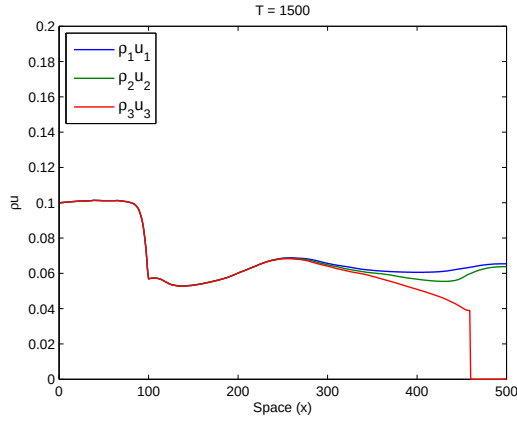
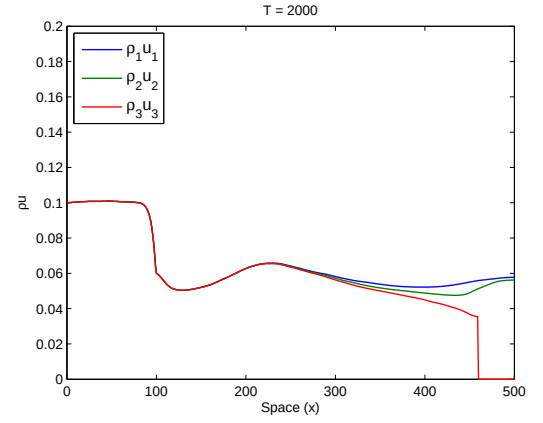
(a) $\rho_\alpha u_\alpha$ at $T=500$ (b) $\rho_\alpha u_\alpha$ at $T=1000$ (c) $\rho_\alpha u_\alpha$ at $T=1500$ (d) $\rho_\alpha u_\alpha$ at $T=2000$

Figure B.2: Macroscopic $\rho_\alpha u_\alpha$ for *Typical* Driver Behavior with Non-Zero Persistence and $f_\alpha^{com}(x, 0) = 0.8$

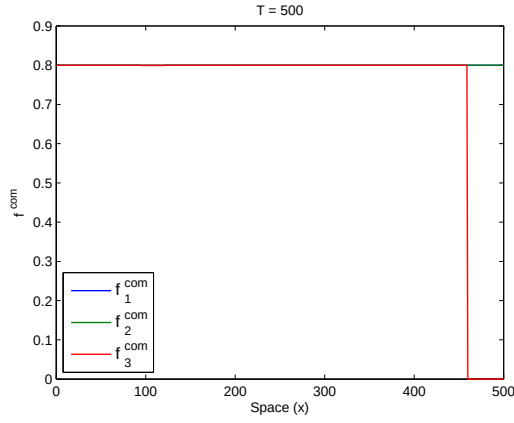
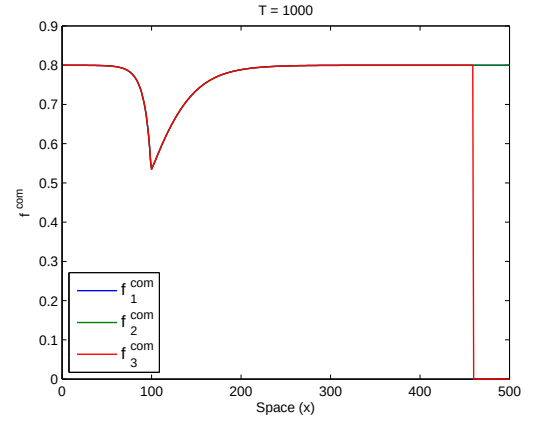
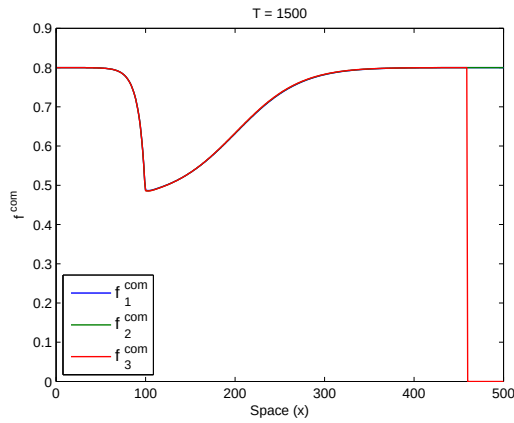
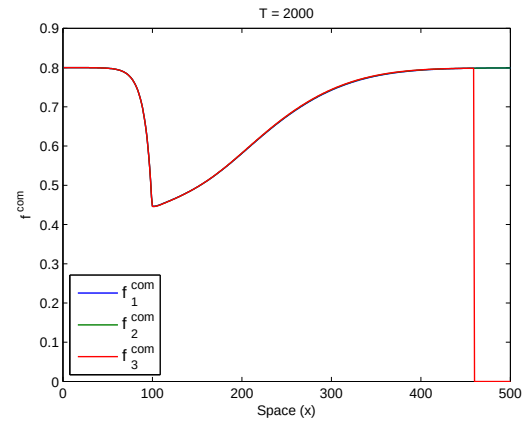
(a) $f_{\alpha}^{com}(x, t)$ at $T=500$ (b) $f_{\alpha}^{com}(x, t)$ at $T=1000$ (c) $f_{\alpha}^{com}(x, t)$ at $T=1500$ (d) $f_{\alpha}^{com}(x, t)$ at $T=2000$

Figure B.3: Macroscopic $f_{\alpha}^{com}(x, t)$ for *Typical* Driver Behavior with Non-Zero Persistence and $f_{\alpha}^{com}(x, 0) = 0.8$

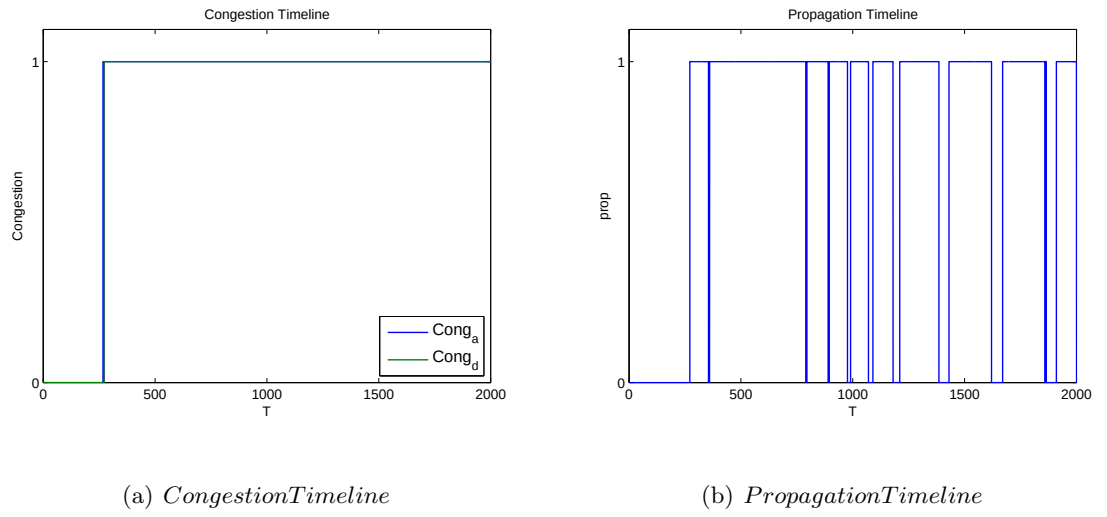


Figure B.4: Macroscopic Communication Timelines for *Typical* Driver Behavior with Non-Zero Persistence and $f_{\alpha}^{com}(x, 0) = 0.8$

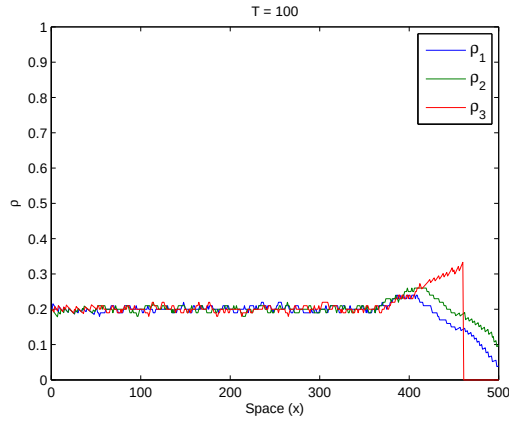
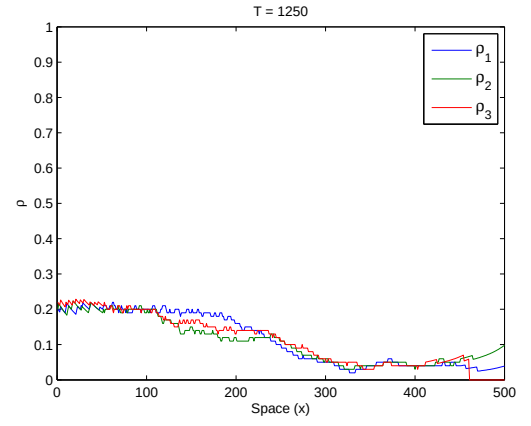
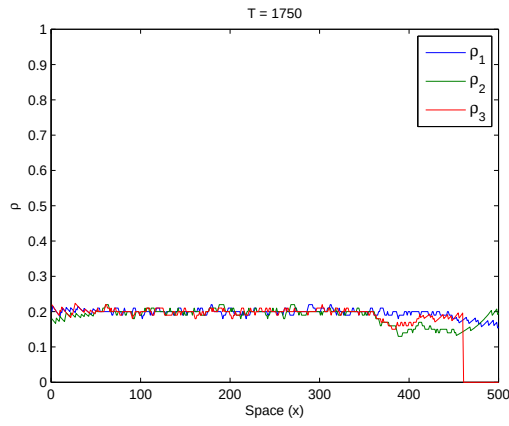
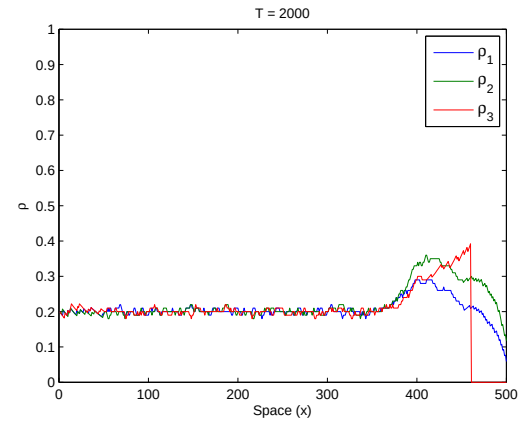
(a) ρ_α at $T=100$ (b) ρ_α at $T=1250$ (c) ρ_α at $T=1750$ (d) ρ_α at $T=2000$

Figure B.5: Microscopic ρ_α for *Typical* Driver Behavior with Non-Zero Persistence and $f_\alpha^{com}(x, 0) = 0.8$

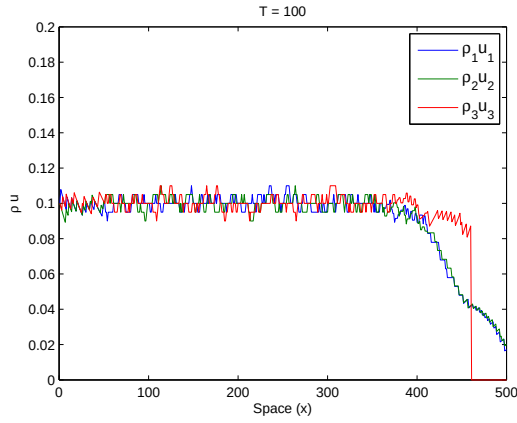
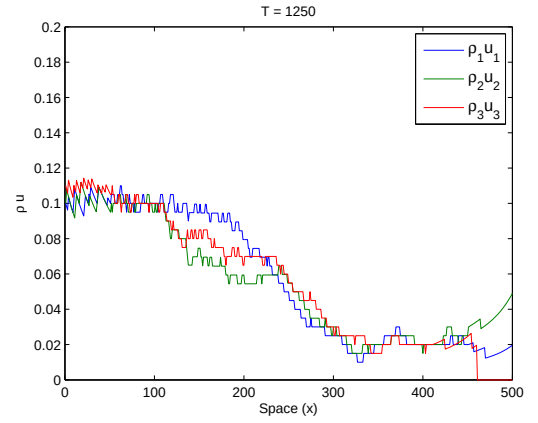
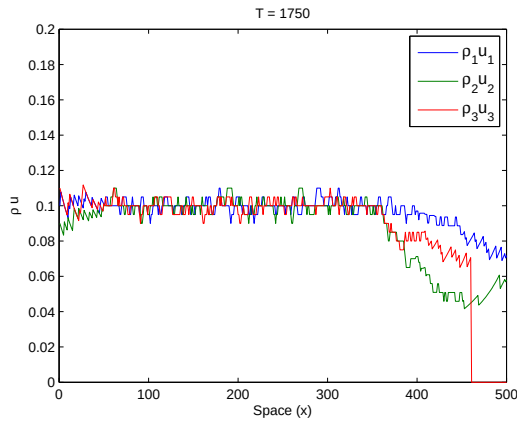
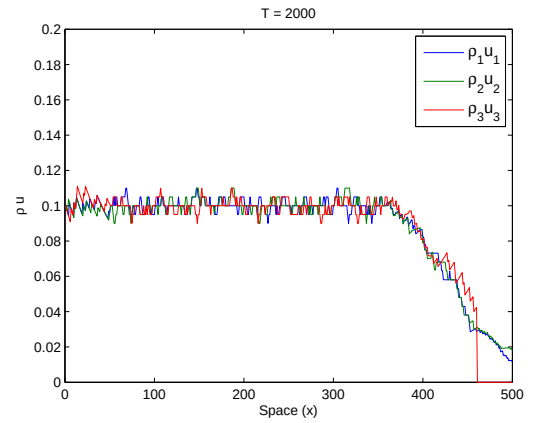
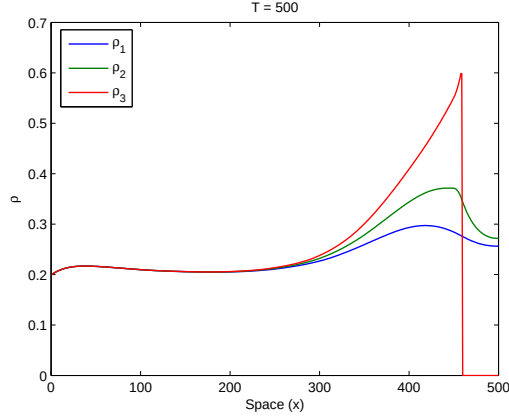
(a) $\rho_\alpha u_\alpha$ at T=100(b) $\rho_\alpha u_\alpha$ at T=1250(c) $\rho_\alpha u_\alpha$ at T=1750(d) $\rho_\alpha u_\alpha$ at T=2000

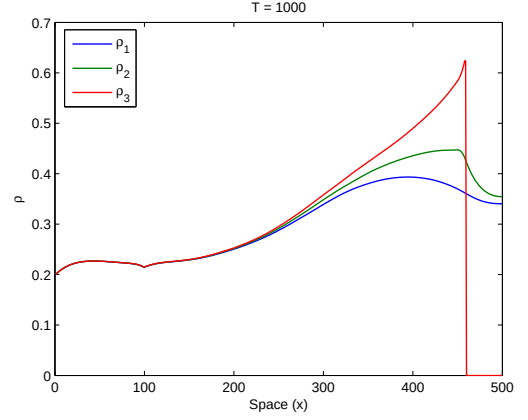
Figure B.6: Microscopic $\rho_\alpha u_\alpha$ for *Typical* Driver Behavior with Non-Zero Persistence and $f_\alpha^{com}(x, 0) = 0.8$

B.2 *Typical* Driver Behavior with Non-Zero Persistence and

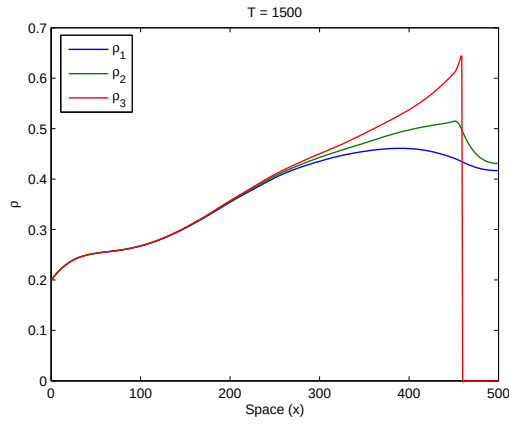
$$f_{\alpha}^{com}(x, 0) = 0.1$$



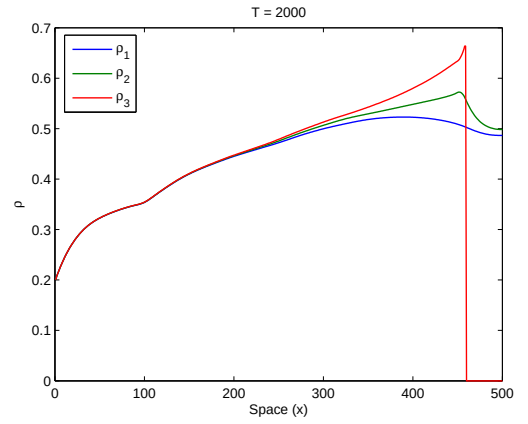
(a) ρ_{α} at $T=500$



(b) ρ_{α} at $T=1000$



(c) ρ_{α} at $T=1500$



(d) ρ_{α} at $T=2000$

Figure B.7: Macroscopic ρ_{α} for *Typical* Driver Behavior with Non-Zero Persistence and $f_{\alpha}^{com}(x, 0) = 0.1$

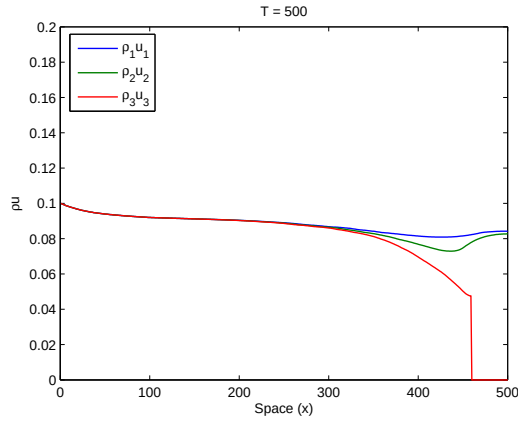
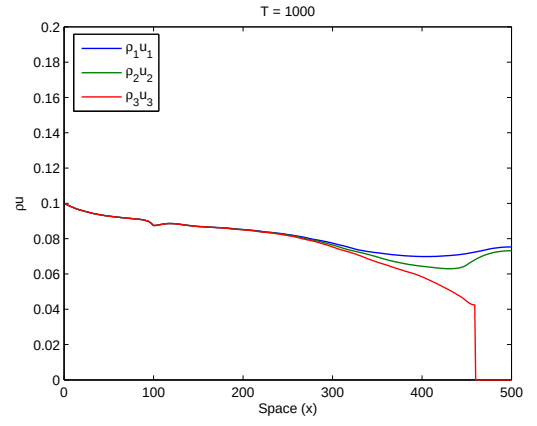
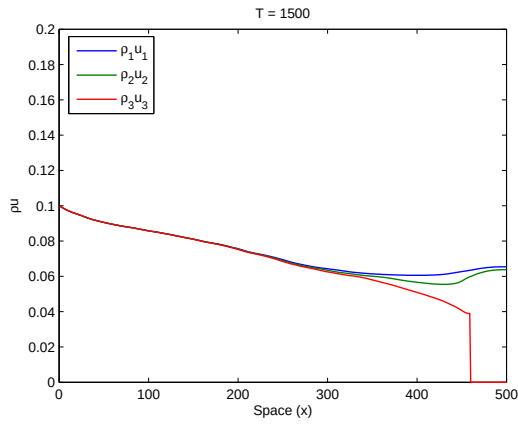
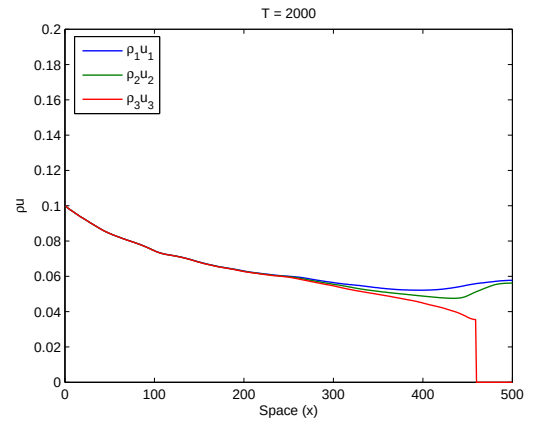
(a) $\rho_\alpha u_\alpha$ at T=500(b) $\rho_\alpha u_\alpha$ at T=1000(c) $\rho_\alpha u_\alpha$ at T=1500(d) $\rho_\alpha u_\alpha$ at T=2000

Figure B.8: Macroscopic $\rho_\alpha u_\alpha$ for *Typical* Driver Behavior with Non-Zero Persistence and $f_\alpha^{com}(x, 0) = 0.1$

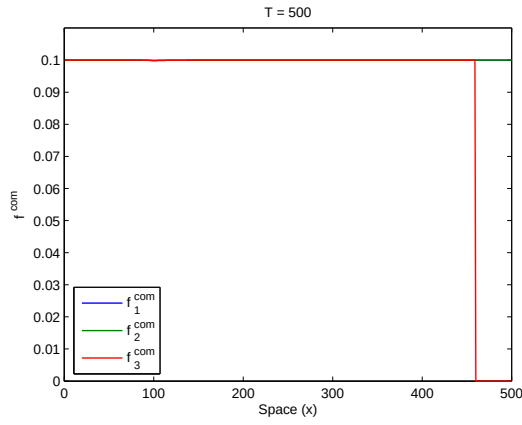
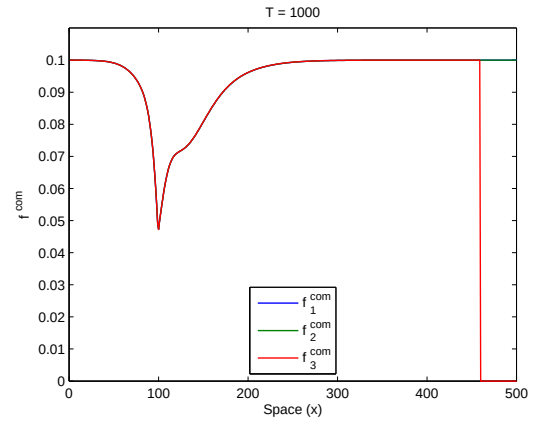
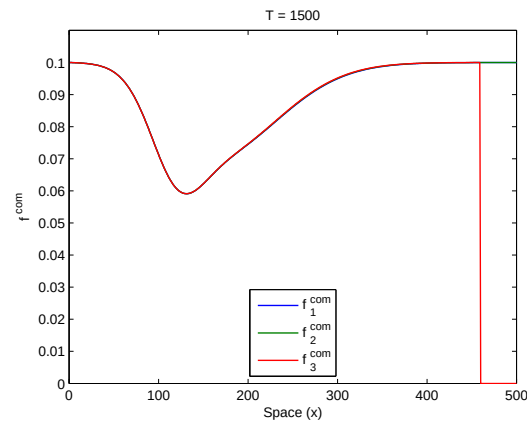
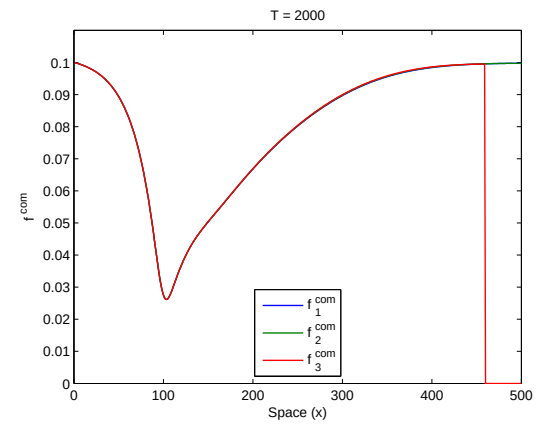
(a) $f_{\alpha}^{com}(x, t)$ at $T=500$ (b) $f_{\alpha}^{com}(x, t)$ at $T=1000$ (c) $f_{\alpha}^{com}(x, t)$ at $T=1500$ (d) $f_{\alpha}^{com}(x, t)$ $T=2000$

Figure B.9: Macroscopic $f_{\alpha}^{com}(x, t)$ for *Typical* Driver Behavior with Non-Zero Persistence and $f_{\alpha}^{com}(x, 0) = 0.1$

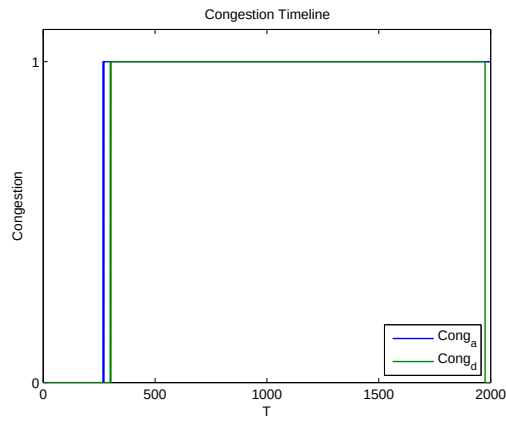
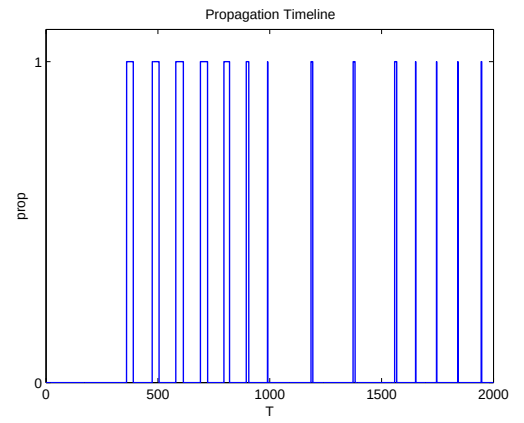
(a) *CongestionTimeline*(b) *PropagationTimeline*

Figure B.10: Macroscopic Communication Timelines for *Typical* Driver Behavior with Non-Zero Persistence and $f_\alpha^{com}(x, 0) = 0.1$

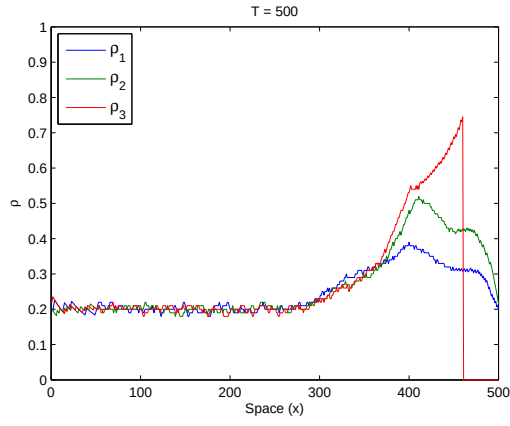
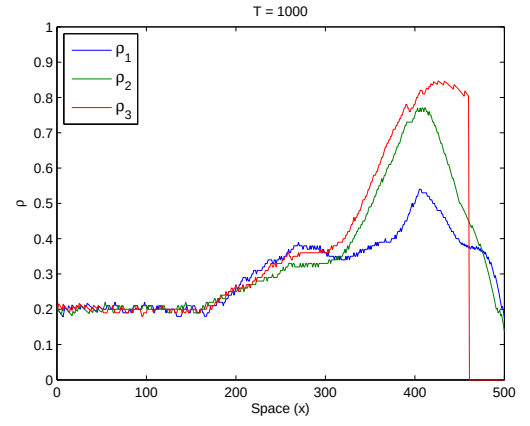
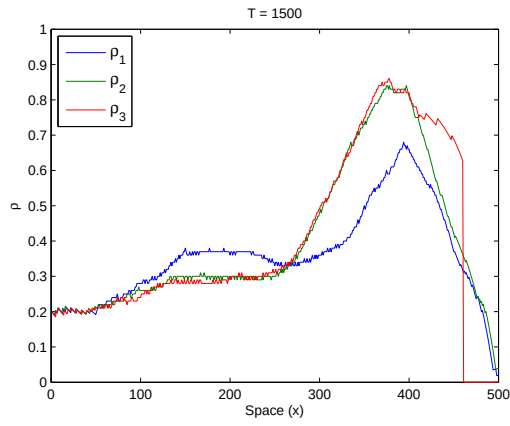
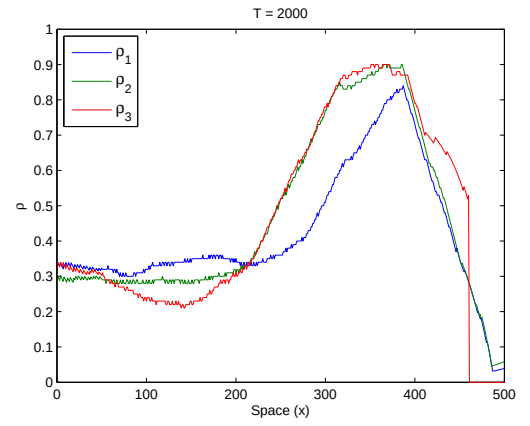
(a) ρ_α at T=500(b) ρ_α at T=1000(c) ρ_α at T=1500(d) ρ_α at T=2000

Figure B.11: Microscopic ρ_α for *Typical* Driver Behavior with Non-Zero Persistence and $f_\alpha^{com}(x, 0) = 0.1$

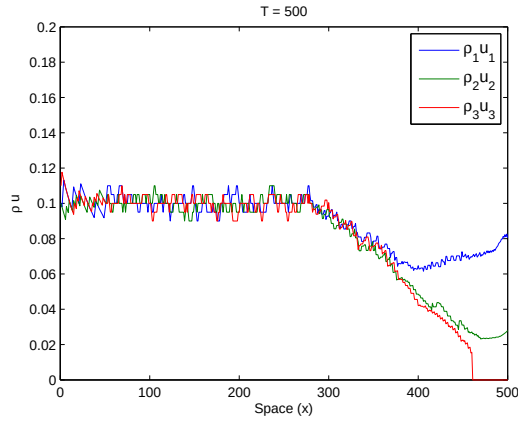
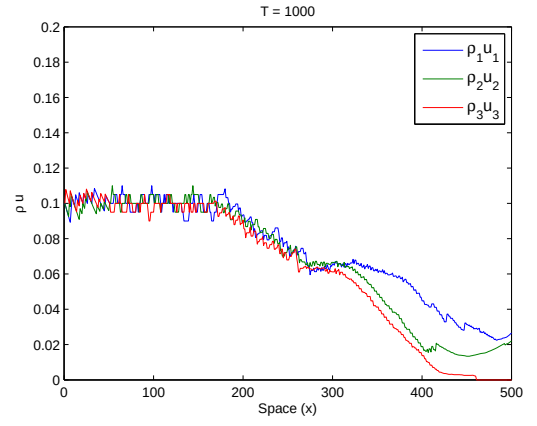
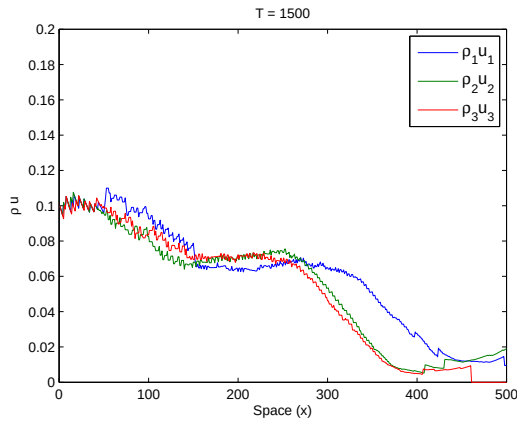
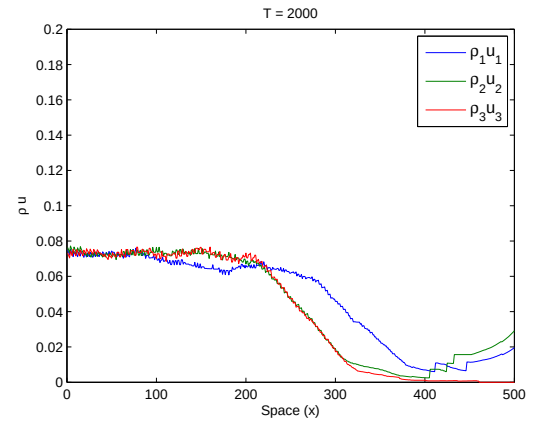
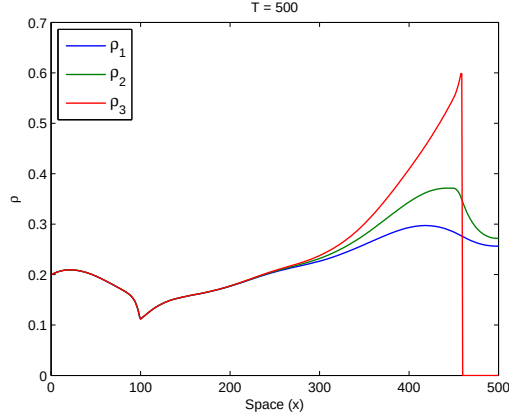
(a) $\rho_\alpha u_\alpha$ at T=500(b) $\rho_\alpha u_\alpha$ at T=1000(c) $\rho_\alpha u_\alpha$ at T=1500(d) $\rho_\alpha u_\alpha$ at T=2000

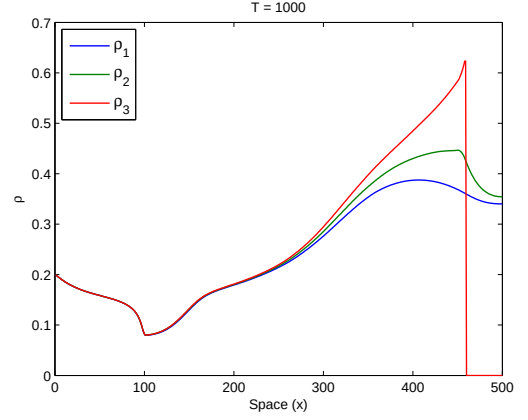
Figure B.12: Microscopic $\rho_\alpha u_\alpha$ for *Typical* Driver Behavior with Non-Zero Persistence and $f_\alpha^{com}(x, 0) = 0.1$

B.3 *Panicky* Driver Behavior with Non-Zero Persistence and

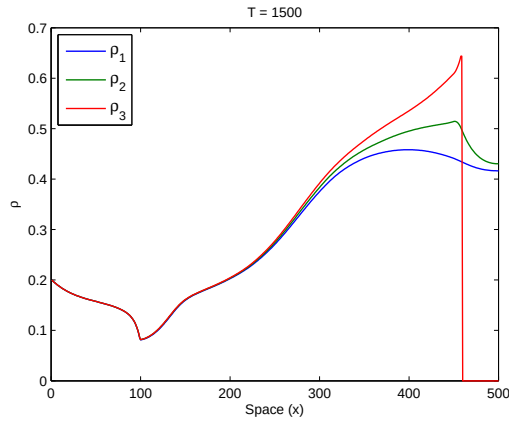
$$f_{\alpha}^{com}(x, 0) = 0.8$$



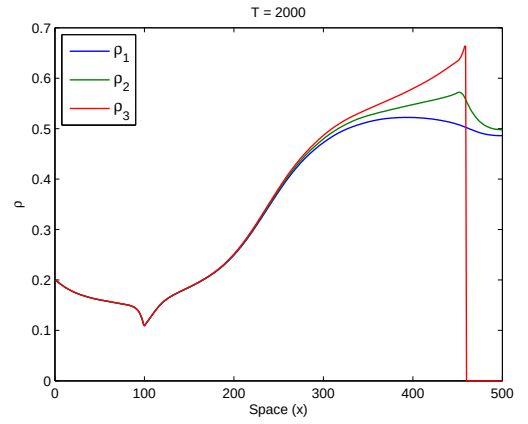
(a) ρ_{α} at $T=500$



(b) ρ_{α} at $T=1000$



(c) ρ_{α} at $T=1500$



(d) ρ_{α} at $T=2000$

Figure B.13: Macroscopic ρ_{α} for *Panicky* Driver Behavior with Non-Zero Persistence and $f_{\alpha}^{com}(x, 0) = 0.8$

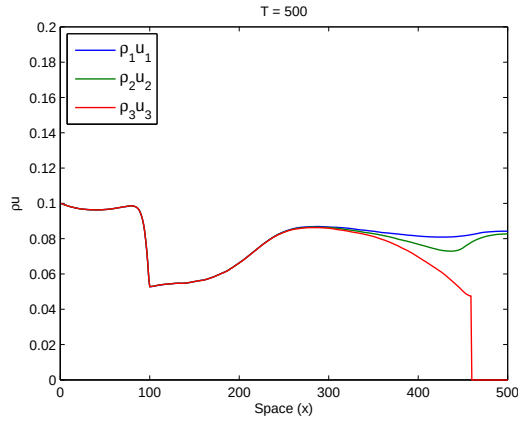
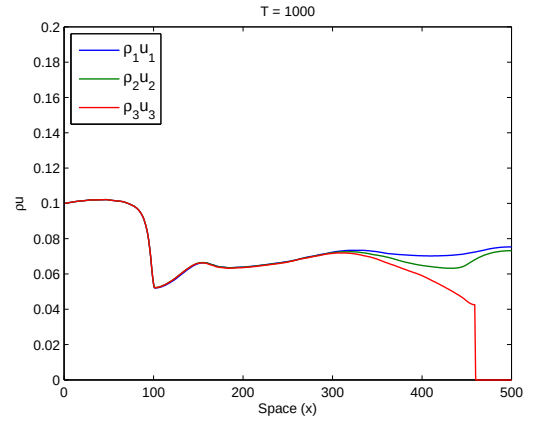
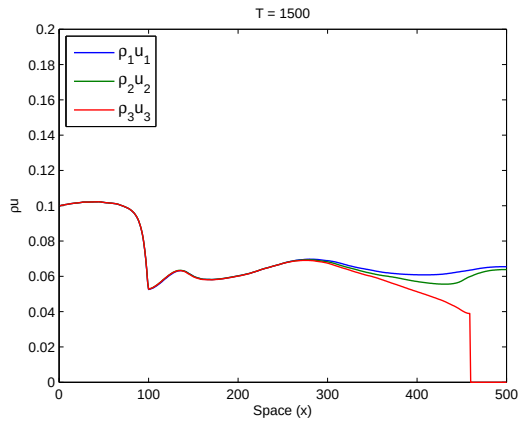
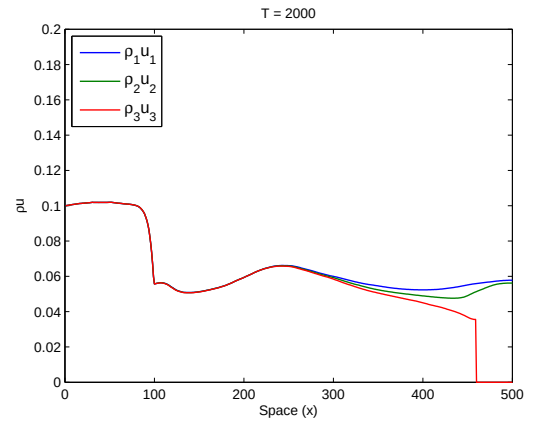
(a) $\rho_\alpha u_\alpha$ at T=500(b) $\rho_\alpha u_\alpha$ at T=1000(c) $\rho_\alpha u_\alpha$ at T=1500(d) $\rho_\alpha u_\alpha$ at T=2000

Figure B.14: Macroscopic $\rho_\alpha u_\alpha$ for *Panicky* Driver Behavior with Non-Zero Persistence and $f_\alpha^{com}(x, 0) = 0.8$

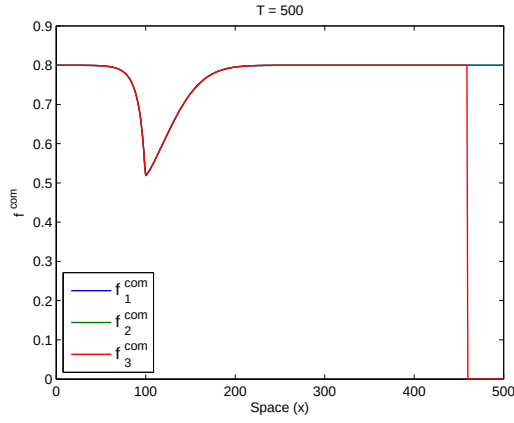
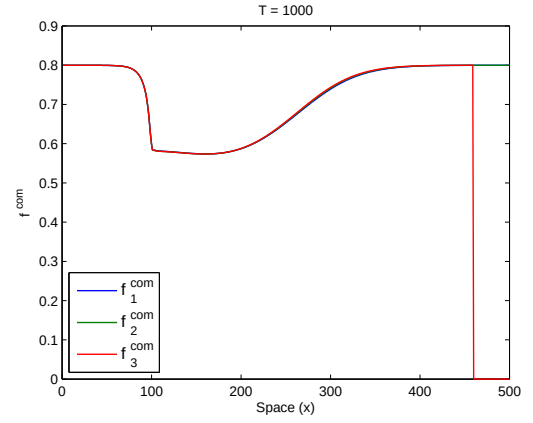
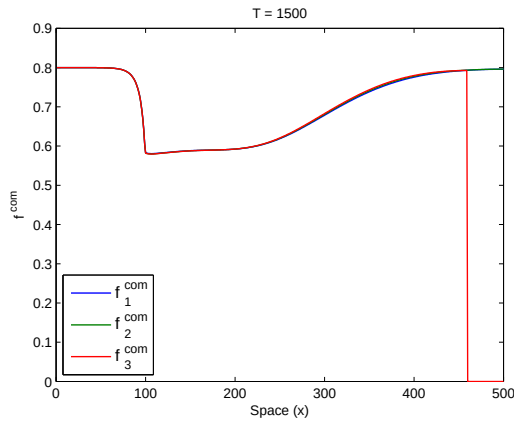
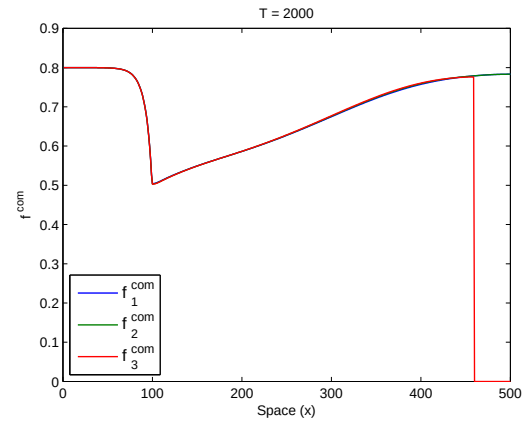
(a) $f_{\alpha}^{com}(x, t)$ at $T=500$ (b) $f_{\alpha}^{com}(x, t)$ at $T=1000$ (c) $f_{\alpha}^{com}(x, t)$ at $T=1500$ (d) $f_{\alpha}^{com}(x, t)$ at $T=2000$

Figure B.15: Macroscopic $f_{\alpha}^{com}(x, t)$ for *Panicky* Driver Behavior with Non-Zero Persistence and $f_{\alpha}^{com}(x, 0) = 0.8$

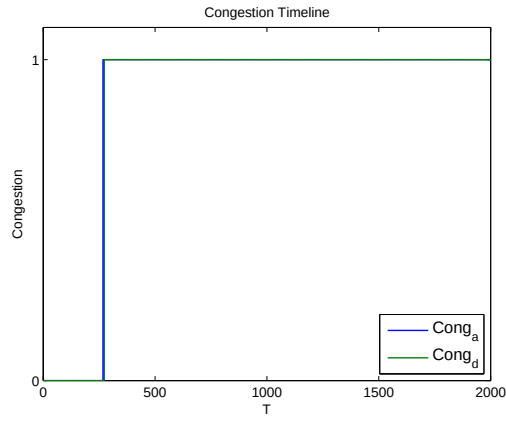
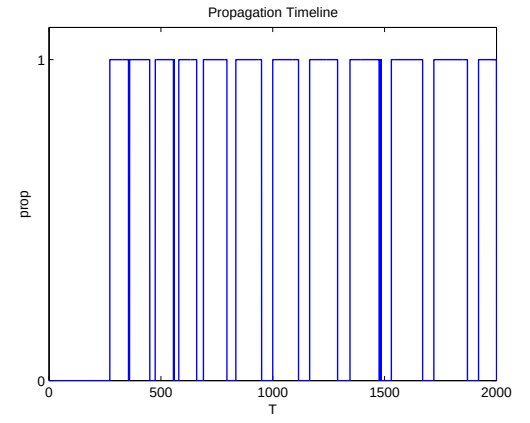
(a) *CongestionTimeline*(b) *PropagationTimeline*

Figure B.16: Macroscopic Communication Timelines for *Panicky* Driver Behavior with Non-Zero Persistence and $f_\alpha^{com}(x, 0) = 0.8$

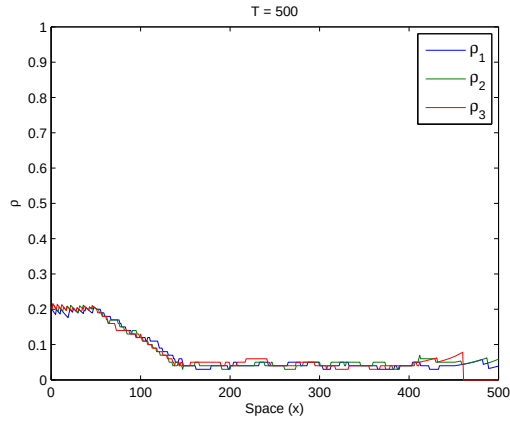
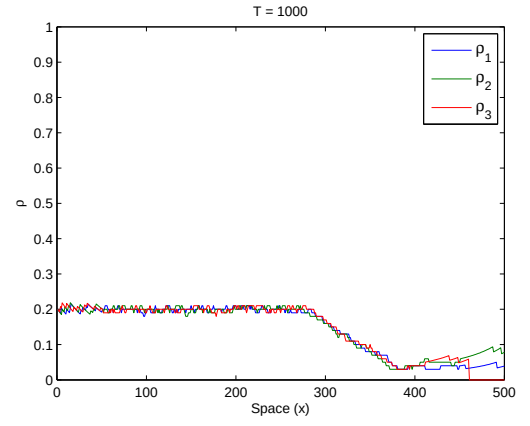
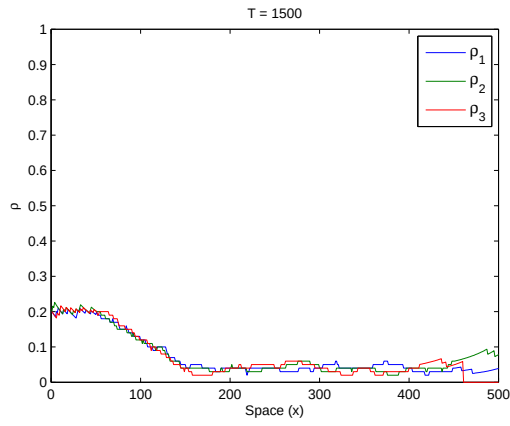
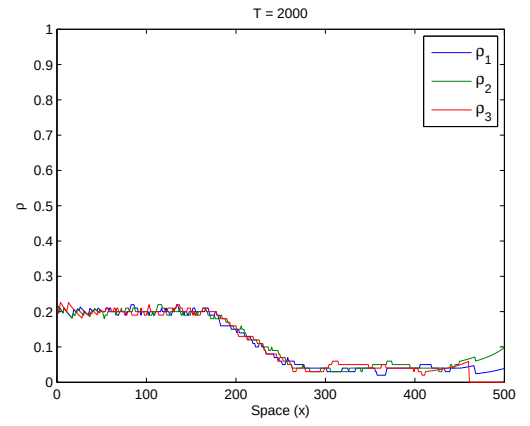
(a) ρ_α at $T=500$ (b) ρ_α at $T=1000$ (c) ρ_α at $T=1500$ (d) ρ_α at $T=2000$

Figure B.17: Microscopic ρ_α for *Panicky* Driver Behavior with Non-Zero Persistence and $f_\alpha^{com}(x, 0) = 0.8$

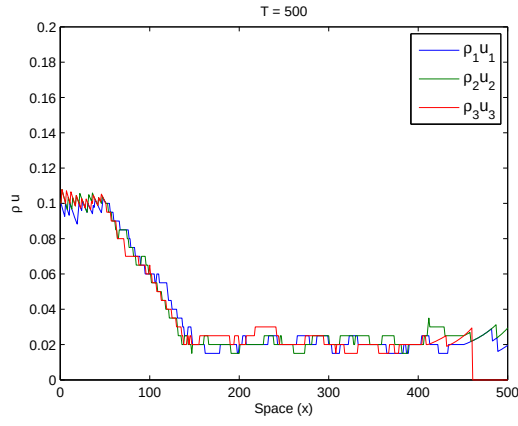
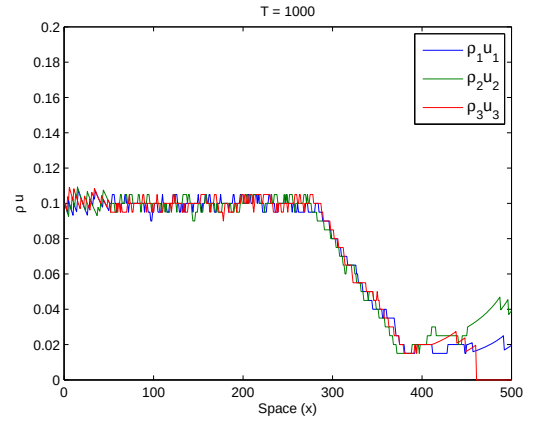
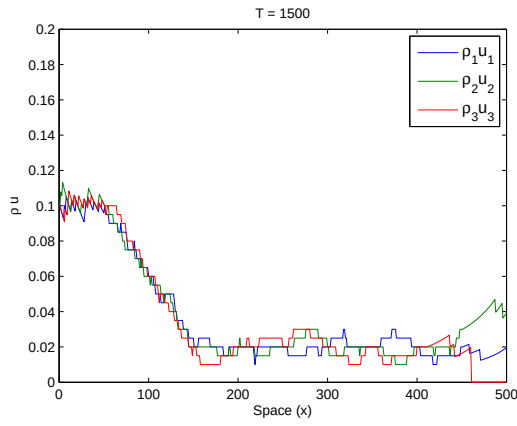
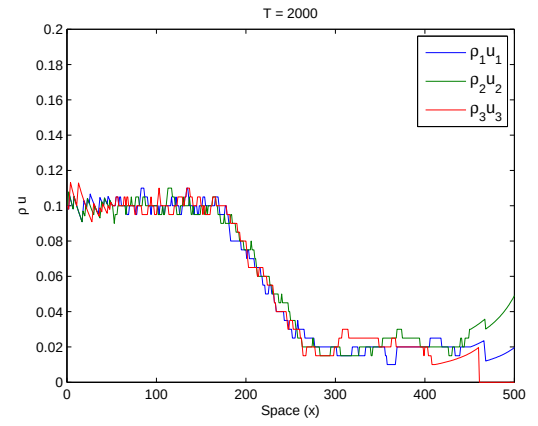
(a) $\rho_\alpha u_\alpha$ at T=500(b) $\rho_\alpha u_\alpha$ at T=1000(c) $\rho_\alpha u_\alpha$ at T=1500(d) $\rho_\alpha u_\alpha$ at T=2000

Figure B.18: Microscopic $\rho_\alpha u_\alpha$ for *Panicky* Driver Behavior with Non-Zero Persistence and $f_\alpha^{com}(x, 0) = 0.8$

Appendix C

Variations in Macroscopic Density and Flow with Space and Time

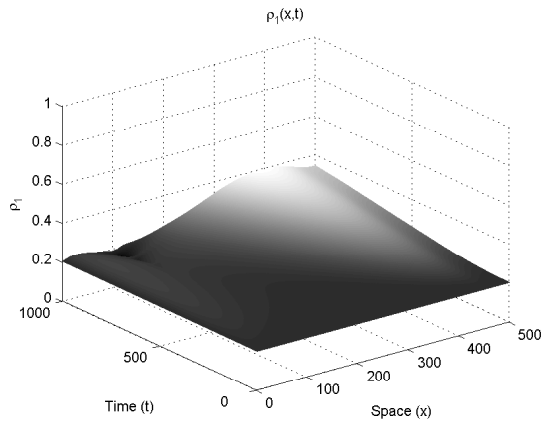
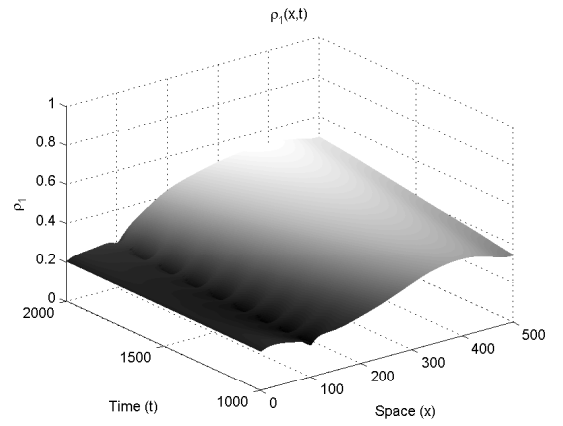
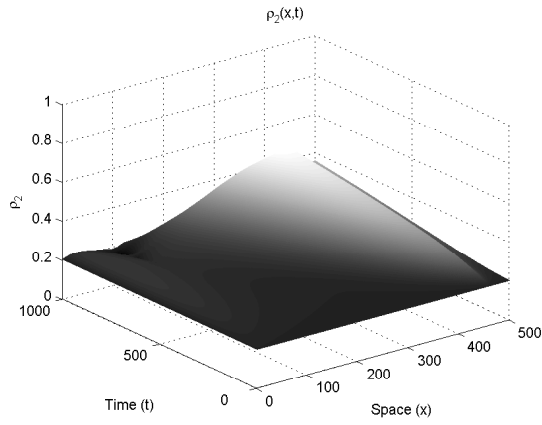
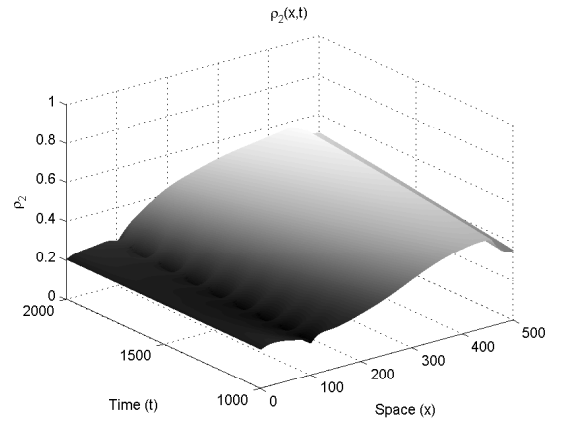
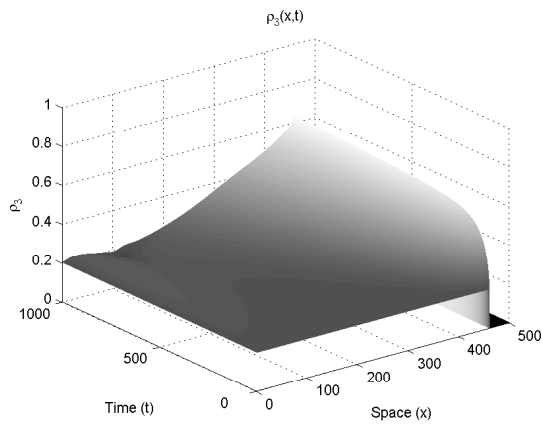
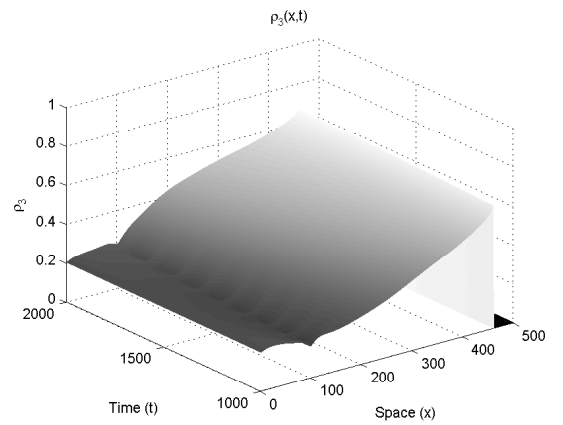
(a) $\rho_1, 0 \leq t \leq 1000$ (b) $\rho_1, 1000 \leq t \leq 2000$ (c) $\rho_2, 0 \leq t \leq 1000$ (d) $\rho_2, 1000 \leq t \leq 2000$ (e) $\rho_3, 0 \leq t \leq 1000$ (f) $\rho_3, 1000 \leq t \leq 2000$

Figure C.1: Variations in Macroscopic ρ_α with Space and Time for *Typical* Driver Behavior with Zero Persistence and $f_\alpha^{com}(x, 0) = 0.5$

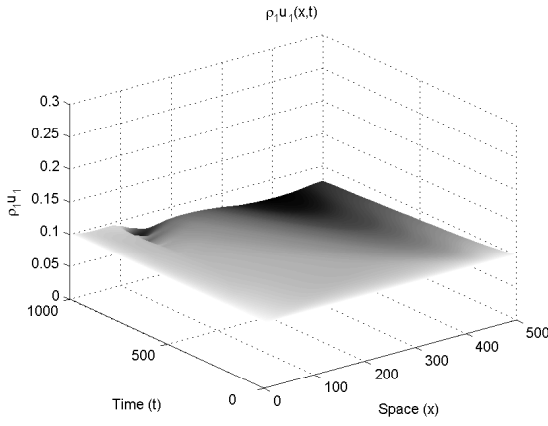
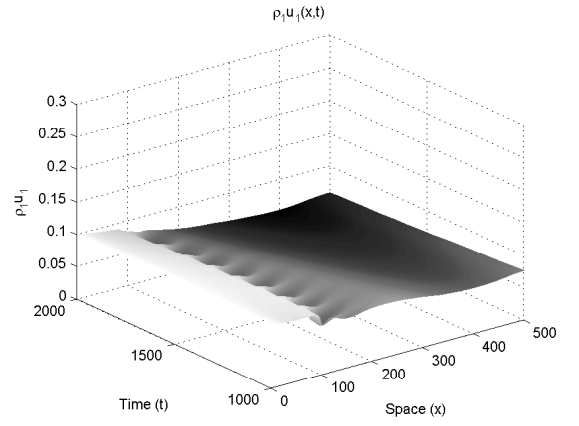
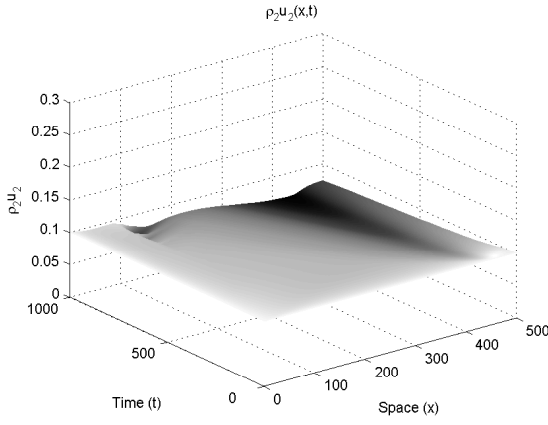
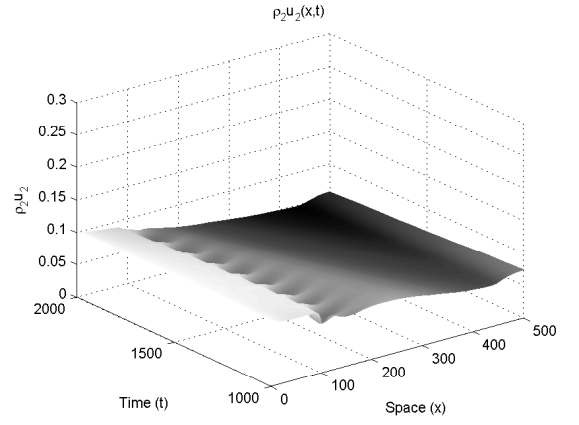
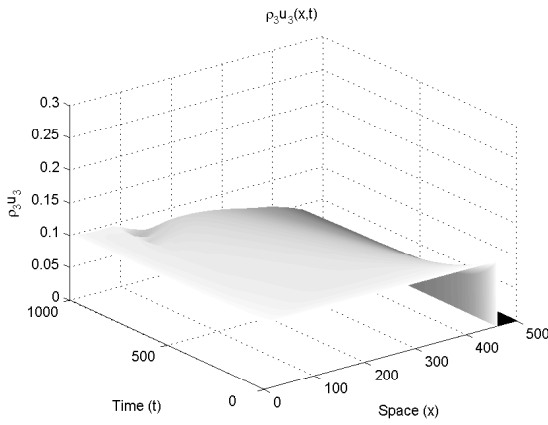
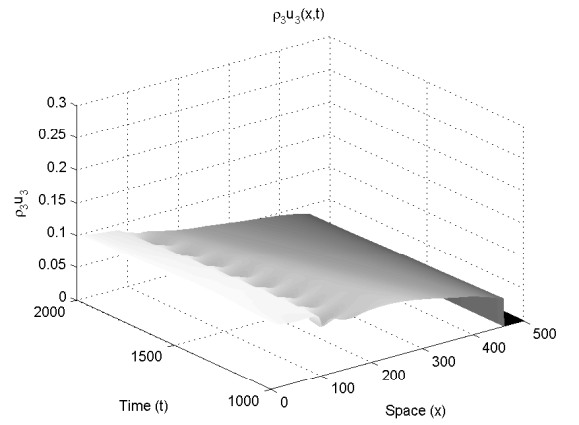
(a) $\rho_1 u_1, 0 \leq t \leq 1000$ (b) $\rho_1 u_1, 1000 \leq t \leq 2000$ (c) $\rho_2 u_2, 0 \leq t \leq 1000$ (d) $\rho_2 u_2, 1000 \leq t \leq 2000$ (e) $\rho_3 u_3, 0 \leq t \leq 1000$ (f) $\rho_3 u_3, 1000 \leq t \leq 2000$

Figure C.2: Variations in Macroscopic $\rho_\alpha u_\alpha$ with Space and Time for *Typical* Driver Behavior with Zero Persistence and $f_\alpha^{com}(x, 0) = 0.5$

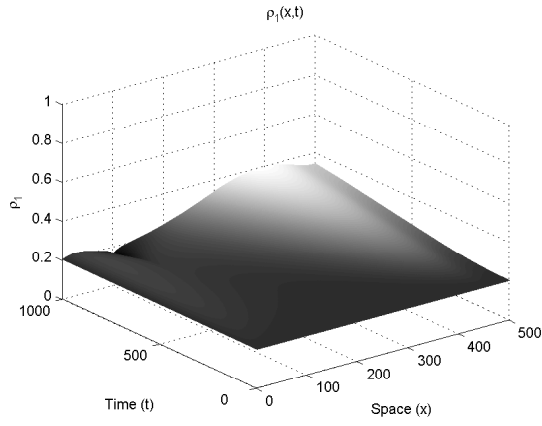
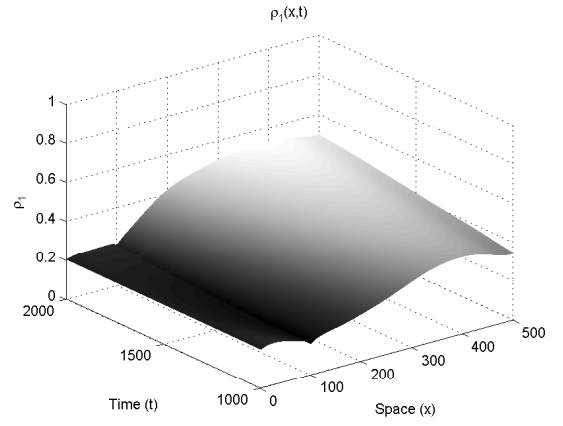
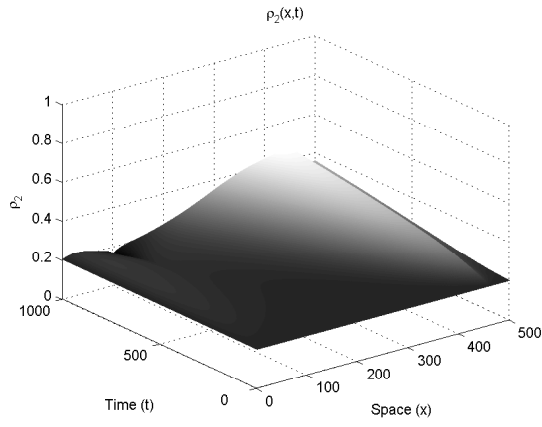
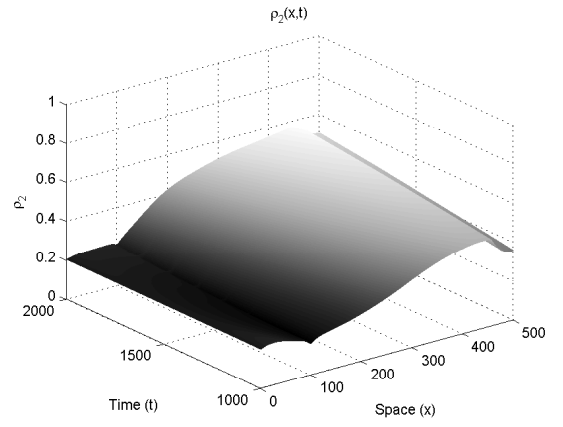
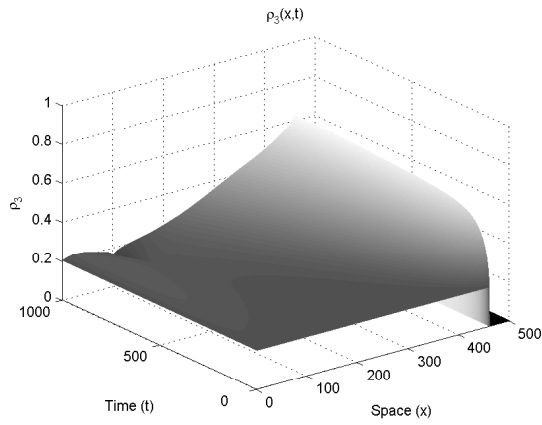
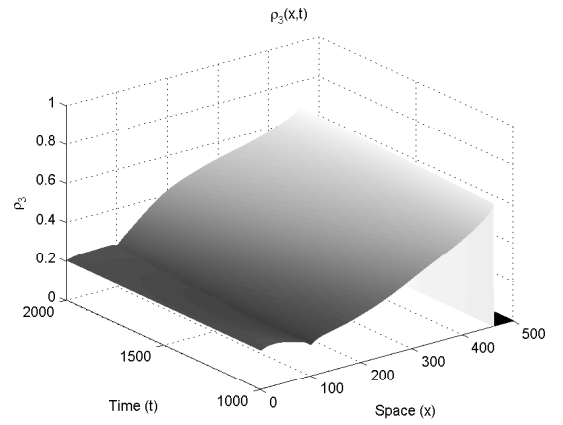
(a) $\rho_1, 0 \leq t \leq 1000$ (b) $\rho_1, 1000 \leq t \leq 2000$ (c) $\rho_2, 0 \leq t \leq 1000$ (d) $\rho_2, 1000 \leq t \leq 2000$ (e) $\rho_3, 0 \leq t \leq 1000$ (f) $\rho_3, 1000 \leq t \leq 2000$

Figure C.3: Variations in Macroscopic ρ_α with Space and Time for *Typical* Driver Behavior with Non-Zero Persistence and $f_\alpha^{com}(x, 0) = 0.5$

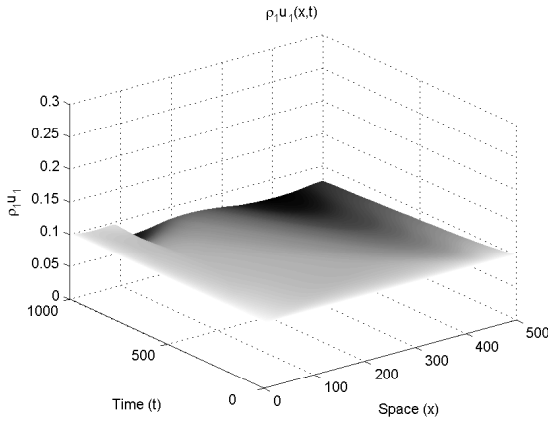
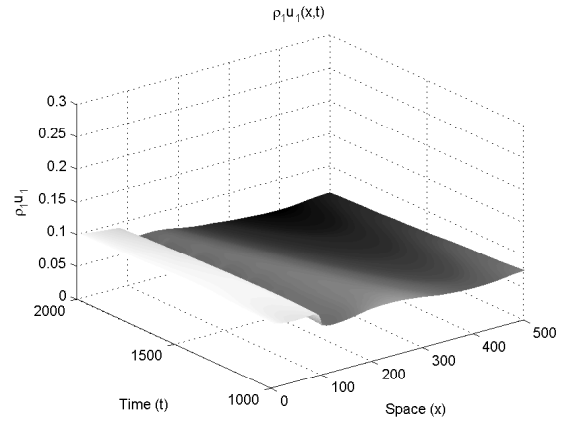
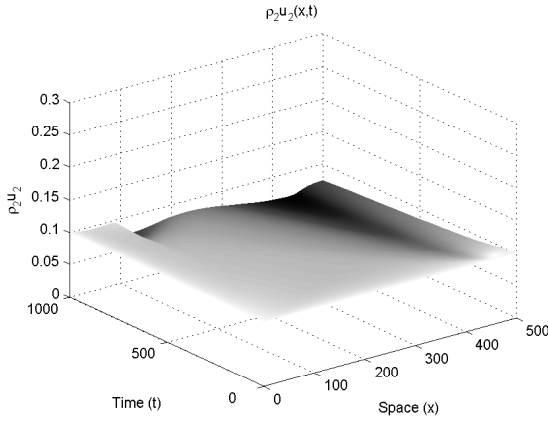
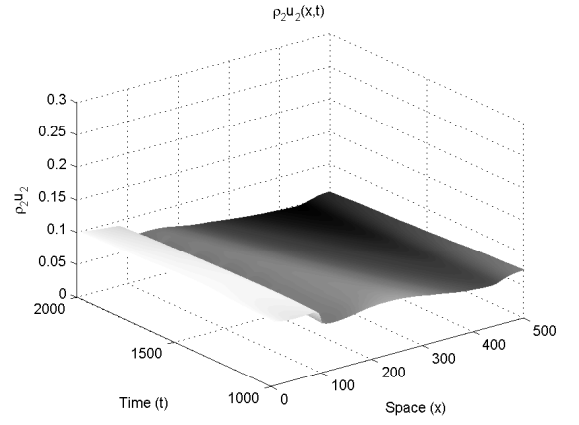
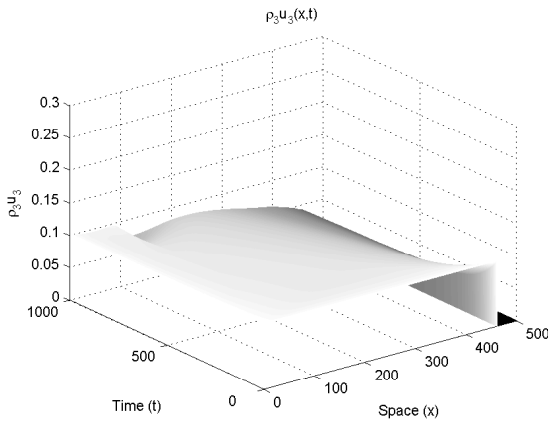
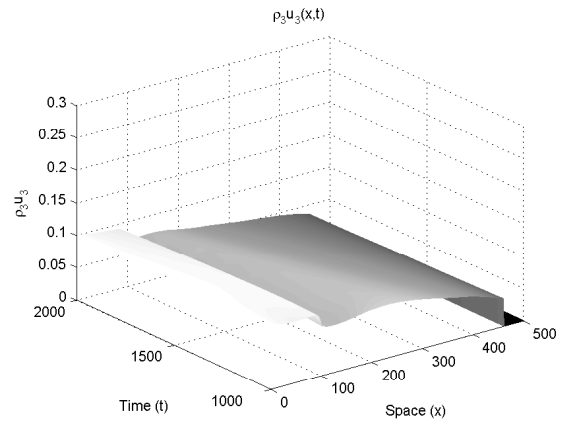
(a) $\rho_1 u_1, 0 \leq t \leq 1000$ (b) $\rho_1 u_1, 1000 \leq t \leq 2000$ (c) $\rho_2 u_2, 0 \leq t \leq 1000$ (d) $\rho_2 u_2, 1000 \leq t \leq 2000$ (e) $\rho_3 u_3, 0 \leq t \leq 1000$ (f) $\rho_3 u_3, 1000 \leq t \leq 2000$

Figure C.4: Variations in Macroscopic $\rho_\alpha u_\alpha$ with Space and Time for *Typical* Driver Behavior with Non-Zero Persistence and $f_\alpha^{com}(x, 0) = 0.5$