Driver Model for Traffic Simulation, with Tactical Lane Changing Behavior

(戦術的な車線変更挙動を含む
交通シミュレーションのためのドライバーモデル)

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論文の内容の要旨

Abstract of Dissertation

Abstract

Until now, the lane change models used in traffic simulators to model driver behavior have only considered the lane change maneuvers one at a time, and the state of the surrounding vehicles has been assumed not to change. To improve the realism and applicability of traffic simulators, a lane changing model which includes sequential planning has been developed. This can better represent real driver behavior in which entire maneuver sequences of multiple lane changes are considered. The states of one's own vehicle and surrounding vehicles are predicted using a forward search tree which branches at each new lane change decision point.

The lane changing algorithm developed in this research is capable of modeling discretionary lane changes, and will be shown to make an improvement in the simulation realism performance in representing driver lane changing behavior, compared to the models used in today's traffic simulators.　A real vehicle trajectory data set is used in the model calibration and validation. The improved algorithm was shown to improve the simulation realism, thereby improving transportation facility planning and management.

戦術的な車線変更挙動を含む
交通シミュレーションのためのドライバーモデル

ウェブスター、ネイット　アレクサンダー

論文要旨

既存の交通シミュレーターに活用される車線変更ドライバーモデルでは個々の車線変更行動しか考慮されず、周辺車両状況は静的であった。交通シミュレーターの再現性および実用可能性を向上するために、本研究では連続計画を含む車線変更モデルが開発された。本モデルは複数の車線変更を含む実際のドライバーの連続運転挙動をより現実性高く表現できる。各々の新しい車線変更機会に枝を分岐させるフォーワードサーチツリー法を活用し、自車及び周辺車両の軌道を予測する。

本研究の車線変更アルゴリズムは discretionary 車線変更をモデル化することができる。本研究のモデルは現在交通シミュレーターに活用されているモデルより、車線変更の運転挙動の再現性が高いことを検証した。実際の車両軌跡データを用いて、キャリブレーション及びバリデーションを行った。本研究のモデルの再現性向上により、交通施設計画、運用、および政策評価の信頼性の向上に役立つ。

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1. INTRODUCTION

1.1 Background

Microscopic traffic simulation is used to test and evaluate infrastructure design, operation, and control policies in a virtual environment, realizing cost savings and flexibility compared to testing or implementing in the real world. The motion of each vehicle is reproduced, and the mutual interactions can allow a richer, more accurate model of the overall system, compared with non-simulation based approaches. However, if the driving behavior of the individual vehicle/driver combinations is unrealistic, then the accuracy of the overall simulation results may suffer.

A driver behavior model determines both longitudinal and lateral control actions. Longitudinal control is the acceleration or deceleration, either to follow the lead vehicle or to attain desired speed if in free flow conditions. A lateral control action is the determination of whether and in what direction to make a lane change.

Considering the vehicle’s response to its environment, driver-vehicle behavior can be classified into three categories. In order of increasing detail, these are: strategic (route planning), tactical, and operational (accelerator / brake pedal, steering). Tactical driver behavior is considered as the development, evaluation, and execution of near-term maneuvers, to realize short-term goals. (Michon, 1985)

A particular feature of human drivers is that the “decisions that we make in our vehicle are largely based on our assumptions about the behavior of other vehicles." Schlenoff et al (2006). It seems that we do not simply consider the present state information of the surrounding vehicles, but follow our expectations about how they will move when making our driving maneuvers such as merging in a weave section, overtaking a slow vehicle, or taking an exit ramp.

1.2 Problem Statement

At a recent conference on traffic simulation, the following commentary was registered:

“By observation of mixed traffic conditions in many Asian mega-cities one may disagree that this driving style has a lot to do with tactical skills while co-operation is of less importance. Especially scooters are trying to advance by positioning themselves ahead of any queues neglecting particular lanes and passing restrictions. In order to advance quickly these drivers have to change the lateral position as soon as possible gaps arise subject to additional gaps downstream. In order to find a sequence of suitable gaps the real driver as much as the simulation model has to have the ability to look ahead for several seconds.” (Fellendorf and Vortisch, 2004).

However, most presently used traffic simulators and those found in the literature do not include such anticipatory and planning behavior. In a meeting of the Federal Highway

Administration's NGSIM program, the traffic simulation model user committee identified "Complex weaving situations under heavy volumes" and "Modeling freeway flow rates before breakdown" as situations in which present day traffic simulation models don't represent the situation very well, and gave them high priority as research topics to improve the state-of-the-art in traffic modeling. (NGSIM, 2003) With the recent advances in sensing and processing of traffic data a movement to higher resolution models can be considered. Also, traffic simulation can potentially be applied in a wider set of applications.

1.3 Research Approach

As a step towards more realistic driving behavior in traffic simulators, this research uses the *forward search algorithm* to represent driver anticipation and maneuver planning behavior. At each step in the simulation, the forward search algorithm generates a branching tree of sequential actions, taking into account the changes in the state of the subject vehicle and surrounding vehicles. The sequence of actions leading to the best outcome is then selected and the subject vehicle applies the first action of that sequence for this time step. This allows the driver to select a current action for which the payoff is delayed.

It is expected that this approach provides a more realistic representation of the lane changing behavior, compared to present-day lane change models and its performance will be judged by comparing the modeled to actual lane change actions from a real world vehicle trajectory data set. The model will be capable of representing the discretionary lane changes, but mandatory lane changes will be left for further works. Improvements to the model recommended to be carried out in later research, such as integrated planning of both lane change and longitudinal control actions, and computational efficiency improvements, will be described.

The proposed model can be enhanced, and incorporated into traffic simulation software which can be practically used in the field, thereby enhancing the effectiveness of infrastructure investment decisions, operational strategy selection, and user traffic information provision.

1.4 Contribution of this Thesis

In this work, a framework is proposed and a prototype model is developed to improve the realism in driver lane changing by incorporating planning over a sequence of actions. This is an improvement over the lane change models used in present-day traffic simulators which consider only the utility of the next lane change and do not consider the planning behavior. Such a model is expected to contribute to the state of the art by improving the realism of traffic simulation especially in complex traffic situations in which consideration of a plan is necessary for correct modeling of lane changing behavior.

1.5 Dissertation overview

Chapter 2 contains a literature review of existing driver models: longitudinal control including car following, as well as lane changing including tactical lane changing models. Previous driver model parameter calibration methods are also described. The situations in which the previous models cannot adequately reflect the real driver behavior are identified, and the way this model can fix the problem is highlighted.

Chapter 3 provides an overview of the analysis methodology. A traffic simulator was developed for use in this research to serve as the operating environment for the lane change model. The simulator features and software architecture are briefly described.

Chapter 4 describes the longitudinal control and basic lane change models which are used in this research. The basic lane change model serves as a “straw man” to represent lane change models such as those used in today’s traffic simulators, which do not contain sequential maneuver planning.

Chapter 5, the core of this dissertation, describes the tactical lane change model which determines the current lane change action by developing a tree of potential sequential maneuver plans, and a model for selection of the current lane change action as part of the plan with the best utility for the driver.

In Chapter 6, the performance of the lane change model is compared to the basic lane change model, in terms of realistic representation of lane change actions of selected vehicles from a real-world trajectory data set. In addition, rudimentary tests of the simulation performance of the model have been performed, including macroscopic traffic flow properties as well as complexity and stability effects on the realism of groups of vehicles through the tactical lane change model.

In Chapter 7, the conclusions of this research are summarized. New technology applications of the research are proposed.

2 LITERATURE REVIEW

In this chapter, previous works relating longitudinal control models and lane change models, tactical driver behavior models, and calibration approaches are presented. The limitations of the previous works are identified, and how the proposed research will address these limitations is explained. An outline of the dissertation is provided.

2.1 Longitudinal Control Models

Longitudinal control is a vehicle's action of accelerating or braking in order to follow a lead car or else drive alone to attain the desired free travel speed.

Research into car following behavior has been carried out for at least 5 decades, with an overall interest in development of driver assistance functions, development of traffic simulation models, and study of microscopic and macroscopic traffic phenomena. The longitudinal control models, which include both car following and free driving behavior, have been classified into major categories including: *stimulus-response models, desired measures models, psycho-physical models,* and *multi-regime models*.

The remainder of this section gives a brief summary of some well-known longitudinal control models. For a thorough review, please refer to other sources such as Cambridge Systematics (2005) or Miska (2006).

The General Motors family of car following models was one of the earliest models, and is an example of a *stimulus-response model*. The response, given as acceleration, is given in terms of the relative speed, relative position, and speed of the subject vehicle. Some models include a reaction time lag. The equation below is a typical form of the GM model:

$$\ddot{x}_{n+1}(t+\Delta t) = \left\{ \frac{\alpha(l,m)(\dot{x}_{n+1}(t+\Delta t))^m}{(x_n(t)-x_{n+1}(t))^l} \right\} \left[\dot{x}_n(t) - \dot{x}_{n+1}(t) \right]$$

where:

$x, \dot{x}, \ddot{x}$	=	Position, velocity, and acceleration of vehicle *n*
t	=	The present time
Δt	=	the driver perception-reaction time, represented as the time lag between the stimulus and response.
l,m	=	user-specified as the relative strengths of the self-speed and headway
$\alpha(l,m)$	=	user-specified sensitivity parameter

The experimenters tested the suitability of various parameters for *l* and *m*, based on field-measured data. (Rothery, 2002).

Chakroborty and Kikuchi (1999) identified some shortcomings in the GM family of car following models. An experimental car was used to collect real-world car following data, and the results were compared to those from the GM equations. In particular, the GM model was found to be deficient in representing the "closing in" and "shying away" behavior found in the real world. Also, with zero relative speed, there would be no acceleration response, even if the following vehicle were very close to the lead car. To overcome such deficiencies, the authors proposed a fuzzy logic car following model, which develops the response function based on "linguistic" causative relationships, the relative strength of which are calibrated from field data. For example, "if distance headway is very large, and relative speed is high (that is, the lead vehicle is pulling away), accelerate strongly".

The *desired measures* models comprise another major family of car following models. In these models, the driver tries to maintain some desired measure. An example could be the minimization of the difference between the actual space headway and the desired space headway, which could be given in terms of various conditions. This type of model addresses the deficiency of the GM model such as for the situation when two vehicles are traveling at the same speed; the GM model allows the resulting spacing between them to assume any value. The Gipps longitudinal control model (1981), which is used in this research and described later in this document, is a member of this family of models. This model will be described in detail along with several others in section 4.1.

In the *psycho-physical* family of car following models, perceived quantities, rather than Newtonian variables are used. Perceptual thresholds are used to limit necessarily small changes in the environment on the driver’s response behavior. When the spacing between vehicles is very large, these models reflect the tendency for the following vehicle’s behavior to be less sensitive to the lead vehicle. The perceptual threshold is very low at small space headways, and increases with the headway size. These models have been found to represent the oscillating phenomenon in which a driver closes in and then falls behind the lead vehicle cyclically. The Wiedemann model (see Cambridge Systematics, 2005) is a well known model of this type.

In this dissertation, the focus is not on development of longitudinal control models. Instead, as an appropriate existing model, the model by Gipps (1981) will be selected and used. This can support the main purpose of this research: the development of a tactical lane changing model. Later in this document, the examination of several candidate longitudinal control models and description of the selected model for use are described (Section 4.1).

2.2 Lane Change Models

The models for determining the driver's lane change action are treated in two separate categories, depending on whether or not they include a concept of planning or anticipation of the change in the subject vehicle's environment. The first section includes only those that make an instantaneous decision, without such anticipation, while the second section includes models which include at least a concept of a plan or anticipation of change in surroundings as well as strategies for resolving conflicts in short-term and long-term goals. In lane change models, the distinction is often made between mandatory lane changes (MLC) and discretionary lane changes (DLC). Mandatory lane changes are those which must be made in order to complete the desired route, while discretionary lane changes are those made in order to overtake a slower vehicle.

2.2.1 Gap Acceptance Models

Ahmed (1999) developed a lane change model which captures both mandatory and discretionary lane changing behavior. The lane change actions are given according to a probabilistic discrete choice decision model. The model also follows a hierarchical decision structure, and takes into account elapsed time from the beginning of a lane change opportunity. Different gap acceptance parameter ranges were proposed for the cases of both mandatory and discretionary lane changes, reflecting the willingness of drivers to accept smaller gaps for the former due to their urgency. The dependency of lane change decisions at each time step was identified, but for the proposed model the lane changes were assumed to be irrespective of the previous lane changing actions in earlier time steps. Difference in parameters for the same driver and across drivers is taken into account. Parameters for the proposed models were estimated using a freeway video trajectory data set and tested in a traffic simulator.

The lane change theoretical framework formulated by Gipps (1986) is one of the most commonly used by lane change models. It is used in both the DRACULA (Liu et al 1995) and AIMSUN (Barceló and Ferrer 1997) microsimulation models. It is a hierarchical decision model which first checks if a lane change is possible. Next it determines if a lane change to one or both of the adjacent lanes (candidate target lanes) is desirable. This decision is made in terms of MLC and DLC considerations. Regarding MLCs, if the driver must be in a certain lane at a downstream diverge, then the model considers the road divided into 3 zones: far, intermediate, and near. In the far zone, the MLC consideration has no influence on the desirability of the candidate target lane. In the near zone, MLC consideration has complete influence, that is, the driver will always make the lane change in the direction of the MLC destination lane. In the intermediate zone, the candidate target lane desirability is dependent on both MLC and DLC considerations. In common implementations such as AIMSUN and DRACULA, to account for MLC, the lane change choice probability gradually increases as the subject vehicle moves closer to the exit ramp. DLC is considered as the relative speed advantage of the candidate target lane, compared to the current lane. This relative speed advantage is based on the allowable speed for which car following can be achieved so as to safely stop without a collision if the lead vehicle were to brake at a maximum deceleration rate. Threshold values to reflect the driving population or individual drivers are used to specify the MLC zones, DLC speed advantage threshold, and gap acceptance for lane changing. Transit lanes, lane blockages, nearby heavy vehicles, and lane termination are mentioned as influencing factors for the MLC decision.

The above lane change models base the driver actions only on the current situation, and do not include any maneuver planning or anticipation of the surrounding vehicles' actions. The next subsection includes models which contain at least some component of short-term planning, anticipation, or resolution of conflicting goals.

2.2.2 Tactical Models

In this section, research regarding the modeling of driver tactical behavior is reviewed. This is short-term behavior such as overtaking over a period of several seconds in order to position the vehicle in the proper lane to reach the desired destination (Mandatory Lane Change, MLC) or to overtake slower vehicles in order to improve travel time performance (Discretionary Lane Change, DLC).

Kita (1999) developed a merging behavior model. In his model, both the merging vehicle's choice of gap and the mainline vehicle's choice of whether or not to cooperatively merge (move to an inner lane to avoid interfering with the merging vehicle), are represented as a two-player game with payoff matrix values according to a risk associated with the maneuver in terms of time to collision (TTC). In the study, a model was estimated empirically from vehicle trajectory data for a case of an acceleration lane onto a freeway. However, several shortcomings have been identified (Hidas, 2005). The model does not consider the minimum safe gap between vehicles, it does not consider the impact of the end of the acceleration lane, and it assumes that all vehicles travel at a constant speed and do not accelerate or decelerate in order to reach a better position for merging.

Wang, et al (2005) developed a behavior model of a merging vehicle's acceleration and lane change actions. It includes the merging vehicle's choice of gap, acceleration into the gap, as well as the cooperative behavior of the mainline vehicles to either slow down to facilitate the merge, or to switch to an inner lane to avoid the conflict. The model was validated through manual analysis of video coverage of a selected freeway merging study site, and was found to correctly reproduce the observed gap distributions.

Sarvi et al. (2002) also developed a merging behavior model. Each vehicle attempts to keep its desired spacing which is based on a linear speed-spacing relationship. In this model, the merging vehicle is assigned to a target gap and the model also includes cooperative merging.

Avoidance merging is also included, that is, upstream mainline vehicles which switch to an inner lane to avoid the interference of merging vehicles from the entry ramp. Models for the various merging behaviors were calibrated for a selected site through manual analysis of video coverage.

Hidas (2002, 2005) has developed a lane changing and car following model based loosely on the framework proposed by Gipps (1986). One difference with Gipps (1986) is the order of operations: the model first checks the feasibility of safely moving into the gap in the adjacent lane. Next the desirability of the target lane is measured in terms of the speed of the lead vehicle in the target lane. If the lead vehicle in the adjacent lane is more than *200 m* ahead, then the allowable speed is considered as the subject vehicle’s desired speed.

Beyond the original Gipps (1986) model, Hidas includes mutual cooperation in MLC by specifying situations in which the rear vehicle in the target lane will slow down to allow the subject vehicle to merge. The willingness of the rear vehicle in the target lane to slow down is modeled according to a vehicle-specific “aggressivity” parameter, the necessity of the lane changing maneuver, and the downstream traffic conditions. This cooperative behavior is represented in the simulator as a “lane change plan”, which consists of a plan of the longitudinal control actions of the involved vehicles in the cooperative lane change.

This is not the subject vehicle’s plan for selecting the target lane or lane change action. Therefore, in the context of tactical maneuver planning, the model by Hidas does not determine lane change actions using planning, but merely considers the utility of the adjacent lanes in terms of speed advantage or MLC considerations. A lane change planning model is included, but the scope of the plan is only the very next lane change, not several lane changes in the near-term. The model was validated with a vehicle trajectory data set on a two-lane directional freeway with a single lane entry ramp having an acceleration lane.

In the Cosmodrive model by Delorme et al. (2001), the driver’s decision-making is subdivided. The observed situation is categorized according to pre-existing situation categories (*schemas*). For each *schema* there is a specified response. In Cosmodrive, the response used to represent the tactical lane change behavior is based on a finite state machine. The states include car following, overtaking, and free driving, with prescribed control actions and thresholds for each case. These can be configured with various threshold values to represent the individual driver’s behavior. For a two lanes per direction freeway, there are states for deciding to change to the overtaking lane, traveling in the overtaking lane to pass by a slower vehicle, and returning to the travel lane.

Toledo (2003) developed a driver model which selects the target lane and a particular gap in that lane as a goal and then determines a sequence of acceleration, deceleration, and lateral motion actions in order to move into the target gap, even if the gap is not directly alongside. He formulated a discrete choice decision model to determine target lane and target gap. The model consists of a set of logit equations with coefficients calculated based on a calibration data set using maximum likelihood estimation techniques. The target lane model integrates mandatory lane change (MLC) and discretionary lane change (DLC) behavior into a single choice model. Variables which were considered to influence the target lane choice included: whether the current lane is the right-most lane, the lead vehicle speed, spacing to the lead vehicle, whether there is a heavy vehicle in the neighboring lane, whether the subject vehicle is being closely followed by a faster vehicle, and whether the lane change leads to the driver's planned route toward his destination. He also specified different longitudinal control (acceleration) models applied to the following cases: (a) when the subject vehicle has chosen to stay in the current lane, (b) when the subject vehicle is making a lane change, and (c) when the subject vehicle is accelerating or decelerating in order to move into a target gap in the adjacent lane which is not directly alongside. He applied the developed model to a test case using a real-world vehicle trajectory data set, and compared the performance of his model to a status quo model which did not include the short-term plan of target gap and found that his model better represented the actual measured traffic conditions.

Toledo suggests a modeling framework for defining sequences of states and maneuver plans over a short-term. He defines the joint probability of a given vehicle at time *t*, conditional on the sequence of previous states as:

$$p\left(o_{t,} s_t \mid S_{t-1}, X\right) = p\left(o_t \mid s_t, S_{t-1}, X\right) p\left(s_t \mid S_{t-1}, X\right)$$

where:

o_t	=	The observed action at time t
s_t	=	The state at time t
S_t	=	The sequence of states up to time t, $S_t = \{s_i : i = 0, 1, \ldots, t\}$
X	=	Explanatory variables

He gives the probability of the entire sequence of states (S_T) and observations (O_T) over T time periods as:

$$p\left(O_T, S_T \mid s_0, X\right) = \prod_{t=1}^{T} p\left(o_t, s_t \mid S_{t-1}, X\right)$$

Finally he gives the joint marginal probability of observations by summing over all possible state sequences.

$$p\left(O_T \mid S_0, X\right) = \sum_{\substack{\forall state \\ sequences}} p\left(O_T, S_T \mid s_0, X\right)$$

Toledo explains that this approach will be computationally infeasible due to the number of alternatives that must be enumerated. Other identified limitations were in inferring the initial state through the real-world data set. Because of these limitations, rather than implementing full enumeration of the potential maneuver sequences, Toledo implemented the “partial short-term plan approach” in his dissertation (2003). In this approach, control actions are made step-by-step, considering only the utility of the very next lane change action, and not considering short-term maneuver sequences. Toledo acknowledges that this may neglect situations in which the decision is affected by the longer-term effect, but he states that the implementation of such a sequence-based approach would be computationally infeasible.

Toledo worked with a research team as part of the U.S. federally-funded NGSIM program to apply the model to a high-resolution vehicle trajectory data set. (Cambridge Systematics. *NGSIM: Lane Selection Model, draft final report, 2004)* Developers of popular commercial traffic simulation software have also tested the lane changing model as a module add-in to their software. PTV System (2006) developers found that the discrete choice formulation in Toledo’s model allowed explicit specification of the High-occupancy vehicle (HOV) lane as an attraction to HOV vehicles, thereby making the HOV lane more attractive than it would otherwise appear in PTV’s existing VISSIM model. They also explained that the performance could be further improved through extending and or improving the accuracy of the existing lane and gap choice utility models.

In Toledo et al. (2005), the model was expanded to consider non-adjacent lanes as the target lane. This enables the model to allow the subject vehicle to move to an adjacent lane in which the situation gets worse for the driver, in order to realize the later goal of a farther destination lane. This expanded model was calibrated to the NGSIM I-80 trajectory data set (Cambridge Systematics, NGSIM Data Analysis, 2004) and was shown to better reproduce observed lane usage distributions and other macroscopic traffic flow characteristics compared to the a myopic lane change model Toledo (2003).

Sukthankar (1997) allowed for the resolution of decision making of sometimes conflicting directives using an arbiter of votes from independent internal components responsible for various tasks, such as lane keeping, reaching the target lane to take an exit, and staying on the road. The possible actions include the steering and acceleration to reach the desired goal (lane and target velocity). Response is represented in terms of a choice from a finite set of acceleration / deceleration and lateral shift maneuvers as a *3x3* action space: *{longitudinal (acceleration, steady, deceleration) x lateral (shift left, center, shift right) }*. However this model did not construct action scenarios or consider planning behavior.

Schlenoff et al (2006) developed a control algorithm for automated driving which selects a vehicle control action by taking into account the probability distribution of maneuvers of surrounding vehicles, so as to avoid collisions. The model contains both an estimation-theoretic short-term prediction component as well as a situation-based long-term prediction component. The short-term model applies Kalman Filtering to make a state prediction based on the surrounding vehicles' recent state information. The long-term model assumes the surrounding vehicles will move so as to maximize an objective function of several variables, such as proximity to other objects, desired speed, number of lane changes, crossing the center line into opposing traffic, and costs associated with various types of acceleration profiles (constant velocity, slowly accelerating and decelerating, rapidly accelerating or decelerating). This objective function uses coefficients selected by the analysts' judgment only and not based on observed data. The authors explain a simulation example for a two-way street (one lane per direction) in which there is an obstacle in the road. However, real data were not used in this study, it was developed for urban streets but not freeways, and it was developed for the purpose of autonomous vehicle control, in which the best driver action is desired. In human driver behavior modeling, on the other hand, what is desired is the realistic representation of human driver behavior, even if it is not the best possible action.

2.3 Calibration Approaches

There have also been many works involving the calibration of car following models to a real-world driver behavior data set. The following studies have calibrated driver models of individual vehicles, from a microscopic perspective.

Ossen et al. (2006) examined the performance of seven different car following models compared to a real driver behavior vehicle trajectory data set. The approach taken was to calibrate each model for each individual vehicle in the data set, comprising 229 triplets of vehicles driving in real traffic. In the calibration, parameter vectors, consisting of reaction time lag and various other parameters, were used and the resulting trajectory was compared to the actual vehicle trajectory data in terms of following distance and following vehicle speed. The optimal parameter set and error function value for each model were calculated for each individual driver using the simplex method in an iterative approach. The performance of each of the various models was compared based on a cumulative distribution function of the performance error over the entire vehicle population. An interesting finding was that the simpler models examined did not adequately capture driver behavior. The Gipps model gave the best overall performance. For some drivers, however, other models offered a better representation. Thus, not only the parameters, but the model form, can vary by driver.

Hourdakis et al. (2002) described a procedure for calibrating a simulator in which various values in the calibration parameter vector space are tested using a goodness-of-fit measure. A technique for automating the process was presented, and the approach was demonstrated using a selected simulator on a real traffic data set.

Delorme and Song (2001) performed a categorization of driver behavior from an existing data set collected from instrumented vehicles, which contained driving data from 108 drivers. The authors classified each driver's mean following time headway and desired speed, as well as critical thresholds to fit the parameters in the Cosmodrive driver behavior model, which is in the psychophysical family of car following models. They classified the drivers into groups according to these values, and found clustering of the drivers into four categories: ultra-conservative, planner, hunter / tailgater, extremist, and flow conformist.

2.4 Unmet needs of present-day traffic simulators

With the exception of Toledo et al. (2005), all of the lane change models and calibration approaches discussed above have the limitation that they do not explicitly represent the planning of sequences of driving maneuvers. Rather, they determine the very next lane change action in terms of its utility for the driver. In this section, the importance of considering such maneuver planning, as well as the limitations of the present-day driver models in providing this, are described.

2.4.1 The importance of modeling sequential maneuver planning

Because human drivers not only consider the present state of their own and surrounding vehicles, but also consider the current lane change actions as part of sequential maneuver plans, leaving this out of models leads to a decrease in realism of the traffic simulator, which can result in less effective policy decisions, inadequate allocation of infrastructure through inferior design, and decreased quality of real time control systems which utilize traffic simulators.

The ability of today's simulators to correctly represent the lane changing behavior may vary depending on the situation being modeled. In some situations, representing lane change decisions one step at a time, as is usually done in the lane change models used in today's traffic simulators, may be adequate. However, the need for improvement at least in some circumstances is underlined by the following four examples. These suggest that the sequential lane change planning can be critical to the simulation realism. The first example is extracted from real-world data, and the remaining three are hypothetical situations.

(1) Discretionary Lane Changes

Consider a case with the subject vehicle on a multi-lane freeway, as in Figure 2. 1. Figure 2.1. The subject vehicle driver would like to travel faster, but is in traffic among slower surrounding vehicles.

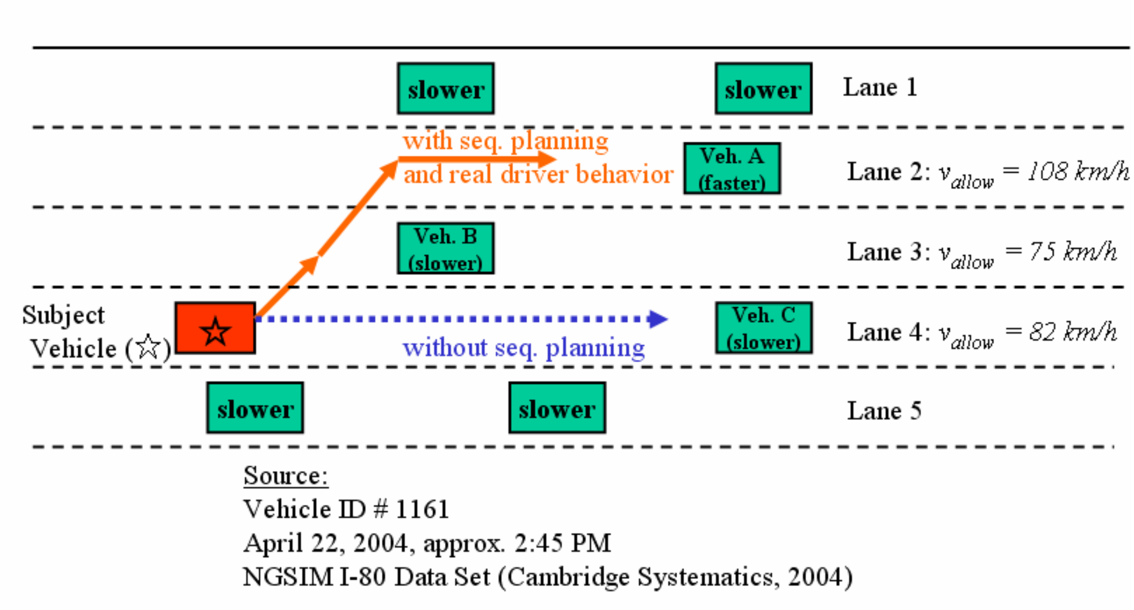


Figure 2. 1: Discretionary Lane Change (DLC) across 2 lanes – real-world data example

This example was recorded in a real vehicle trajectory data set (Cambridge Systematics, 2004). At the time shown, there are no available gaps in the lane to the right (Lane 5), and the driver is making the current lane change decision whether to stay in the current lane (Lane 4) or to move one lane to the left (Lane 3) (solid-line arrow). The utility of each lane to the subject vehicle could be described in terms of the *allowable speed.* This is the maximum speed that the subject vehicle could safely travel in the current longitudinal position while avoiding a collision if the lead vehicle were to decelerate at maximum, shown as v_{allow} in the same figure.

The behavior of the real driver was to move into Lane 3 with lower utility, in order to advance into Lane 2 with better utility, which is shown by the solid-line arrow in the figure. A driver model which includes sequential planning could also represent this behavior. However, if the lane change models such as those in present-day traffic simulators are used, which do not include sequential planning, the driver would decide each lane change action one by one, and decide to stay in Lane 4 (dashed-line arrow).

In this road section, all exits are on the right-hand-side. Because in this maneuver, the subject vehicle was observed to move to the left, this lane change maneuver can be considered entirely motivated by improvement of travel speed i.e. discretionary lane change (DLC).

(2) HOV lane

A particular case where the representation of tactical lane changing is critical is the access to a High-Occupancy Vehicle (HOV) lane (Toledo et al, 2005). HOV lanes restrict their access to specific classes of vehicles, for example, vehicles with two or more people in the car (the driver plus at least one passenger). They are placed in the median side and allow improved travel time during the peak period for users who are willing to share rides, thereby increasing the efficiency of the transportation system as a whole. Road managers, when making decisions about the design of such system by evaluating the performance of the designs, often use simulation because it is less expensive than testing an actual operating system. Further, because the system's configuration and operation are complex, it is sometimes difficult to use empirical findings from similar existing systems. In such a simulation evaluation it is important to have a simulator which can realistically represent the traffic performance.

Consider a simulation of a HOV system shown in Figure 2. 2. The HOV lane is the left-most lane marked with the diamond symbol. The vehicle entering the freeway will attempt to weave across several lanes with high traffic density into the free flowing HOV lane in order to realize improved travel time. But with existing models, which consider actions one at a time without sequential maneuver planning, the short-term payoff of weaving into a lane of slightly higher density is less than staying where he is. However the long-term goal of reaching the HOV lane would offer improved travel time, but in the non-sequential planning model the driver doesn't recognize this long-term benefit.

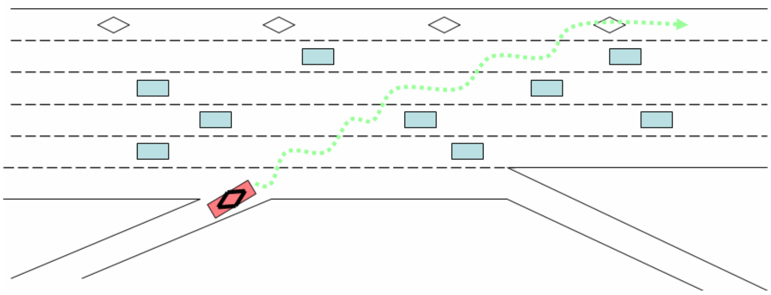


Figure 2. 2: High-occupancy vehicle lane simulation

Therefore, in the system modeled by a present-day traffic simulator, the subject vehicle would not be able to reach the HOV lane. The traffic simulation results would show that the HOV lane would be under-utilized, compared to the actual situation. Also, the travel time for HOV vehicles entering at the entry ramp would be longer in the simulation than the actual situation. This could lead to a policy decision which is less favorable for the HOV lane.

(3) Sag section on intercity freeway

Consider an intercity freeway with two lanes per direction, as in Figure 2.3. The right lane is the travel lane and the left lane is the overtaking lane. The desired speed of the vehicles in the traffic stream is distributed with a wide variation, so there are slow and faster drivers. Consider that the right lane is the travel lane and the left lane is the overtaking lane.

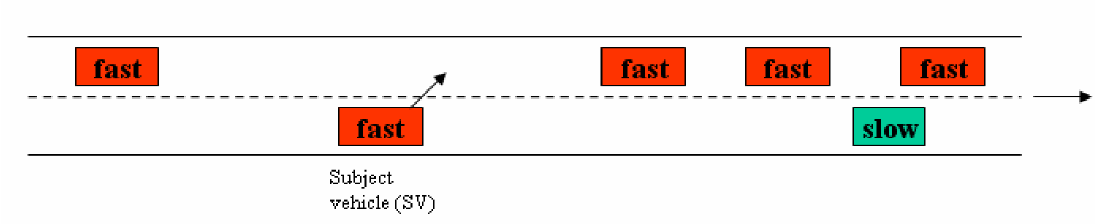


Figure 2. 3: Sag section on intercity freeway, example

Following the *lane discipline* (rule of keeping out of the overtaking lane unless overtaking), the slow vehicles move along in the travel lane. Approaching fast vehicles move into the left lane to pass the slow car. Next, as new fast vehicles approach, they begin to queue in the left lane. Consider the lane change decision of the subject vehicle which is a fast car in the right lane. He considers two plans:

(A) Continue in the right lane, and be forced to wait a long time before joining the queue to pass the slow car.

(B) Change to the left lane now and queue in the left lane until passing the slow car.

Considering that the driver would incur more delay in alternative A, it is easy to understand why the driver would more likely choose alternative B. The overall effect of many drivers making this decision is that the overtaking lane occupancy is much higher than the travel lane. If the road contains a *sag section* (a downward slope followed by an uphill slope), then the vehicles which are concentrated in the overtaking lane are suddenly slowed by drivers who unconsciously decrease their speed at the beginning of the uphill section, and the effect creates a backward shockwave in the overtaking lane resulting ultimately in a traffic jam. Therefore the traffic jam occurrence is caused by uneven lane usage distribution, and has been shown to cause a reduction in overall freeway capacity. (Hatakenaka et al., 2006) Operational strategies such as guidance to persuade more even use of both lanes through in-vehicle or roadside static or dynamic signing have been proposed. To evaluate such strategies using a microscopic traffic simulator, the representation of driver lane choice is expected to be critical in the effectiveness of such evaluation.

(4) Traffic policy evaluation of speed limiter device in mixed traffic

The use of an in-vehicle speed limitation device to achieve policy goals such as improved safety and reduced emissions impacts has been a subject of discussion. Simulation studies such as the one by Wilmink et al. (2004) have been conducted to evaluate the impacts of a hypothetical in-vehicle speed limitation device in which various percentages of the traffic stream are equipped. In the mixed traffic scenarios in which the speed limitation causes a large variation in achievable speeds, it is expected that the representation of driver lane changing behavior would be critical to the correct result of the simulation analysis. Will slower vehicles travel beside each other for a long time, obstructing drivers who wish to travel faster? If so, this could increase overall system travel time, and could lead to backward propagating shockwaves or even traffic jams. Will the faster vehicles attempt to weave through a cluster of slower vehicles? If not, then a moving traffic queue could build up, perhaps ultimately causing a traffic jam. Depending on the details of driver lane changing behavior, the results of such simulation studies may show widely differing results of the policy scenarios analyzed.

2.4.2 Previous models and their limitations

The existing lane changing models including tactical lane changing models were reviewed above. With the exception of Toledo et al (2005) and Schlenoff et al (2006), none of the above models, including Hidas (2002, 2005), contained planning of sequential maneuvers. Rather they determine the utility of the current lane change action according to the relative speed advantage in the adjacent lane. In light of the motivation to analyze situations such as described above, the proposed approach for representing sequential maneuver plans is expected to be able to improve the model realism compared to these models. Specifically, the proposed approach includes planning of maneuver sequences which is thought to be done by actual drivers, which is not included in the lane change models of most present-day traffic simulators.

The model by Schlenoff et al. (2006), although it considers sequential maneuver plans by the subject and surrounding vehicles, did not use a real data set for validation, nor was it applied to a freeway, which is topic of this study.

The model by Toledo et al (2005), which allows the subject vehicle to select a non-adjacent target lane, has been shown to improve the realism of the HOV situation (1) above. The approach of Toledo et al (2005) differs from that proposed in this dissertation, specifically the former applies lane-based utility to determine the lane change action, while the proposed model considers a set of plans for the exact situation at hand. The model of Toledo et al (2005) has been published only recently and its development was concurrent with the approach in this research. Therefore a full comparison is left out of the scope of this dissertation.

Of the models reviewed, if they did contain planning or anticipatory behavior, either they did not include the sequential planning behavior beyond the next lane change action (as in the model of Hidas), they did not use a real data set in their validation (Schlenoff’s model), or they are still in research and development and not widely used by the traffic simulation community (Toledo et al (2005) model). Because of the importance of the influence of situations in which a reward is delayed over several lane changes, it is thought that it can be improved by further research in tactical lane change behavior modeling.

The lane changing algorithm developed in this research is capable of modeling discretionary lane changes, and will be shown to make an improvement in the simulation realism performance in representing driver lane changing behavior, compared to the models used in today's traffic simulators.

2._ Summary

The chapter reviewed previous research in longitudinal control and lane change driver models, including tactical and anticipatory driver behavior models. The inadequacies of existing lane change models to model real driver tactical lane change behavior were illustrated through situational cases as well as a real data example.

3 MODELING FRAMEWORK

This chapter discusses the framework of the analysis that was implemented in this research work. First the overall approach is described. Next the structure of the traffic simulator is described.

3.1 Overall Approach

The approach is to create a *straw man* lane change model, such as those used in present-day traffic simulators, which does not contain the sequential planning lane change behavior functionality. This will be referred to as the *basic lane change model* in this manuscript. The basic lane change model is compared to the proposed tactical lane change model, which does contain a sequential planning capability. The comparison will be which model better represents the actual lane change behavior of a real vehicle from vehicle trajectory data. And the comparison will be repeated for other vehicles.

For such a comparison as desired in this research, it was not sufficient to design and implement a lane change model on its own. Features such as road geometry, vehicle management, data I/O, and visualization were also needed in order to conduct various analysis tasks. These functions are provided by a traffic simulator. The two options were to use an existing (already developed) traffic simulator, or to develop a new one. The latter was chosen because it allows greater flexibility in data interchange between the lane change model and simulator, software implementation (e.g. programming language in which to implement the lane change model), and the range of input and output data to and from the simulator.

The comparison takes place in a simulator. The intent is to show that the individual vehicle behavior can be better represented by the proposed model. The surrounding vehicles except for the subject vehicle are represented as they actually drove. The comparison can be visualized in Figure 3. 1:.

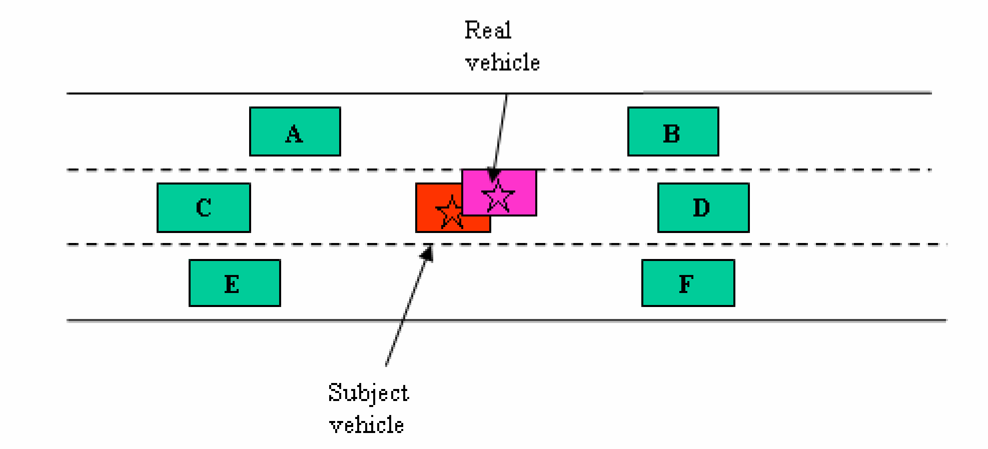


Figure 3. 1: **Model comparison framework**

The simulated subject vehicle is placed in the same environment (surrounding vehicle positions and speeds, road geometry, and its own recent trajectory history) as the real vehicle, and the result of the model is compared to that result which was actually performed by the real vehicle. Over the course of the real vehicle's trajectory, the model vehicle's position is reset to that of the real vehicle at each new gap situation. Next the traffic simulator developed in this study is described.

3.2 Traffic Simulator

In this research, a traffic simulator has been developed which represents the driver's longitudinal control and lane change behavior. This is a discrete time simulator where each vehicle's action is determined at each time step. For a selected vehicle from the vehicle trajectory data, the surrounding vehicles are represented as they actually traveled, and the subject vehicle is started at the initial position and velocity, and then control is turned over to the driver behavior models. The lateral position representation is discrete, in terms of the lane number as an integer. The overview of the components in the simulator are shown inFigure 3. 2.

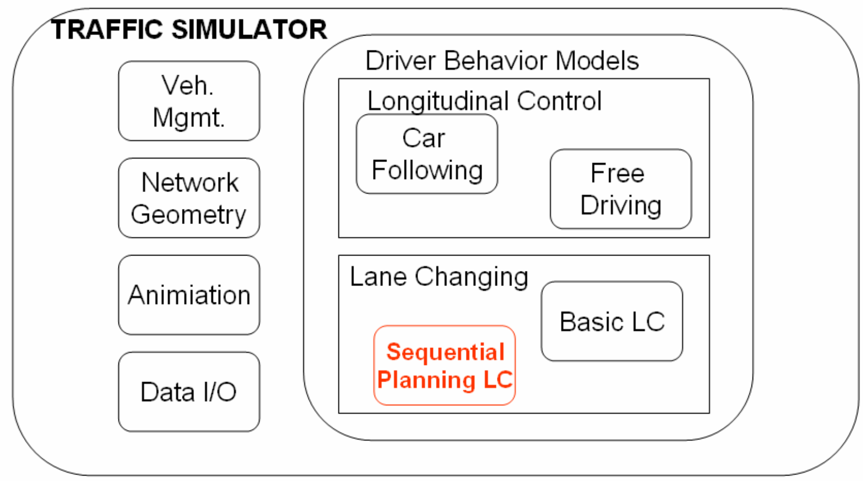


Figure 3. 2: Simulator components

In this simulator, as is often the case in other traffic simulators, the driver behavior has been decomposed into longitudinal and lateral control action components, with each being processed independently at each simulation time step. It is acknowledged that integrating these two components can improve the realism. For example, if a vehicle attempts to make a lane change, it may accelerate or decelerate so as to more easily move into the target gap. (Toledo, 2003) However, because of greater model complexity, such consideration has been left for future works.

As mentioned, two separate interchangeable lateral control models have been developed: (a) a basic lateral control model, which does not include sequential lane change planning, and (b) a tactical driver behavior model, which does include sequential lane change planning. As explained later in this manuscript, both have been calibrated to best fit the behavior of selected individual vehicles. The evaluation of the performance of the best-fitted models will be described in a later section.

The simulator, which is time-step-based, updates the positions of each vehicle at every time step. To determine the motions of the subject vehicle(s), the longitudinal control and lane change models are applied, and the real vehicles are moved according to the real trajectory data. A flowchart of the simulation cycle is shown in Figure 3. 3.

This simulator is deterministic in its implementation of all the models and data management. The driver behavior models in the simulator give values rather than probability distributions. This approach is the simplest and most straightforward approach as it allows a direct comparison of the modeled and actual trajectories of the individual vehicle in the performance evaluation. Incorporation of stochastic elements may be desirable when developing a traffic simulator for practical use and such work is recommended as further work. If it is desired to consider random effects, a slight variation of the initial conditions could be helpful to generate a range of results.

The model has been developed as a heuristic to be used in traffic simulation software in order to improve the realism of simulated traffic especially on particular road geometries such as weaving sections and sections with high-occupancy vehicle (HOV) lanes in which are thought to have many tactical maneuvers.

Next the functionality and software architecture are described.

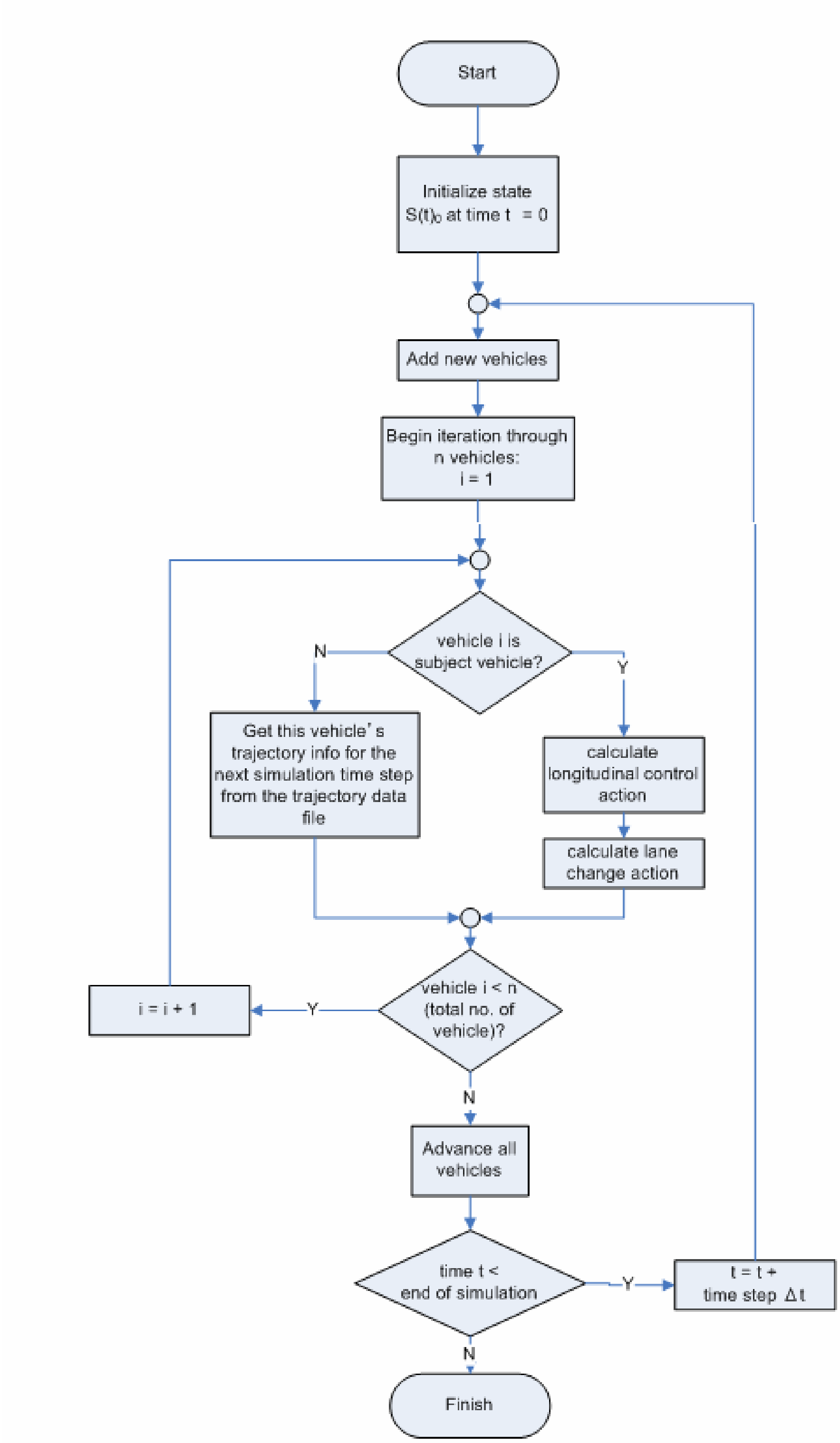


Figure 3. 3: **Simulation cycle**

3.2.1 Functionality

The simulator is capable of running in two modes: “Simulation” and “Mixed”. In “Simulation” mode, all the vehicles are initially placed on the network and their behavior is controlled by the driver models. In “Mixed” mode, only selected vehicles are controlled by the driver model, and the remaining vehicles are moved according to pre-existing vehicle trajectory data. Here the simulator functions are described briefly. The detailed workings of the longitudinal control and lane change driver models will be described in the next two chapters.

Vehicle Management

The simulator represents the set of vehicles currently present on the simulated network, including the subject vehicle(s).

Network Geometry

The simulator has the functions necessary to handle both regular and also *wraparound* link coordinate systems. In the former the vehicle is removed from the simulation when it reaches the end of the final link, while in the latter, the vehicle is placed at the beginning of the link. The network geometry is specified in to a user input data file, and is capable of handling multiple links, each containing up to 9 lanes, as well as entry and exit ramps. Various issues of lane connectivity are handled, for example a vehicle at the end of one link being able to see traffic on the upstream end of the immediate downstream link.

Animation

The road geometry, vehicles, current simulation time, and potential subject vehicle maneuver plans are displayed on the screen. The road geometry can be displayed in rectangular or radial coordinate systems with specified view center points and zoom ranges. Figure 3. 4 shows a screen shot of the simulator with radial display containing all the elements.

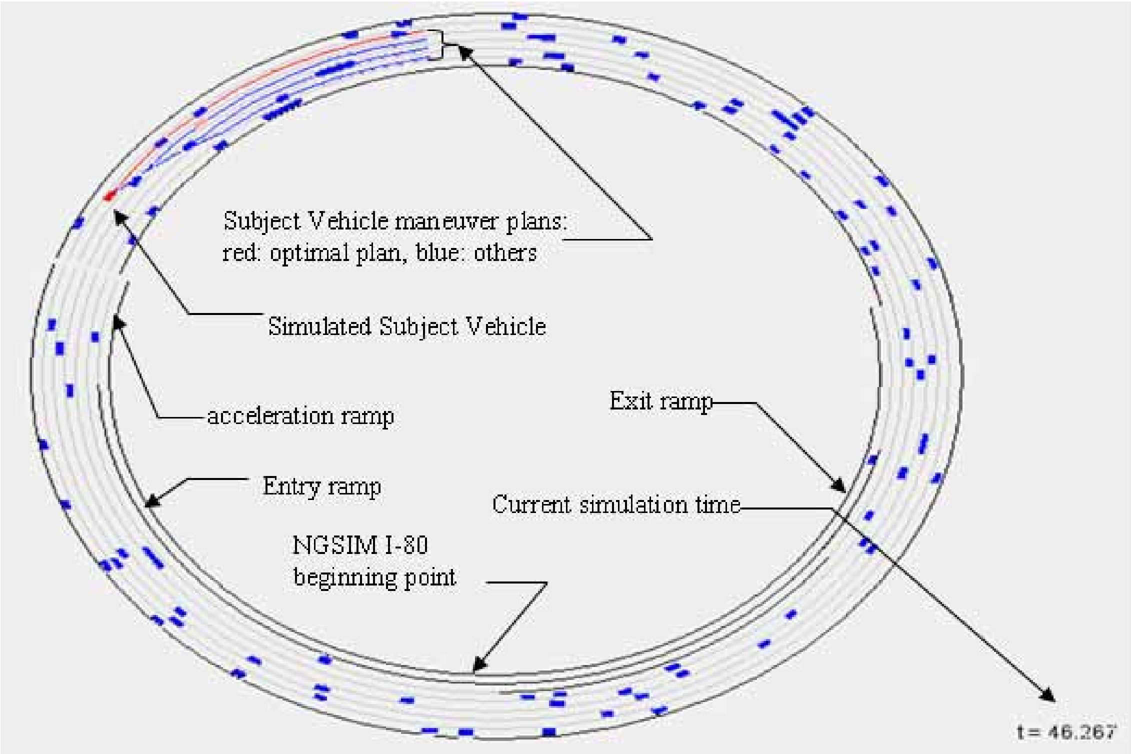


Figure 3. 4: Animation Display

Data I/O

These functions include reading trajectory data, road geometry, and vehicle driver behavior parameter information, as well as writing the simulated trajectories to output files. The elements of the input and output trajectory data files are identical:

- Time (s)
- Vehicle ID
- Link ID
- Lane
- Longitudinal position (m)
- Vehicle Length (m)
- Vehicle Speed (m)

3.2.2 Software Architecture

This section describes the various processes and data elements which make up the traffic simulator. The implementation is in Java, and *object oriented* programming language (Sun Microsystems, 1995).Therefore the processes and data elements are integrated into independent elements known as *classes*. In this section, the various classes and their roles are summarized. Details of the driver models in the simulator will be described in the next two chapters. Table 3. 1 summarizes the classes:

Table 3. 1: Simulator Software Classes

Class	Attributes	Methods
`World`	• Road geometry (`NetGeo` class) • Vehicles (`Vehicle` class)	• Manage each time step of the simulation • Call the driver models, update vehicle positions • Screen visualization • Initial trajectory file data reading and initialization • Vehicle generation • Simulator output trajectory data recording
`Vehicle`	• Vehicle driver behavior parameters • Vehicle position and speed • Vehicle recent trajectory history • Vehicle environment state `EnvirState`	• Compute longitudinal control action • Compute lane change action (if tactical lane change model is used, then the forward search tree class `FSTree` is created)
`EnvirState`	• Information on surrounding vehicles and road geometry information as perceived and understood by the modeled driver of a vehicle. Not necessarily identical to the real state information in `World`.	• Find the speed and position of the vehicles immediately surrounding the subject vehicle • Process representations and state transformations of hypothetical subject vehicle and surrounding vehicle state information for the near-term planning in the Forward Search Tree
`NetGeo`	• Links and their	• Finding distances in the network

	coordinates ● Number of lanes ● Interconnections between lanes	● Converting between link and *(x,y)* coordinates
`Gipps_CF_Model`		● compute target velocity according to Gipps Longitudinal Control Model
`Gipps_LC_Model`		● determine if gaps in adjacent lanes are acceptable, if so compute desired speed ● compute the lane change action of the *basic lane change model*
`FSTree`	● current and potential future states (instances of `EnvirState` class) and control actions	● build the forward search tree by enumerating the hypothetical maneuver plans ● evaluate the utility of each maneuver plan and return the best lane change control action ● provide the enumerated and best maneuver plan trajectories for screen display

3._ Summary

This chapter explained about the overall analysis approach in this research, as well as the traffic simulator environment which was developed to provide the necessary functions to realize analysis of the performance of the proposed and existing lane change models. The overall approach of the analysis is to estimate the tactical lane change model and compare its performance based on the individual vehicle in real trajectory data. A brief overview of the simulator data and processes was given. In the next two chapters, the driver models are described.

4 CAR FOLLOWING AND BASIC LANE CHANGE MODELS

This chapter describes the longitudinal control model always used in the traffic simulator, features common to all lane change models, and the basic lane change model. The sequential planning lane change model will be described in the next chapter.

4.1 Longitudinal Control Model

The available longitudinal models were considered from the literature and the model by Gipps was selected for use as the longitudinal control model. First an overview is provided of the longitudinal control models which were examined. Next, the decision and rationale are discussed.

4.1.1 Gipps Longitudinal Control Model

The Gipps longitudinal model (1981) contains both a free driving model and a car following model, and allows a smooth transition between the two. In addition, by its design it prevents the collisions between vehicles from occurring in the simulator. The Gipps model has relatively few parameters: a given vehicle's longitudinal control behavior can be specified by just four parameters: reaction time τ, maximum acceleration and deceleration, and desired speed. This allows a best-fit calibration of the model to an individual vehicle to be easily achieved due to the small parameter search space.

This is the form of the Gipps longitudinal control model given in the original 1981 paper.

$$v_{trg}(t+\tau) = \min\begin{cases} v_n(t) + 2.5a\tau\left(1-\frac{v_n(t)}{V_n}\right)\sqrt{0.025+\frac{v_n(t)}{V_n}}, \\ b\tau + \sqrt{b^2\tau^2 - b\left[2\left[x_{n-1}(t) - s_{n-1} - x_n(t)\right] - v_n(t)\tau - \frac{v_{n-1}(t)^2}{b}\right]} \end{cases} \quad (1)$$

where:

τ_n	=	reaction time lag parameter for vehicle *n*
a_n	=	driver's acceleration
b_n	=	driver's deceleration
s_n	=	effective length of vehicle *n*
V_n	=	driver's desired speed
$x_n(t)$	=	location of vehicle *n* at time *t*
$v_n(t)$	=	speed of vehicle *n* at time *t*
$v_{trg\|n}(t)$	=	the target speed to be applied over the time interval $[t, \Delta t]$
Δt	=	simulation time step

In this model, the result is not acceleration, but rather the target velocity selected by the vehicle over the simulation time step Δt. The vehicle performance limits of acceleration and deceleration are reflected internally in the equation. The first term inside is the free drive constraint, which allows influence of the vehicle performance limits on acceleration as well as the desired speed on the subject vehicle's target velocity. The second term contains the influence of following the lead vehicle to allow a safe stopping distance.

The Gipps car following model equation has been derived as described here, and depicted in Figure 4.1.

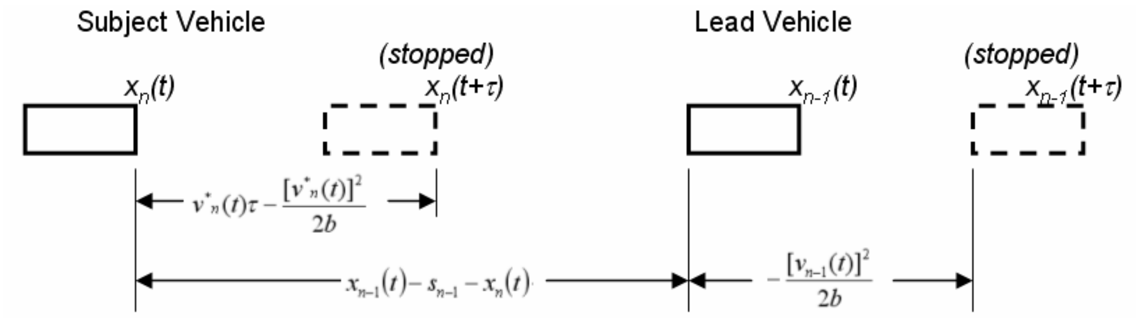


Figure 4. 1: Safe stopping in the Gipps longitudinal control model

(1) Calculate the safe speed for the current following distance. If the lead car were to decelerate at maximum, it would travel a distance of

$$-\frac{v_{n-1}}{2b} \qquad (1a)$$

before coming to a stop (negative sign is added because the value for b is negative). The subject vehicle (which is following the lead car), would first travel a distance of

$$v_n\tau \qquad (2)$$

before the driver perceives and is able to react to the lead vehicle's sudden deceleration. After which the subject vehicle will decelerate at maximum and travel a distance

$$-\frac{v_n}{2b} \qquad (3)$$

before coming to a stop. Therefore the total distance that the following car has available to stop is

(A) the spacing to the rear bumper of the lead car

$$x_{n-1}(t) - s_{n-1} - x_n(t) \qquad (4)$$

plus (B) the distance the lead car will travel (1a);

while the distance that the subject vehicle will travels at its current speed is (2) + (3).

The safe speed $v^*_{n-1}(t)$ is the speed such that the distance required to stop (2) + (3) is equal to the distance available to stop (4) + (1a). That is,

$$v^*{}_n(t)\tau - \frac{[v^*{}_n(t)]^2}{2b} = x_{n-1}(t) - s_{n-1} - x_n(t) - \frac{[v_{n-1}(t)]^2}{2b} \qquad (5)$$

Solving for $v^*_n(t)$ using the quadratic formula gives:

$$v^*{}_n(t) = b\tau \pm \sqrt{(b\tau)^2 - [2b(x_{n-1}(t) - s_{n-1} - x_n(t)) - [v_{n-1}(t)]^2)} \qquad (6)$$

Discarding the negative solution, and arranging terms, the latter half of (1) is obtained.

4.1.2 Speed-Spacing Model

This model, formulated by Newell (2002), is popular because of its simplicity. It assumes that the subject vehicle (vehicle *n*) (which is following another vehicle) attempts to maintain a spacing (front-bumper to front-bumper distance with the lead vehicle *n-1*) which is proportional to the travel speed.

$$x_{n-1}(t) - x_n(t) = Tv_n(t) + s_{n-1} \qquad (7)$$

where:

$x_{n-1}(t)$	=	the position of the LV at time t (m)
$x_n(t)$	=	the position of the LV at time t (m)
T	=	the car following sensitivity parameter (s)
v_n	=	speed (m/s)
s_{n-1}	=	a constant spacing term which represents the length of the lead vehicle as well as a safety spacing as preferred by the following vehicle

Consider the situation where the lead vehicle (LV) is stopped and the following vehicle (FV) is approaching at speed v_0, as depicted in Figure 4.2.

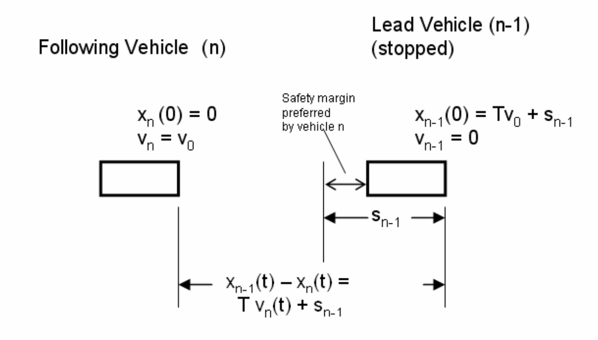


Figure 4. 2: Speed-spacing model with lead vehicle decelerating at maximum

For initial conditions *(t = 0)*, the LV is stopped, and the FV is at $x = 0$, with an initial speed of v_0. According to the SV rule (7), the lead vehicle should be at position:

$$x_{n-1}(0) = Tv_0 + s_{n-1} \tag{8}$$

To find the motion of the FV, the initial LV position (8) can be substituted into (7) to get:

$$Tv_0 + s_{n-1} - x_n(t) = Tv_n(t) + s_{n-1} \tag{9}$$

Solving for $v_n(t)$:

$$Tv_n(t) = Tv_0 - x_n(t)$$

$$v_n(t) = v_0 - \frac{x_n(t)}{T} \tag{10}$$

Let's examine the FV position, speed and acceleration at a very small time interval from $t = 0$ until $t = \Delta t$.

Position: for very small Δt:

$$x_n(t + \Delta t) \approx x_n(t) + v_n(t)\Delta t$$

$$x_n(\Delta t) \approx x_n(0) + v_n(0)\Delta t = 0 + v_0\Delta t = v_0\Delta t \tag{11}$$

Speed:

$$v_n(0) = v_0$$

from (10), (11):

$$v_n(\Delta t) = v_0 - \frac{x_n(\Delta t)}{T} = v_0 - \frac{v_0\Delta t}{T} \tag{12}$$

The acceleration is the change in speed divided by change in time, taken to the very small limit of change in time.

$$a_n(0) = \lim_{\Delta t \to 0} \frac{v_n(\Delta t) - v_n(0)}{\Delta t}$$

$$a_n(0) = \lim_{\Delta t \to 0} \frac{\left[v_0 - \frac{v_0 \Delta t}{T} \right] - v_0}{\Delta t}$$

$$a_n(0) = \lim_{\Delta t \to 0} \frac{-\frac{v_0 \Delta t}{T}}{\Delta t} = \lim_{\Delta t \to 0} \frac{-v_0}{T} \frac{\Delta t}{\Delta t}$$

$$a_n(0) = \frac{-v_0}{T} \tag{13}$$

With a large enough initial speed, and small enough sensitivity parameter *T*, the acceleration specified by the SV car following rule can easily exceed the max deceleration limit *b*. (*b* is negative)

$$a_n(0) = \frac{-v_0}{T} < b \tag{14}$$

Then the acceleration which is called for by the SV model may *not be allowable* by the deceleration limits of the vehicle. This means that if the SV model is used, and there is a lead vehicle which is stopped and the following vehicle is approaching with the conditions in (7), then there may be a collision.

In summary, the SV model was determined not to be suitable for use in this simulation study because (a) it calls for extraordinarily high decelerations, and (b) if these decelerations are not provided, the model will result in collisions.

4.1.3 Helly Model

The linear Helly model (Klunder et al., 2006), also known as the PD model (Fang et al., 2001), has the following form:

$$a(t+\tau) = k_p[D_r(t) - D_d(t)] + k_d V_r(t) \tag{15}$$

where:

a(t)	=	the subject vehicle acceleration (m/s^2) at time *t*
τ	=	Reaction time lag (s)
$D_r(t)$	=	relative distance at time *t* (m)
$D_d(t)$	=	the desired following distance at time *t*. This can be expressed as a speed-spacing

relationship such as in the linear SV model, explained in the previous section.

$V_r(t)$ = Relative velocity at time t

K_p, K_d = gains for relative distance and velocity

Considering the Helly model, with a simple linear speed-to-distance relationship for the desired following distance:

$$D_d(t) = k_w v_n(t) \quad (16)$$

where:

k_w = Coefficient (s)

$v_n(t)$ = Subject vehicle's speed (m/s)

The relative velocity can be expressed as follows:

$$V_r(t) = v_{n-1}(t) - v_n(t) \quad (17)$$

where:

$v_{n-1}(t)$ = Lead vehicle speed (m/s)

Substituting (16) and (17) into (15), the expression becomes:

$$a(t+\tau) = k_p D_r(t) - (k_p k_w + k_d) v_n(t) + k_d v_{n-1}(t) \quad (18)$$

Introducing a new coefficient $k_v = k_p k_w + k_d$, the expression becomes:

$$a(t+\tau) = k_p D_r(t) - k_v v_n(t) + k_d v_{n-1}(t) \quad (19)$$

The Helly model thus has three independent parameters. For the analysis to be performed in this research, the Gipps model can express the driver following behavior using only two parameters. Additionally there is no guarantee that the model will avoid collisions.

4.1.4 Other models

The reference "NGSIM E1-1 core algorithm assessment" (Cambridge Systematics, 2004) contains some of the latest findings. In further works, other models could be considered to replace the selected model.

4.1.5 Longitudinal Control Model Selection

Of the models considered, the Gipps longitudinal control model was selected. It has the following advantages:

(I) The Gipps model contains both a free driving model and a car following model, and allows a smooth transition between the two. The free driving model accounts for vehicle dynamics limitations on acceleration and deceleration internally. The other models considered (Helly and speed-spacing) only describe the car following situation, and the speed-spacing model was shown to call for unrealistic accelerations in some situations.

(II) The Gipps model is designed with kinematics equations to prevent collisions between vehicles from occurring in the simulator. It has relatively few parameters: a given vehicle's longitudinal control behavior can be specified by just four parameters: reaction time τ, maximum acceleration and deceleration, and desired speed. If the acceleration and deceleration are taken as constants from a literature reference source, this leaves *two* parameters for calibration. By contrast the Helly model can have at least *three* parameters which must be estimated. As the number of model parameters is increased, the search time is expected to increase exponentially, as this represents the dimension of the parameter search space.

In conclusion, the Gipps longitudinal control was selected for use. The implementation is as described above, and the formula used is exactly the same as in the original 1981 paper, as shown in (1) above.

4.2 Lane Change Modeling Framework

For this research, two types of lane change (lateral control) models have been developed: (1) a basic lateral control model and (2) the proposed tactical lane change model based on sequential maneuver planning. The basic lane change model is explained below, and the tactical lane change model is described in the following chapter.

Both the basic and tactical lane change models have a user setting regarding overtaking in the slow lane, (i.e. *lane discipline*), which can be set to "keep left", "keep right", or "free lane" to match the observed behavior of the traffic data set being analyzed. The default setting used is "free lane", which allows no preference for overtaking on either curb- or median-side. It should be noted that the regulatory and compliance situations regarding overtaking in the slow lane may vary by country or region, and to transfer to another region, the analyst should adjust this setting to best reflect local conditions.

4.3 Basic Lane Change Model

The basic lane change model has been developed using a form of the Gipps (1986) lane change model. The lane change model proposed by Gipps (1986) is more of a framework than a detailed implementation. In this section, the details of the implementation of the Gipps (1986) framework in the basic lane change model are described. Next, the implementation is compared to the Gipps (1986) framework as well as the lane change models in present-day traffic simulators to show that it can adequately similar to serve as a *straw man* status quo model with which to compare the proposed sequential planning tactical lane change model performance.

4.3.1 Implementation

In this basic lane change model, at every time step the subject vehicle first checks if a lane change to either adjacent lane is possible, in terms of gap availability. The gap availability is judged in terms of both lead and rear gaps, calculated according to the Gipps Car Following Model criteria for safe speed and following distance.

Figure 4.3 shows an example of the subject vehicle checking for available gaps in the lane to the left.

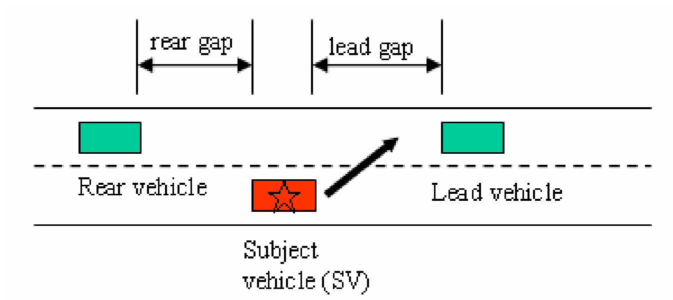


Figure 4. 3: Gap availability

For a given adjacent lane, both the lead and rear gap must satisfy the criteria of being no less than the adjusted critical gap size, as described in (Eq. 20, 21, 22).

$$d_{crit} = \frac{v_L^{\ 2} - v_F^{\ 2} + 3 v_F b \tau}{2b} \tag{20}$$

$$d = x_L - len_L - x_F \tag{21}$$

acceptable gap if: $d \geq F\, d_{crit}$ (22)

where:

x_L, x_F	=	the lead and following vehicle longitudinal positions (m)
v_L, v_F	=	the lead and following vehicle speeds (m/s)
len_L	=	the lead vehicle's length (m)
b	=	vehicle maximum deceleration (m/s^2) (Assumed identical for all vehicles and known by all drivers)
τ	=	the car following sensitivity parameter (s)
d_{crit}	=	the distance below which the car following would

be unsafe (m)

d = the actual car following distance if the vehicle moved into the gap (m)

F = gap adjustment factor (unitless), unique for each vehicle

$$= \frac{\text{smallest acceptable gap}}{\text{gap size which would allow safe stopping}}$$

Each vehicle has its own value of F, which shows the vehicle's smallest acceptable gap size compared to the safe stopping gap size d_{crit} given by the equation (20) above. For example, if a vehicle has a smallest acceptable gap which is exactly equal to the gap size which would allow safe stopping, then the value of F would be *1.0*. If the vehicle has a smallest acceptable gap one half the size then F would be *0.5*.

Because Mandatory Lane Changing (MLC) is not included in the proposed model, the implementation of these features have not been included in the basic lane change model implementation of the Gipps (1986) model framework. All that remains is the choice of the current lane change action in terms of the desirability of the candidate lane compared to the current lane. The implementation of DLC is described here.

If the change is possible, that is, the lead and lag gaps in the adjacent lane are acceptable, then the next check is if it is desirable. This is the case where the allowable speed can be improved up to the desired speed, compared to the present lane. If several lanes receive the same allowable speed, the lane is chosen according to the lane discipline rule. The formula for allowable speed is:

$$v_{allow} = \min\left(\frac{3}{2}b\tau \pm \sqrt{{v_L}^2 - 2b(x_L - len_L - x_F) + \frac{9}{4}b^2\tau^2}, v_{des}\right) \quad (23)$$

where:

v_{des} = the subject vehicle's desired free driving speed

In this simulator, lane changes are assumed to take place over a time interval of length equal to the vehicle's reaction time lag, τ, and once a lane change occurs, no new lane changes are permitted until this time interval elapses.

4.3.2 Suitability for use in performance comparison

First the differences of the basic lane change model with the framework proposed in the Gipps (1986) are described. Then the basic lane change model is compared to the lane change models in present day simulators to show that can adequately serve as a status quo model for the lane change model performance comparisons.

Generally, the implementation of the basic lane change model in this research conforms to the Gipps (1986) framework. Rather, it is a subset of the Gipps (1986) model framework in that this implementation omits many of the details prescribed by the Gipps (1986) framework, namely MLCs, lane usage restrictions, and the influence of heavy nearby heavy vehicles on the subject vehicle. With these simplifications, the model can be considered to conform strictly to the Gipps (1986) framework.

One difference with the Gipps (1986) framework is that the basic lane change model implemented here allows for the customization of gap selection by individual vehicles. The Gipps (1986) framework did not rule that out, but it did not provide the implementation details. This is the only difference with the Gipps (1986) framework to the basic lane change model included in this research.

Now the implementation of the basic lane change model is compared to those in present day traffic simulators, including that of Hidas (2002, 2005). These do not have any planning of the lane change action that take into account sequences of maneuvers. These models generally conform to the Gipps (1986) framework in which the utility of the lane change is based on consideration of the possible improvement of the subject vehicle's situation in terms of the allowable safe travel speed in the candidate target lane. The basic lane change model in this research is implemented likewise; for this reason it is claimed that the basic lane change model can adequately represent not only the simpler gap acceptance models, but also the model by Hidas as a status quo model in the performance comparison with the model in this research.

In conclusion, with the exception the new model by Toledo (2005) which does allow a kind of sequential plan of lane change maneuvers, the basic lane change model is found to be adequate in serving as a status quo model to represent the lane change model in present-day traffic simulators for the performance comparison.

4.4 Reaction time lag and the short term prediction model

In all of its driver models, including longitudinal, as well as basic and tactical lane changing models, this simulator takes into account the lag in response time of each simulated vehicle. The driver has available only the perceived information from the environment until time $t - \tau$. In all the models described above, rather than directly using the actual current state information

$S(t) = \{x(t), l(t), v(t)\},\ \forall n$ vehicles,

the model uses a short-term estimate of the current state based on the information from most recently perceived information at a time τ into the past:

$$
\begin{aligned}
\hat{S}(t) &= \{\hat{x}(t)_n, \hat{l}(t)_n, \hat{v}(t)_n\}, \forall n \\
&= \{\hat{x}(t)_n = x(t-\tau)_n + \tau v(t-\tau), \\
&\quad \hat{l}(t)_n = l(t-\tau)_n, \\
&\quad \hat{v}(t)_n = v(t-\tau)_n\}
\end{aligned} \tag{24}
$$

where:

$\hat{S}(t)$	=	The estimate of the current state based on short-term prediction
n	=	Index number of subject vehicle or nearby non-subject vehicle
$x(t)_n$	=	Longitudinal vehicle position
$l(t)_n$	=	Vehicle lane
$v(t)_n$	=	Vehicle speed

The vehicle positions are updated assuming they travel at a constant speed, and they are assumed not to make any lane changes.

This can be visualized in Figure 4.4. The current state is not known (solid line for $t > t - \tau$), but rather it is estimated based on information from time $t - \tau$. A short-term first-order estimation of the subject vehicle and that of other vehicles position is made (shown as the dashed line). Using this estimated state information at time t, the control action to be applied at time t can be determined and executed.

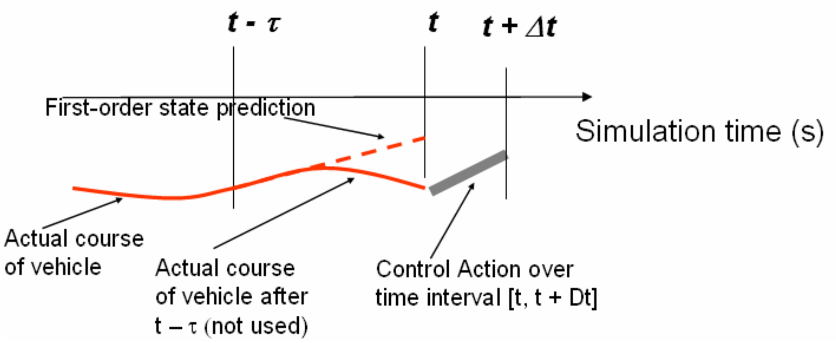


Figure 4. 4: Reaction time lag

4._ Summary

This chapter described the car following model and basic lane changing model used in the simulation framework within this research. Several candidate longitudinal control models were considered for use. The Gipps longitudinal model was selected because it avoids collisions, provides driving behavior for both car following and free driving conditions, and has relatively few parameters. The Gipps lane change modeling framework is used for the basic lane change model. The model checks if lane changes are possible, in terms of available gaps in the adjacent lanes, and then assesses the utility of the lane change in terms of the allowable speed in the adjacent lane. Finally reaction time lag and its implementation in the simulator, including all driver models, is described. In the next chapter, the tactical lane change model is described.

The model compares well with most lane change models in present-day traffic simulators in that it determines the utility of the current lane change action only, and this in terms of the relative speed advantage of the adjacent lane.

5 TACTICAL LANE CHANGE MODEL

This chapter describes the framework for representing the human driver's lane change decision process. In the model, the human driver considers all maneuver sequences as they unfold over a planning time horizon, and selects the action sequence which best satisfies his or her goals. The collection of maneuver sequences is considered as a forward search tree. The enumeration of the maneuver sequences and selection of an action sequence and control action are explained in this chapter. Restrictions to be applied on enumeration as well as possible feature additions are also considered.

5.1 Forward Search Tree

The Forward Search Tree is constructed starting at the present time, and projecting forward each planning time step until the time horizon. The maneuver sequences to be considered must allow safe following and lane changes into safe gaps under the same gap acceptance criteria of the basic lane change model, presented in the previous chapter. The structure of the Forward Search Tree is shown in Figure 5.1; it represents the enumeration of possible maneuver sequences. Like the basic lane change model, the sequential planning lane change model is executed every simulation time step, and returns an integer representing the lane change control action to be executed at the current time step: *-1* for *left*, *+1* for *right*, and *0* for *no lane change*.

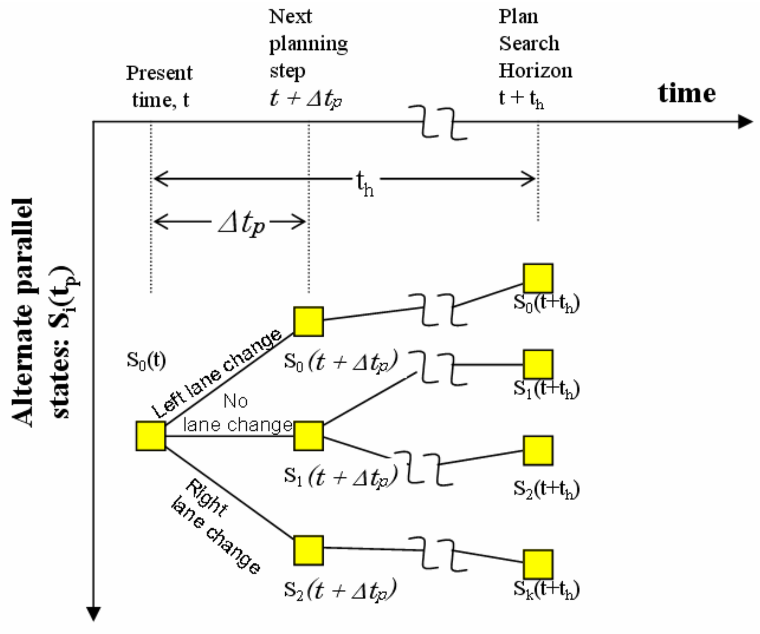


Figure 5. 1: **Forward Search Tree**

The nodes in the Forward Search Tree represent the possible sequences of states of subject vehicle and nearby vehicles at each planning time t_p. During the sequential planning from the present time t until the planning horizon $t + t_h$, the subject vehicle will predict not only its own position and velocity, but that of each of the surrounding vehicles, represented collectively as state $S_j(t_p)$ (yellow square in Figure 5.1). For a given planning time t_p there will be one or more unique states $S_j(t_p)$ with index j.

$$S_j(t_p) = \{ \hat{x}_n(t_p), \hat{l}_n(t_p), \hat{v}_n(t_p) \mid n = 1,2,........,N \} \tag{1}$$

where:

$S_j(t_p)$	=	The state j at time planning time t_p, which includes the position and speed of all vehicles
n	=	Index number of subject vehicle or nearby non-subject vehicle
N	=	The last in the list of subject vehicles
$\hat{x}_n(t_p)$	=	Predicted longitudinal position of vehicle n
$\hat{l}_n(t_p)$	=	Predicted lane of vehicle n
$\hat{v}_n(t_p)$	=	Predicted speed of vehicle n

The lines connecting the squares in the figure represent the subject vehicle lane change actions {*left lane change, no lane change,* or *right lane change*} at a given planning time. A given state $S_i(t_p)$ may connect to one or more succeeding states $S_j(t+\Delta t_p)$ (different values of j). In the proposed model, the planning time step size is set equal to a user-specified parameter, Δt_p. In this analysis, Δt_p is set to 1.0 s. Note that the planning step size Δt_p should not be confused with the simulation time step size Δt. Also, in the proposed model, Δt_p is necessarily a multiple of Δt. This is not a problem when Δt is very small (e.g. $\Delta t \leq 0.2\ s$) as is the case for the data set analyzed in Chapter 6, in which $\Delta t = 0.0667\ s$. Thus any errors due to rounding of Δt_p are very small and can be ignored.

5.2 Enumeration

The Forward Search Tree is built starting at initial state $S_0(t)$, which consists of the speed and position of all nearby vehicles upstream or downstream of the subject vehicle within a *view distance* specified as a model parameter. In the prototype model, a view distance of *200 m* in each direction was assumed, being able to recognize the first vehicle ahead or behind with a following time of 6 seconds at free flow speed of 30 m/s. *(6 s x 30 m/s = 180 m ≤ 200 m view distance)* Next, all possible states $S_j(t_p)$ are successively estimated for each planning time t_p at planning increments Δt_p until the time horizon, $t + t_h$, as shown in Figure 5.2.

This is a *breadth-first* search. See Russell (2003) Chapter 3 for a treatment of *breadth-first* and *depth-first* searches for action planning. To estimate one or more resulting states $S_j(t_p)$ from the previous planning state $S_i(t_p - \Delta t_p)$, the surrounding vehicles (non-subject vehicles) are simply advanced in the same lane at their current speed, constrained by safe car following (according to the longitudinal control equation described in Chapter 4). Subject vehicle longitudinal control actions are represented as maximum achievable velocity allowed by the vehicle's performance, constrained by safe car following and the driver's desired speed. For the subject vehicle, every state $S_i(t_p - \Delta t_p)$ will have at least the *no-lane-change* result state $S_j(t_p)$, and if a new gap is available on one or both of the adjacent lanes, then additional result states $S_{j+1}(t_p)$ and $S_{j+2}(t_p)$ may be added, thus making a branch in the Forward Search Tree.

Note that because the car following behavior is included in the vehicle state prediction, the proposed model can not only predict motion at constant speeds, but also capture the driver behavior in response to changing conditions, such as lane changing to avoid a downstream backward propagating congestion front, provided that the *view distance* reaches far enough ahead to the congestion front.

Regarding the length of the time horizon, t_h, it is possible that a driver's planning time horizon may vary depending on the complexity of the situation: maneuvering a weaving section may require a longer planning horizon than ordinary driving on a basic roadway section.

The completed Forward Search Tree enumerates a complete set of subject vehicle maneuver sequences, and each sequence can be evaluated in terms of how it improves the situation for the driver. The method for selecting the maneuver sequence best representative of the subject vehicle is described in the next subsection.

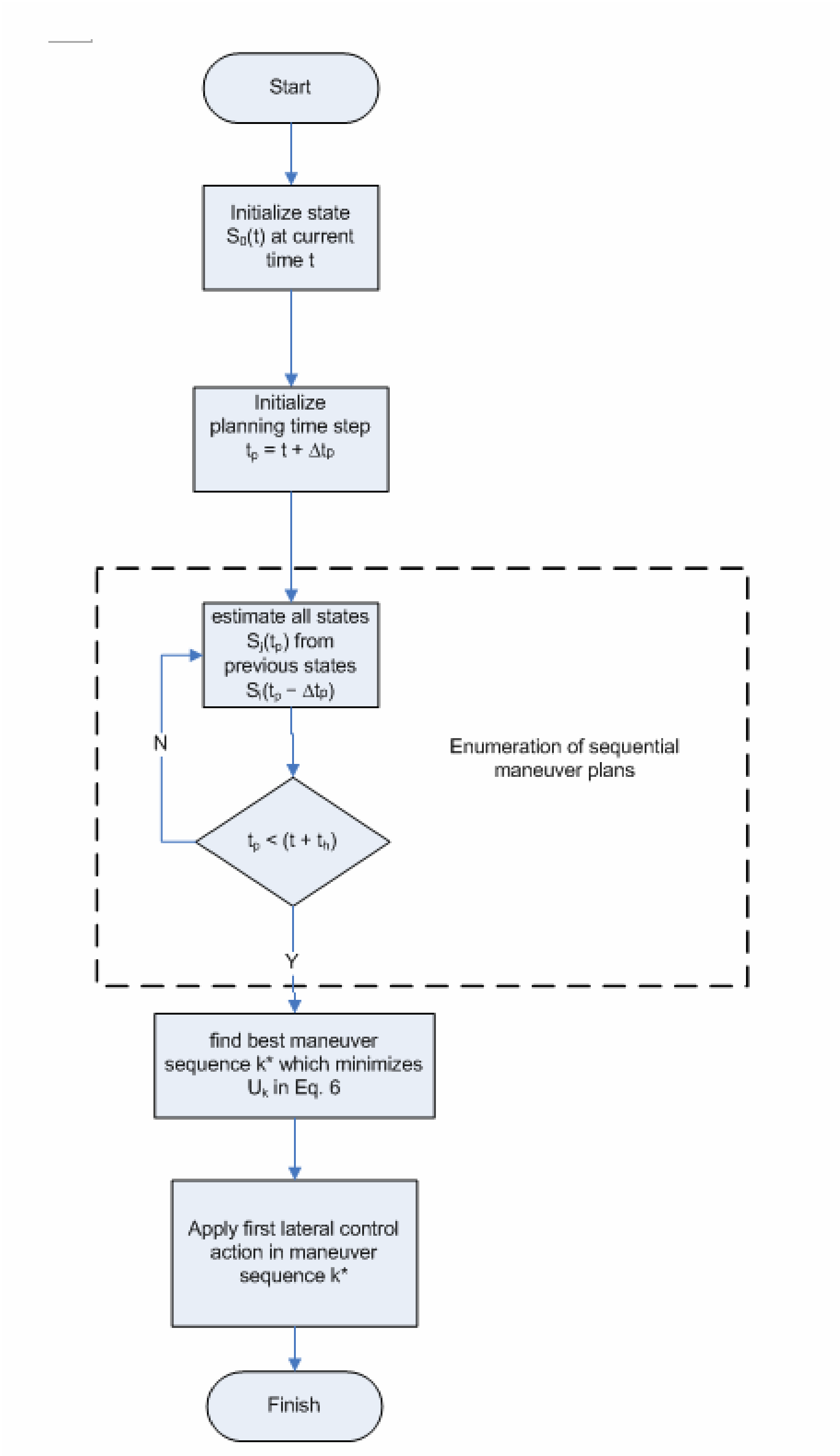


Figure 5. 2: Tactical lane change model using Forward Search Tree.

5.3 Action Selection

The subject vehicle selects the maneuver sequence from the collection of maneuver sequences enumerated in the Forward Search Tree as described above. To select which action to perform at the current time, each maneuver sequence is evaluated in terms of its utility based on one or more performance measures. In the current version of the proposed model, only one performance measure is used: the distance gained over the search horizon. Thus the model can represent discretionary lane changes only, but not mandatory lane changes.

In the existing prototype model, the best maneuver sequence k^* is selected as that which maximizes U_k over all enumerated maneuver sequences:

$$U_k = d_x\left(S_k(t+t_h), S_0(t)\right) \tag{2}$$

where:

U_k	=	The utility of maneuver sequence which results with state $S_k(t+t_h)$ at the time horizon
$S_0(t)$	=	The state at the present time, with the current longitudinal position of the subject vehicle
$S_k(t+t_h)$	=	The final state of maneuver sequence k, at the time horizon
$d_x(a,b)$	=	The difference in longitudinal position of the subject vehicle in states a and b. A large value will give better performance of the objective function.

Finally the lane change (or no lane change) action leading to the selected lane change sequence k^* is acted on for the current time step. In cases of equal value of U for several movement plans, the plan will be selected according to the *lane discipline* user setting. For example, if the lane discipline setting is set to “free lane” then the plan among the tied best-scoring plans which has an initial “no lane change” action would be selected.

In this way, the enumeration of all possible lane change actions until the search time horizon serves to increase the realism of the modeled lane change actions by taking into consideration the near-term consequences of the lane change action.

In the Figure 5.3, the subject vehicle generates four maneuver sequences in the Forward Search Tree, *{P1, P2, P3, P4}*. Over the time horizon, each plan allows a certain distance to be gained. Because the distance gained by plan *P4* is the longest, this plan gets the maximum (optimum) utility in the objective function and is selected as the best maneuver plan. It is shown in red in the figure. The current action in this plan is to make a left lane change, so that left lane change is selected as the lane change action which is the tactical lane change model's result.

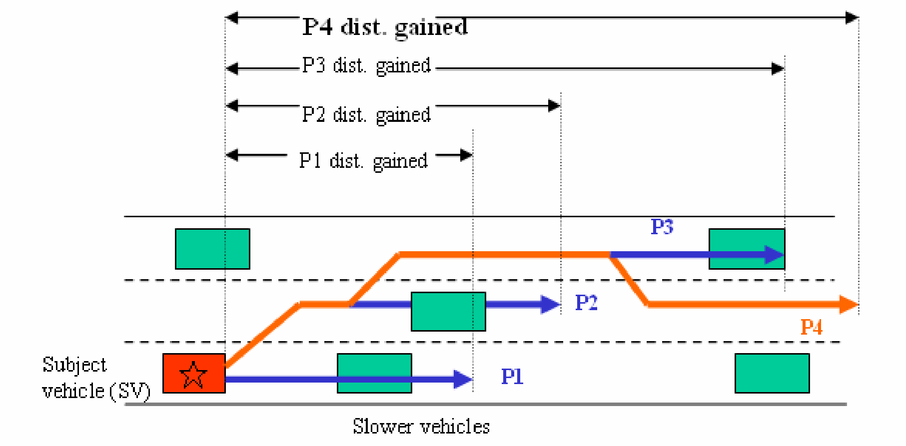


Figure 5. 3: Selection of lane change action, example

In later work to improve the performance of the model, other information can be added to the utility function, such as minimizing the number of lane changes or avoidance of delaying faster rear vehicles.

In the proposed model, the driver always chooses the alternative with the best utility, as a deterministic choice model. An improvement, which could be considered in further research, would be to represent the driver's control action as a stochastic choice, with probabilities according to the utility of each maneuver plan.

5.4 Feature Additions

The following subsections describe features which could be or have been considered for addition to the prototype sequential planning tactical lane change model to potentially improve its performance. The first feature: "lane change penalty" has been implemented in the prototype. The remaining ones are being left for later work. The table below shows a summary of each feature and the component of the model (enumeration or objective function) in which it plays a part. Also, for each feature added, in order to allow a fair comparison to the basic lane change model, it must be considered whether a corresponding enhancement should also be added to the basic lane change model as well. Table 5.1 shows the feature additions considered or recommended for consideration, and the necessary changes to the basic and sequential planning models.

Table 5. 1: **Model changes necessary for feature additions**

Feature addition	**Change to basic lane change model**	**Component which requires a change**
Lane change penalty	None	Objective function
Avoid delaying a faster rear vehicle	None	Objective function
Add longitudinal control decisions to tactical model	None	Enumeration
Accept risky short-term situations	None	Enumeration and Objective function
Mandatory lane changes	Mandatory lane change rules	Enumeration or Objective function
Cooperative lane changes	None	Both Enumeration and Objective function

5.4.1 Lane Change Penalty

This is an additional feature which has been added to the tactical lane change model. For a given sequential maneuver plan *k*, which has been enumerated in the forward search tree, the utility function takes into account not only the distance gained by the maneuver, but also the number of lane changes in the maneuver. It is thought that a maneuver with many lane changes is less desirable than a maneuver with fewer lane changes. The following model is proposed:

$$U_k = d_x\left(S_k(t+t_h), S_0(t)\right) - 10^{c_l} n_{LC}(k) \tag{3}$$

where:

$n_{LC}(k)$	=	Number of lane changes that would be made by the subject vehicle over the maneuver sequence k
c_l	=	Lane change penalty weighting coefficient

A driver is thought to have a unique value of c_l. A driver with no penalty would have a very low value (negative) for c_l . The objective function was designed with coefficient c_l in *base-10* form in order to facilitate the calibration parameter search process. In this way, the parameter can be searched over a set of values incremented on the normal scale, but exert a logarithmic effect on the calculated objective function value. For selected vehicles, the performance of this feature was evaluated as described in Section 6.6.6.

It is noted that this feature would also serve to prevent a maneuver plan which hops back and forth from being selected as the best plan.

5.4.2 Avoiding delay to faster rear vehicle

Consider the situation in which a subject vehicle is traveling slowly at its desired speed and is being followed closely by another vehicle. In the real-world traffic, the subject vehicle may have, to some degree, the tendency to desire to get out of the way of the faster vehicle or avoid being in such a situation. This could be represented in the sequential planning by penalizing the utility score of maneuver plans in which the subject vehicle is blocking a faster vehicle. An example is shown in Figure 5.4.

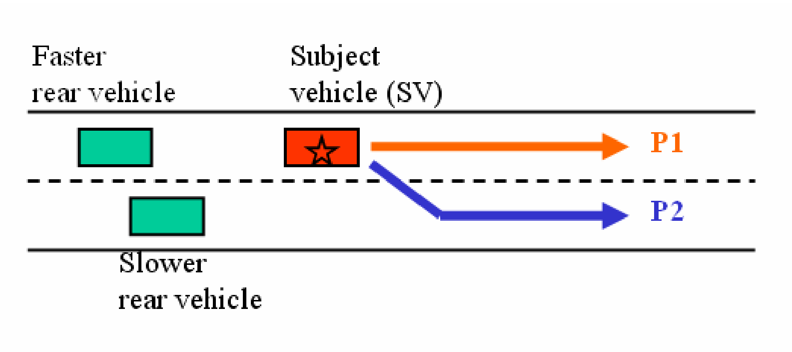


Figure 5. 4: Avoiding delay to faster rear vehicle, example

In this example, in which the right lane is considered as the travel lane, the subject vehicle has just overtaken the slower vehicle, and is being followed closely by a faster rear vehicle which has a greater desired speed. The subject vehicle has two possible maneuver plans: *P1* to stay in the overtaking lane, and *P2* to return to the travel lane. In terms of distance gained, both plans score the same. However, plan P1 would be penalized by an additional term which could be added to the objective function and is explained below:

$$U_k = \ldots + c_d delay(S_k) + \ldots$$

U_k	=	The utility of maneuver sequence k which begins at state $S(t)$ and ends at $S_k(t + t_h)$
c_d	=	Weighting coefficient
$delay\ (S_k)$	=	Delay index in maneuver sequence k

(defined below)

A coefficient c_d (negative), which is unique and can be best-fit estimated for each vehicle, controls the strength of the penalty to be applied. The penalty is in terms of a delay index as defined above. The conditions for the delay index to be realized are listed here:

$$delay(S_k) = \frac{\sum_{\forall i} \delta_i}{n}$$

i	=	Index number of planning time step t_p over the duration of the maneuver S_k in time steps of τ
n	=	Total number of planning time steps = $\frac{t_h}{\Delta t_p}$
δ_i	=	1 if the delay is judged (meeting all 3 conditions below), *0* otherwise

Condition 1: SV traveling at near desired speed:

$$\left| v - v_{des} \right| \le c_{d1}$$

Condition 2: Rear vehicle is following closely:

$$\frac{gap_{rear}}{v_{rear}} \le c_{d2}$$

Condition 3: Rear vehicle is closing in or else traveling at approximately the same speed as the subject vehicle:

$$v_{rear} \ge v - c_{d3}$$

c_{d1}, c_{d2}, c_{d3}	=	coefficients
v	=	Subject vehicle speed (m/s)
v_{des}	=	Subject vehicle desired speed (m/s)
v_{rear}	=	Rear vehicle speed (m/s)
gap_{rear}	=	Distance from subject vehicle's back bumper to the rear vehicle's front bumper (m)

With the above framework, it is thought that this driver behavior could be included in the model. Examination of this has been left for further research.

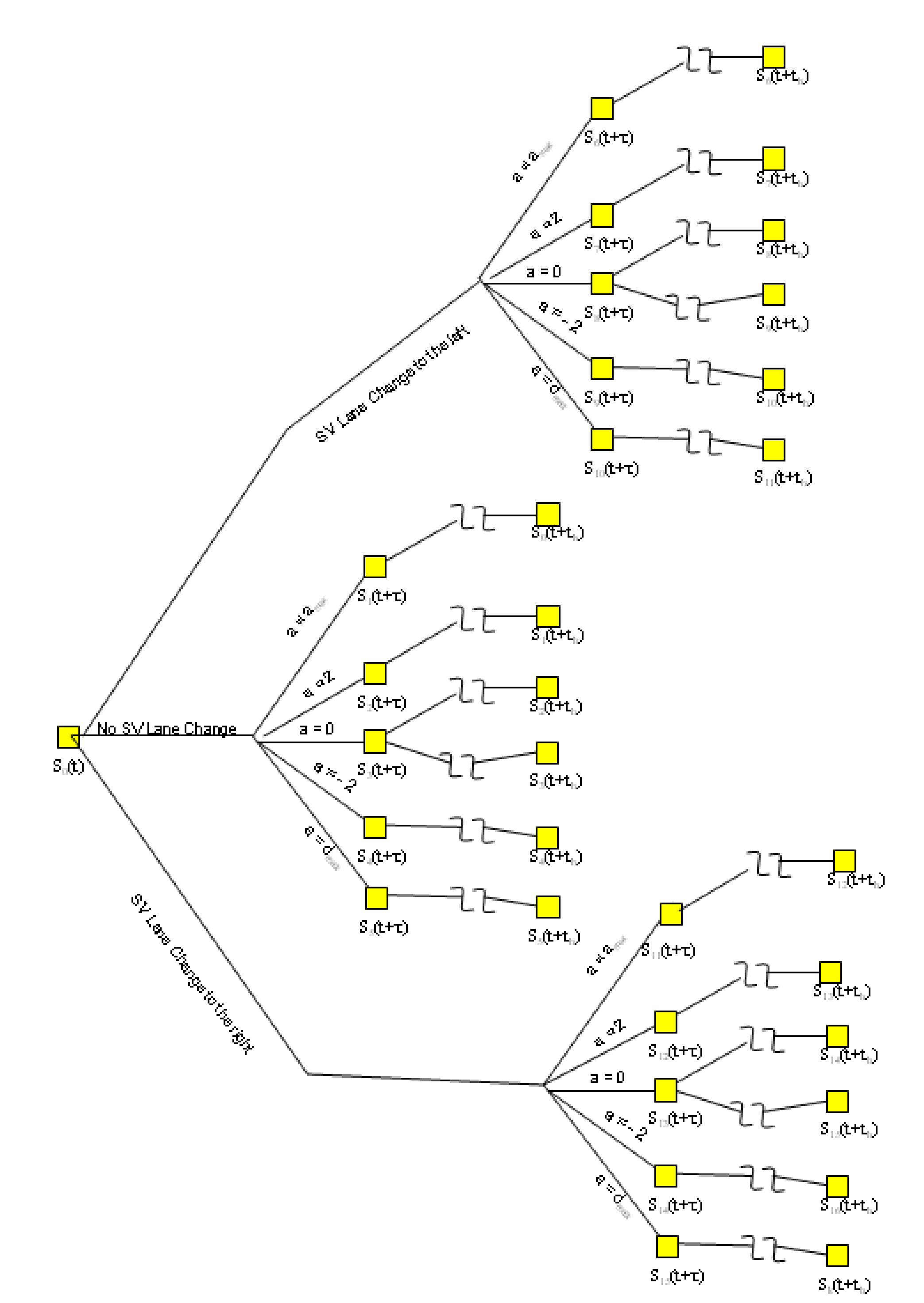


Figure 5. 5: **Integrated enumeration of lane change and longitudinal control planning maneuvers**

5.4.3 Longitudinal control planning

In this feature, the control options available to the subject vehicle at each planning time step are expanded to include a set of target velocity control actions within the allowable accelerations and decelerations according to vehicle performance limits. The enumeration is shown conceptually in the Figure 5.5.

To implement this feature, the choices of longitudinal acceleration or deceleration action, which are continuous, are made discrete. Although the computation time would be costly due to the large number of sequences, this feature would allow a richer representation of the subject vehicle's maneuvering, including the ability to slow down or speed up in order to merge into a gap in an adjacent lane that is not directly alongside.

It is recognized that this capability would greatly add to the realism of the modeled tactical behavior. Further, this functionality has been implemented in Toledo (2003) albeit without sequential planning of multiple lane change maneuvers. Such a development has been left out of this work due to the above-mentioned computational costs, further complexity of implementation of the algorithm in the software, and design issues involving the discretization of the longitudinal control action. Regarding the computational time costs, two approaches are probably necessary to bring about this feature: (1) reducing the computational demand through heuristics such as *tree pruning*, or (2) increasing the computational capacity through the use of distributed computing over a network of PCs (e.g. cluster computing, grid computing, etc.), or the use of a powerful mainframe computer. Being out of the scope of the work of this PhD, this feature has been left for further works.

5.4.4 Accepting risky short-term situations

In this feature, during the enumeration phase, the subject vehicle is allowed to accept any gap which is physically available, that is any gap which the space allows, even if it is very small, and dangerous. In order to allow evaluation of a greater range of lane change initiation times, the "first gap opportunity" enumeration restriction is waived (however, the "no reversal" restriction remains). Figure 5.6 can be considered.

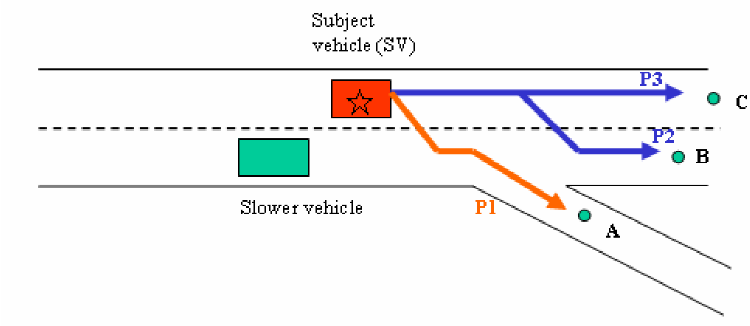


Figure 5. 6: Accepting risky short-term situations, example

In the example, which assumes that mandatory lane changes have been implemented, the subject vehicle has the off-ramp as its destination. In order to reach the off-ramp, a lane change must be made at the present time, although it is somewhat dangerous because of the slower rear vehicle. Although unsafe, such aggressive driving behavior is often seen in the real world. In the driver's plan enumeration, plan *P1* allows reaching the destination lane, consequently avoiding a large score penalty, even though at the same time it incurs a *short-term risk penalty* (explained below). The other two plans, *P2* and *P3*, are inferior because they fail to reach the destination lane. The element added to the objective function is as follows, where a risk index is calculated and weighted according to a vehicle-specific coefficient c_r (negative):

$$U_k = \ldots + c_r risk(S_k) + \ldots$$

$$risk(S_k) = \frac{\sum_{\forall i} r_i}{n}$$

i	=	Index number of planning time step t_p over the duration of the maneuver S_k in time steps of τ
n	=	Total number of planning time steps = $\frac{t_h}{\Delta t_p}$
r_i	=	For planning time step i, 1 if the SV is in a situation in which either the lead or rear gaps in same lane are less than $F\, d_{crit}$, where F is the SV's unique value and d_{crit} is the Gipps safe following distance

$$d_{crit} = \frac{v_L^2 - v_F^2 + 3v_F b\tau}{2b}$$

5.4.5 Modeling mandatory lane changes

A mandatory lane change (MLC) is illustrated in Figure 5.7:

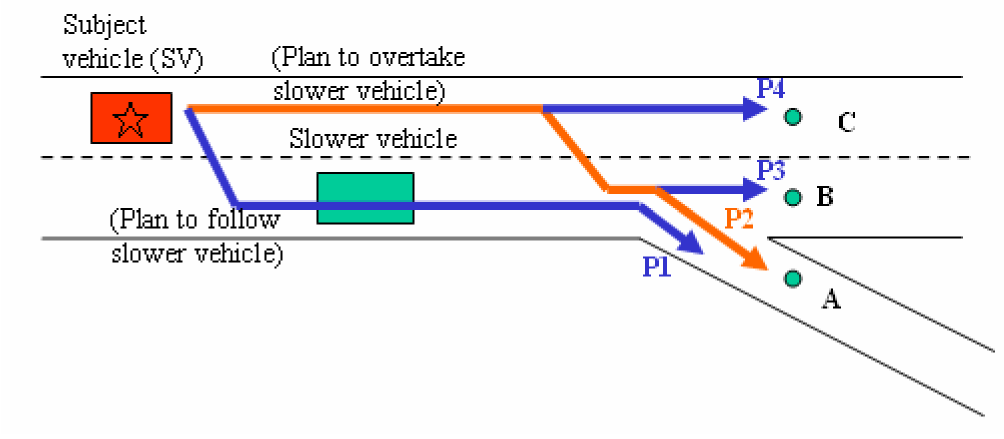


Figure 5. 7: Modeling mandatory lane changes, example

The subject vehicle (SV) in this situation is planning the maneuver sequences until the time horizon, *{P1,P2,P3,P4}*, which lead to end points *{A,B,C}*. He must decide whether (plans *{P2,P3,P4}*) or not (plan *P1*) to overtake the slower vehicle. He makes a prediction about the state of his vehicle and the nearby vehicles for each alternative. In addition to the distance ahead, he must consider whether the desired lane has been reached at the end of the maneuver plan. With the already known information about the SV destination as the off-ramp, the subject vehicle's lane at the time horizon can be added to the objective function. Specifically, the following utility function can be used:

$$U_k = d_x(S_k(t+t_h), S_0(t)) + \ldots + k_{MLC}\delta_k(t+t_h) \qquad (2)$$

where:

k_{MLC}	=	Coefficient for the importance of the mandatory lane change. Takes a negative value.
$\delta_k(t+t_h)$	=	*0* if the subject vehicle's lane at the time horizon is the same as destination lane, *1* otherwise

In the example, $\delta_k(t+t_h)$ would be *0* for plan *P1*, and *1* for the other plans. The total distance gained is greater in plan *P2* than plan *P1*, because in plan *P1* the subject vehicle was forced to travel behind the slow vehicle. Therefore, plan *P2* is shown highlighted in red as the optimum (maximum) of the objective function (2).

The value of the coefficient k_{MLC} (negative) could be specified for the individual vehicle. If relatively smaller values of k_{MLC} were used, in the simulation the subject vehicle would have a greater likelihood of selecting a maneuver plan which does not result in the destination lane, and this is unlikely to occur because motorists have a strong imperative to reach their destination. Therefore it is expected that the value of the k_{MLC} coefficient will be very high relative to other coefficients in the maneuver plan selection utility function.

An alternative approach in implementing this feature would be to consider the mandatory lane change as a constraint in the Forward Search Tree enumeration phase. The subject vehicle would consider only the maneuver plans going the desired direction past the diverge point. In Figure 5.7, only plans {P1,P2} would be enumerated. With this approach, the possibility in the traffic simulator (as well as in real traffic) of the subject vehicle being caught in a situation of *not being able to reach* his desired destination past the diverge must be dealt with somehow.

To include MLCs in a model, it is required to know the downstream destination of the subject vehicle. For present-day video trajectory data sets, such as the data set examined later in this dissertation, this is somewhat problematic, because, although the first downstream off-ramp is contained within the view area of the cameras, ramps further downstream are out of the view area. Therefore the destination lane information is not readily available.

Another possible limitation in representing MLCs is the observation that drivers try to position themselves on or nearby the destination lane a long time in advance, much longer than the scope of the planning for the proposed tactical model, which is at most *10* seconds. Because of the errors and uncertainty in predicting the states of the subject and surrounding vehicles, longer predictions are unrealistic. To account for this pre-positioning driver behavior, it is recommended that empirically derived heuristic utility values for each lane and longitudinal position be developed. Specifically, far upstream from the off-ramp, the difference in the utility between lanes should be negligible; while closer to the off-ramp the difference in lane utility should become very large.

Because of the complexity of formulating a such as the lane utility model, as well as the unknowns information about the vehicle destinations at further downstream off-ramps in the data set considered in this dissertation, inclusion of MLC has been left for further works. For the analyzed vehicles in the performance comparison, the vehicles were all selected from those which left the video monitoring area on the mainline.

5.4.6 Modeling cooperative lane changes

The *cooperative lane change* is the case in which one vehicle will decelerate to allow a larger gap ahead to accommodate a lane changing vehicle. In an example shown in Figure 5.8, the Subject Vehicle slows down to give a larger gap to Vehicle A which is making a left lane change. In the example it is a MLC due to the merge ramp, such cooperative behavior is not limited to MLC, and can occur on mainline sections as well as entry or exit ramps.

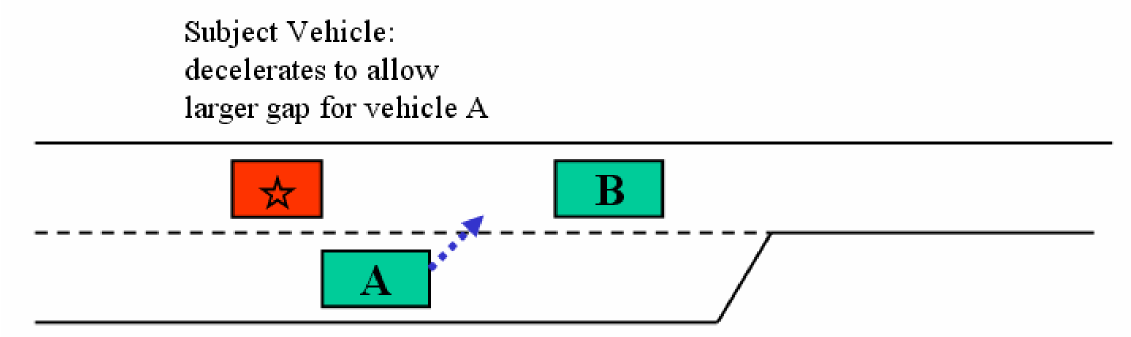


Figure 5. 8: Modeling cooperative lane changes, example

Previous approaches in which the mutual behavior of the *giving-way vehicle* and the *gap-taking vehicle* are determined have been described in Hidas (2002, 2005) and Kita (2002). An alternative approach is proposed here in which the giving-way vehicle anticipates the lane change maneuver of the gap-taking vehicle. The following are the necessary modifications for implementation.

First, a utility for each of the surrounding vehicles (NSV Utility) should be added to the maneuver plan selection objective function (Eq. 1), such as distance gained. The relative weight of the NSV and SV Utilities could be specified in terms of a driver-vehicle specific *cooperativeness* parameter. Second, in the maneuver plan enumeration, the potential lane change actions of surrounding vehicles should be included, along with a model of the likelihood of the various actions as anticipated by the SV. Third, the longitudinal control actions by the SV should also be included in the maneuver plan enumerations. As a further research topic, the tradeoff of realism gains from expanding the maneuver plan enumerations to the computational cost should be kept in mind.

An example of cooperative behavior has been found in a real vehicle trajectory data set (Cambridge Systematics 2004). The situation is shown in Figure 5.9.

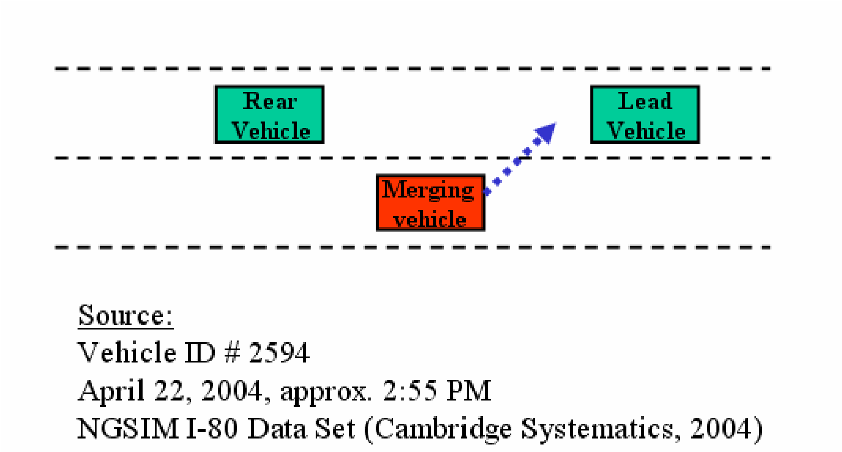


Figure 5. 9: Cooperative lane changes, example from real data: configuration

In this example, the merging vehicle pulls up along the gap. The rear vehicle then begins to show cooperative behavior by slowing down to allow a larger gap with the lead vehicle. This allows the merging vehicle to more easily and safely merge into the gap. The slowing down of the rear vehicle has been recorded in the trajectory data and is shown in Figure 5.10. The time of the merge is *1218.667 s* after the beginning of the trajectory data set recording, shown by a vertical line. It can be seen that approximately *2* seconds prior to the merge, the rear vehicle begins to fall back to allow bigger lead gaps with the merging and lead vehicles.

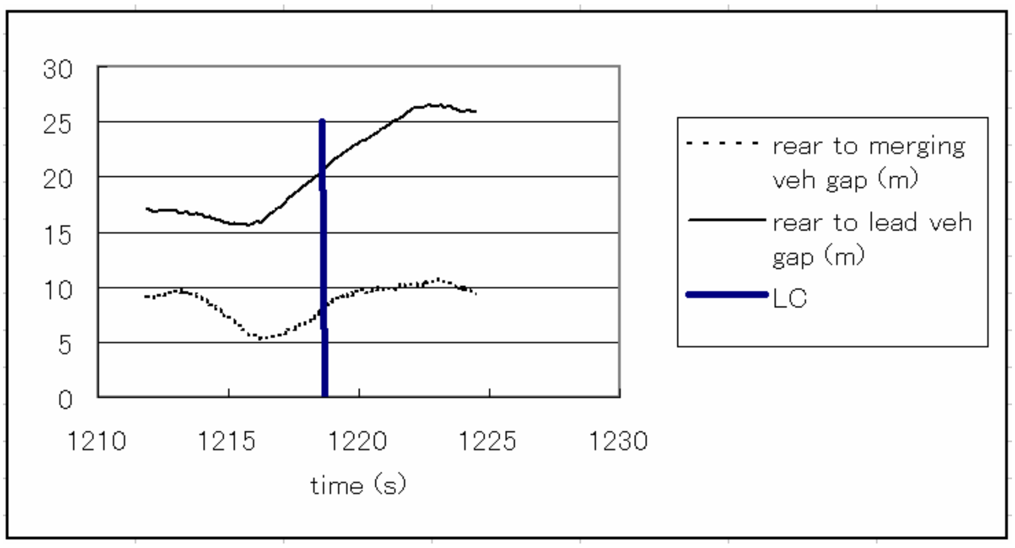


Figure 5. 10: Cooperative lane changes, example from real data: gap sizes

5._ Summary

The sequential planning model addresses limitations of the driver behavior models used in existing simulators: the ability to consider the motion of the surrounding vehicles rather than only their current state, the ability to make a maneuver which leads to a longer-term gain when there is no evident short-term advantage, such as weaving across several crowded lanes of traffic to a less-crowded lane. The algorithm for enumeration, envisioned as as the enumeration of branches Forward Search Tree, which represent sequential maneuver plans by the subject over the planning horizon, predicting the motions and future state of the subject and surrounding vehicles for each given sequential plan. From the enumerated maneuver plans, the best is selected as that which gets the subject vehicle the furthest ahead on the road. Approaches for implementation of model features including mandatory lane change modeling, integration with longitudinal control planning, and others which have not been implemented in this work, are proposed.

In the next chapter, the tactical lane change model is estimated for selected vehicles in a real trajectory data set, and its performance in comparison to the basic lane change model is evaluated.

6. VERIFICATION AND PERFORMANCE COMPARISON

This chapter includes a verification of the model's basic functions to represent driver behavior as part of a traffic simulator. The trajectory data set and selection of vehicles for analysis are described. The procedure for best fit parameter estimation for the longitudinal control and lane change models is described. The performance of the tactical lane change model is compared with that of a status quo basic lane change model, which does not include sequential planning and anticipation. Finally, an experiment about the complexity of simulating multiple vehicles with the proposed model is described.

6.1 Model Verification

The verification is performed to determine the degree to which a simulator using the proposed lane changing driver behavior model can replicate the real system. This is done by comparing the closeness of selected quantitative or qualitative measures of performance (for example, similarity of macroscopic flow-speed relations with theoretical ones) from the simulated and real systems. This section describes the tests to verify that the proposed tactical lane change model can function adequately to represent basic driver behavior as well as the emergent macroscopic traffic flow relations.

6.1.1 Verification of Longitudinal Driver Behavior

Various tests on the car following model used in the simulator were performed, and are explained in this section. The model uses the Gipps car following model, which is described in a previous chapter of this dissertation. The following tests were performed:

- Transition from car following into free drive conditions
- Transition from free drive to car following conditions
- Longitudinal car following stability

(1) Transition from car following to free drive

In this test, a hypothetical lead and following vehicle pair are simulated. Initially the lead vehicle is traveling at a constant speed which is much slower than the following vehicle's desired speed, as shown in Figure 6.1. The following vehicle is initially traveling at the same speed as the lead vehicle and positioned at a following distance which is exactly equal to safe following speed as determined by the Gipps car following model (see Chapter 4 of this dissertation).

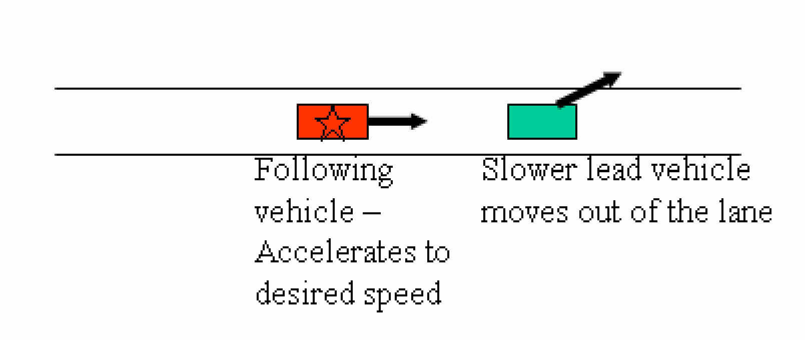


Figure 6. 1: Transition from car following to free drive: test scenario

Next, the lead vehicle is removed from the simulation system, as if it has made a lane change. The trajectory of the following vehicle in the simulator is then checked for its realism. In a real system it is expected that the following vehicle will transition from the car following to the free driving mode. The test is to observe if the simulated system will replicate this behavior.

Table 6.1 shows the values used in the simulation test case:

Table 6. 1: Parameter values in test of transition to free drive

Parameter	**Value**
Initial speed of both vehicles	15 m/s (54 km/h)
Initial following distance (lead vehicle's front bumper to following vehicle's front bumper)	22.5 m
Reaction time lag τ	1 s
Maximum acceleration (both vehicles)	3.0 m/s^2
Maximum deceleration(both vehicles)	-4.6 m/s^2
Following vehicle's desired speed v_{des}	30 m/s
Time of lead vehicle removal	$t = 10.0\ s$
Simulation time length	30 s

The simulation results are shown in Figure 6.2, as the trajectories of the lead vehicle and following vehicles. The line shown in the key as "x_lv" is the lead vehicle, and the line "x_fv_sim" is the simulated following vehicle. The following vehicle is under control of the Gipps longitudinal control model.

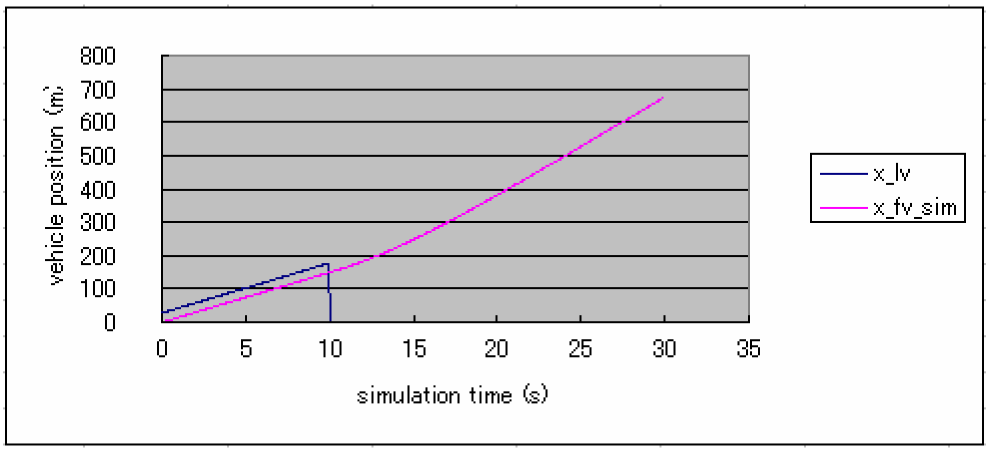


Figure 6. 2: Test of transition to free drive: vehicle positions

In Figure 6.3, the velocities of the two vehicles are shown. The line "v_lv" is the velocity of the lead vehicle. Even though the lead vehicle is removed from the simulation at $t = 10.0\ s$, it is shown as traveling at a constant speed until $t = 30.0\ s$ for ease of reference. The following vehicle speed is shown on the line "v_fv_sim". Soon after the lead vehicle is removed at $t = 10.0\ s$, the following vehicle's speed increases until it reaches the desired speed.

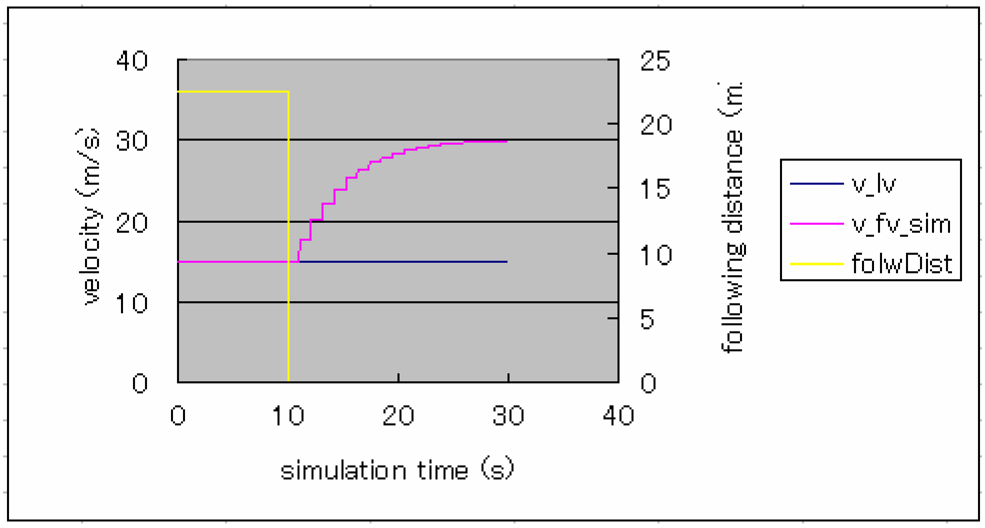


Figure 6. 3: Test of transition to free drive: speeds and following distance

Beginning at time $t = 11.0\ s$, 1 second after the change in the surrounding state, the following vehicle responds to the state at time $t = 10.0\ s$. This is the time when the change in the surrounding vehicle conditions is first recognized by the simulated driver. Between $t = 10.0\ s$ and $t = 11.0\ s$, the following vehicle has not yet recognized the change in the conditions, due to the reaction time lag. After $t = 11.0\ s$, the free drive equation in the Gipps car following model governs. The velocity increases step-wise at intervals. When examined over a time interval, the velocity can be seen to be consistent with the vehicle's acceleration limits. The following vehicle's speed under the car following and free driving regimes of the Gipps car following equation are seen to be continuous with a smooth transition, as would be expected in the real world. Therefore the result of this test is that the simulated behavior is consistent with real-world behavior.

(2) Transition from free drive to car following

In this test, the performance of the model in replicating real world driver behavior of closing in on a slower vehicle is considered. The following vehicle is initially traveling at its desired speed. The lead vehicle is traveling much slower at a constant speed and is initially far enough ahead to not influence the following vehicle, as shown in Figure 6.4.

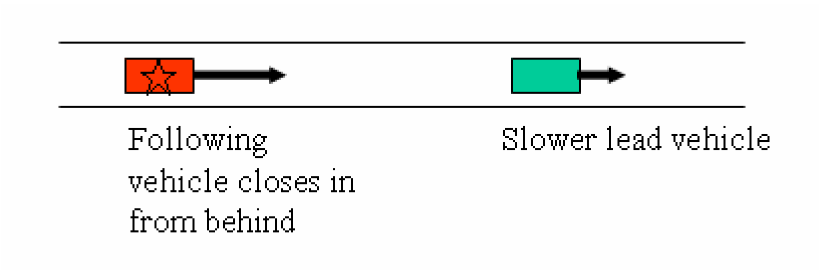


Figure 6. 4: Transition from free drive to car following: test scenario

In a real system, the following vehicle would begin to slow down as it approaches the lead vehicle, and converge to a safe following speed. The test is to observe if the simulated system will replicate this behavior.

In this test, the parameter values shown in Table 6.2 are used:

Table 6. 2: Parameter values in test of transition to car following

Parameter	Value
Following vehicle initial speed	30 m/s
Following vehicle desired speed	30 m/s
Lead vehicle travel speed (slow)	15 m/s
Initial following distance (front bumper to front bumper)	200 m
Reaction time lag τ	1 s
Maximum acceleration (both vehicles)	3.0 m/s^2
Maximum deceleration(both vehicles)	-4.6 m/s^2
Begin time of following vehicle longitudinal control by Gipps car following model	t = 3.0 s
Simulation time length	30 s

The result of the simulation is shown here. In Figure 6.5, the trajectories of the lead vehicle and simulated following vehicle are shown. The line "x_lv" represents the trajectory of the lead vehicle, and the line "x_fv_sim" represents the following vehicle's simulated trajectory. We can see that the expected closing-in converging behavior is observed.

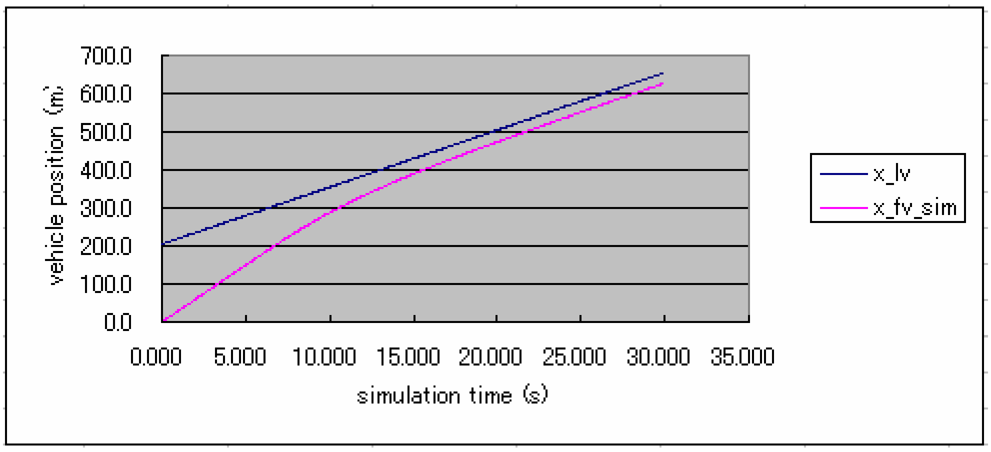


Figure 6. 5: Transition from free drive to car following: vehicle positions

Likewise, the speeds of the two vehicles, shown in Figure 6.6 as "v_lv" and "v_fv_sim" as the lead and following vehicles' speeds respectively, are shown in Figure 6.6. The following vehicle speed remains at *30.0 m/s* until the time that it becomes close enough to be influenced by the lead vehicle. From then, the speed begins to drop and converges to the safe following speed by approximately $t = 25.0$ *s*. The closing in motion seems natural as expected, with a gradual decrease in the following distance until the Gipps safe following headway is achieved at around $t = 15.0\ s$.

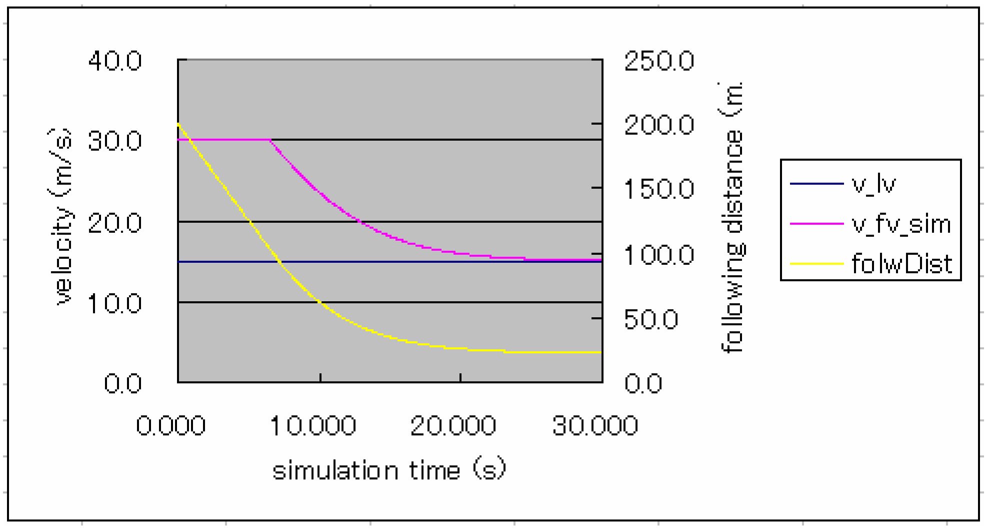


Figure 6. 6: Transition from free drive to car following: vehicle speeds and following distance

In the result of this test, the simulated behavior is qualitatively similar to that which is expected from the real system. Therefore this test is judged to be satisfactory.

(3) Serial car following stability

In this test the effect of the car following behavior is examined through successive vehicles. The lead vehicle of the platoon is subjected to a sawtooth-shaped oscillation, so that it start at an initial speed, and takes a cyclical acceleration as shown in Figure 6.7. The size of the platoon is *10* vehicles and they are traveling on a one-lane section. The acceleration and deceleration are the same, and a cycle length of *T* is used.

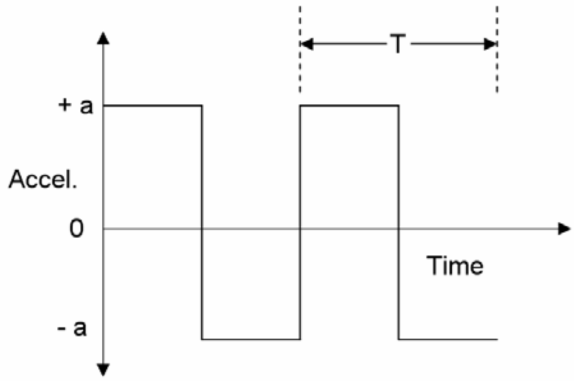


Figure 6. 7: Test of car following serial stability: acceleration driver

In this test the car following behavior is checked for stability over the *10*-vehicle platoon over a range of cycle conditions, without collisions. I tested the following combinations: *{T = 10 s, a = 5 m/s²}, {T = 5 s, a = 5 m/s²}, {T = 10 s, a = 3 m/s²}, {T = 5 s, a = 3 m/s²}*. In all the scenarios tested, no collisions occurred, although there were sudden stops. As an example, Figure 6.8 shows the time space trajectories of the platoon vehicles for the case of $T = 10\ s$, and $a = 3.0\ m/s^2$.

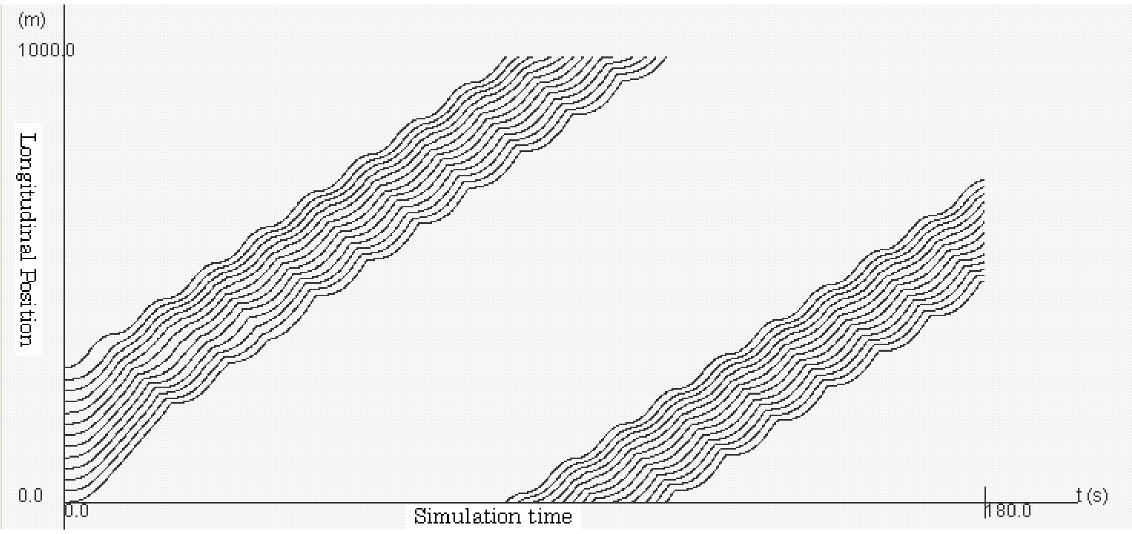


Figure 6. 8: **Test of car following serial stability: simulated trajectories**

6.1.2 Verification of Macroscopic Traffic Performance

The ability of the model to represent the traffic situations in a macroscopic context has also been considered. In this test, the traffic flow relations (flow *q*, speed *u*, density *k*) of the proposed model are checked for agreement with the relations observed in real traffic. In Hall (2002) and Cambridge Systematics (2004), techniques for estimation of macroscopic traffic measures are described. The techniques can be used for both real and simulated vehicle trajectory data. Because complete trajectory data are available for all vehicles, rather than using point-based measures, space-based measures are made directly. Consider the section shown in Figure 6.9:

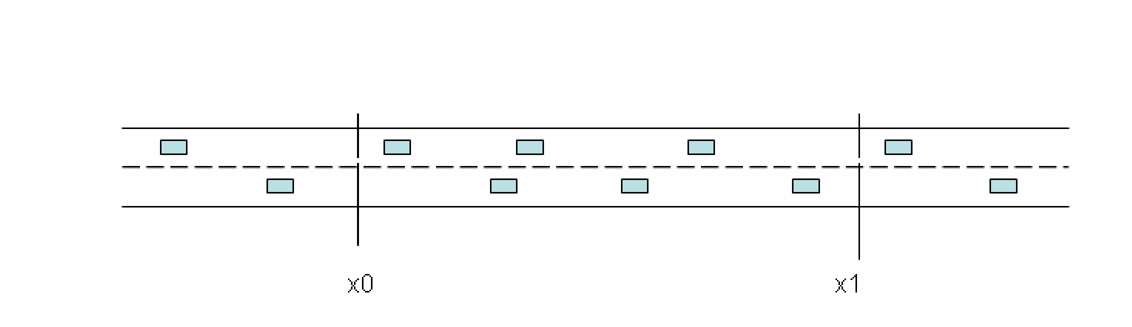


Figure 6. 9: Macroscopic performance data collection section

The traffic flow measures used are calculated as shown here:

$$q = \frac{0.5(N_0 + N_1)3600}{t_{agg} n_L}$$

q	=	Traffic flow rate (vehicles per hour)
N_0, N_1	=	Count of vehicles crossing sections 1 and 2, respectively, over the time aggregation interval t_{agg}
t_{agg}	=	Time aggregation interval (seconds)
n_L	=	Number of lanes

$$u = \frac{3600}{1000} \frac{\sum_i d(t,s)_i}{\sum_i tt(t,s)_i}$$

u	=	Space mean speed (km per hour)
$d(t,s)_i$	=	Distance traveled by vehicle i in section s during time period t
$tt(t,s)_i$	=	Travel time of vehicle i in section s during time period t

$$k(s) = \frac{1000 \Delta t \sum_t n(t,s)}{t_{agg} n_L L}$$

k	=	Traffic density (vehicles per lane-km) on section s
t	=	Time instant in the trajectory of simulation data
Δt	=	Time step size in trajectory data (s)
$n(t,s)$	=	Count of vehicles at time instant t over section s
n_L	=	Number of lanes
t_{agg}	=	Time aggregation interval (seconds)
L	=	Aggregation section length (meters)

In this test, a *2*-lane ring of length *1000* m is simulated starting with a small initial number of vehicles operating freely, and adding one vehicle every *15* seconds into the largest gap then existing on the ring. Each new vehicle is assigned a desired speed at random according to the normal distribution in Table 6.3. Gradually the flow increases from an empty road until it becomes a traffic jam. Macroscopic statistics are collected every time aggregation interval and q u k relations are checked, for various cases. By using a ring for this test, the impact of adding vehicles is minimized. (In comparison, a test of a straight section in which the traffic volume is added at the entrance, may artificially undergo a traffic breakdown at the entry point and capacity not be reached. In a straight section, the vehicles arriving can often interfere with each other, placed at small arrival headways they soon slow down and cause a bottleneck at the entry point. Although there is some interference in the ring setup because of the gradual addition of vehicles, this can be minimized by adding traffic very slowly.)

The parameters used for the simulated vehicles were as in Table 6.3. The *time search horizon* parameter was arbitrarily set at 4 seconds for all vehicles.

Table 6. 3: Macroscopic performance analysis: vehicle parameters

Parameter	**Value**
Reaction time lag τ (all vehicles)	1.0 s
Gap adjustment factor F (as described in section 4.3 of this dissertation) (all vehicles)	1.0
Time search horizon t_h (sequential planning lane change model only) (all vehicles)	4 s
Mean desired speed v_{des}	30.0 m/s (108.0 km/h)
s.d. desired speed v_{des}	2.5 m/s (9.0 km/h)
Vehicle maximum acceleration (all vehicles)	3.0 m/s^2
Vehicle maximum deceleration (all vehicles)	-4.6 m/s^2
Lane discipline (all vehicles)	Free lane choice
Vehicle length (all vehicles)	5 m

In the calculation of macroscopic traffic parameters, the values shown in Table 6.4 were used.

Table 6. 4: Macroscopic performance analysis: simulation parameters

Parameter	**Value**
Data collection section $[x_0,x_1]$	[500 m, 600 m]
Data collection section length $L = x_1 - x_0$	100 m
Time aggregation interval t_{agg}	30 s
Simulation time step size Δt	1/15 s
Number of lanes n_L	2

The traffic flow parameters were computed over both lanes. The values were computed for two cases:

1) using the basic lane change model

2) using the sequential planning lane change model

The resulting q u curves from the simulator are shown here. Figure 6.10 shows the simulated speed-flow curve using the basic and sequential planning lane change models. Generally both curves appear similar over their extent.

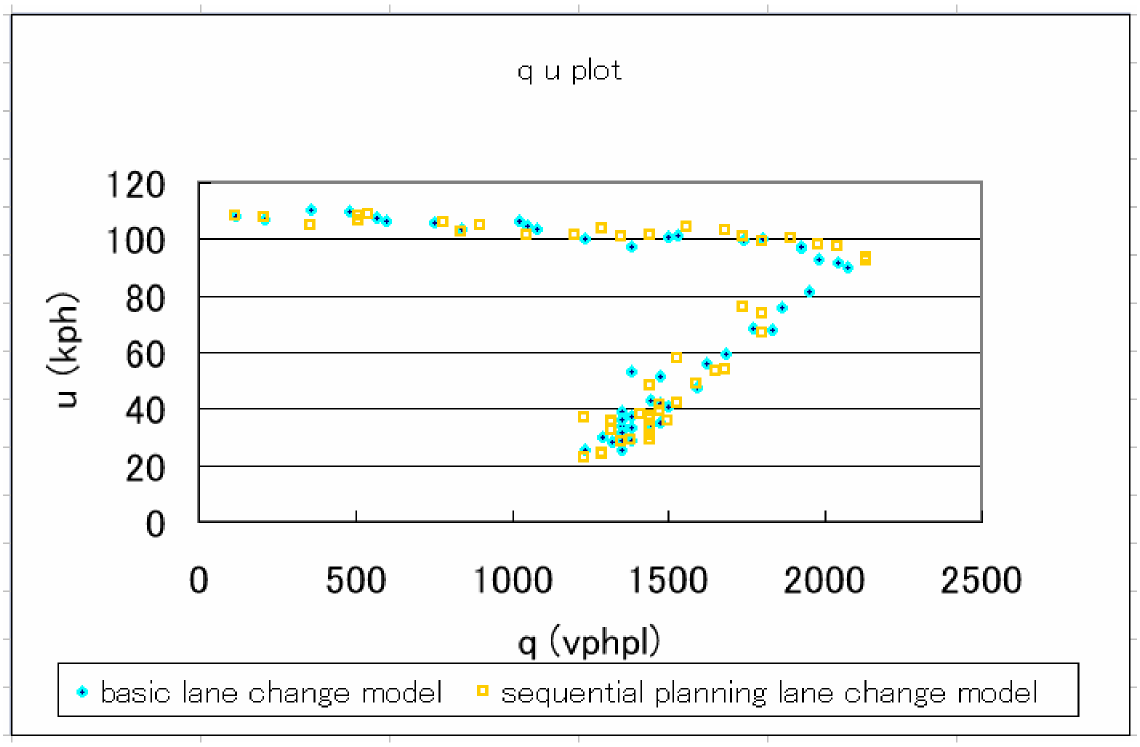


Figure 6. 10: Speed (u) vs. flow (q) plot: simulator with basic and sequential planning lane change models

The speed-flow curves found in the HCM [ref: Highway Capacity Manual] are excerpted in Figure 6.11. These are a generalization of empirical results from various studies of actual freeway traffic. Next, a theoretical curve summarizing the current understanding of the freeway traffic flow under the queue-discharge regime is shown. The characteristics can be seen to be similar by visual inspection of both the simulated speed-flow curves from the proposed model, and those in the HCM.

(1) the curve stays constant at the free-flow speed for low volumes until the volume reaches 1300 to 1750 vphpl (vehicles per hour per lane), after which it shows a slight downward curvature.

(2) the lower half of the capacity curve under queue-discharge conditions has the same general trend of decreasing speed as flow decreases

In summary, these plots can generally be seen to compare reasonably in shape to those in the HCM. Although out of the scope of this research, it is expected that an even greater degree of conformance could be achieved through parameter fine tuning.

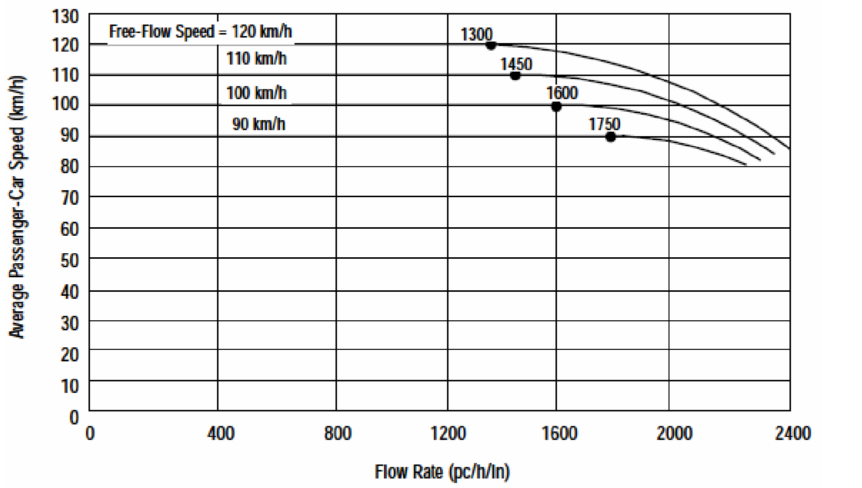
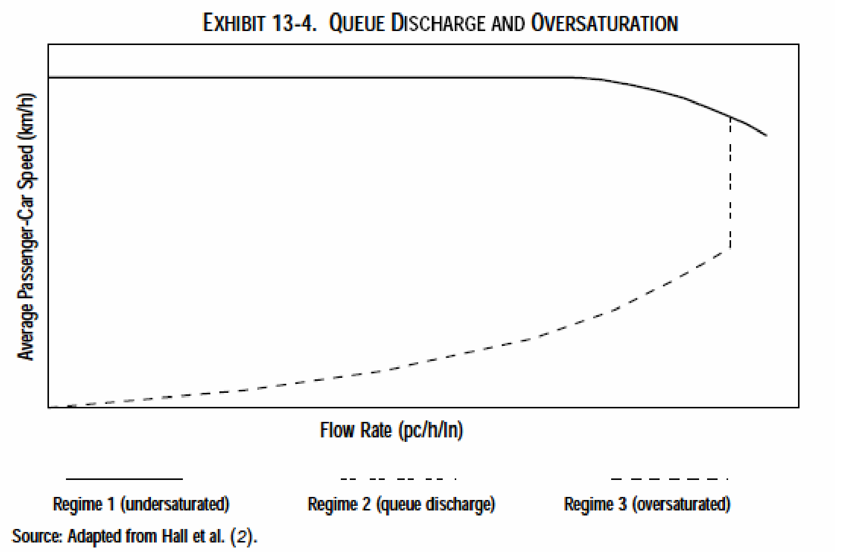
	(Taken from the Highway Capacity Manual 2000 ed.) p. 13-3, Exhibit 13-2. Speed-Flow relationships for basic freeway segments.
	(Taken from the Highway Capacity Manual 2000 ed.) p. 13-5, Exhibit 13-4. Queue discharge and oversaturation.)

Figure 6. 11: Speed-flow relationships from the Highway Capacity Manual

Therefore, regarding this test, the simulated system can be judged to have qualitatively similar performance to the real system, and the performance of this test is satisfactory.

Macroscopic Performance Sensitivity Analysis

A sensitivity analysis was conducted to find the effect of changing some of the simulation parameters on the macroscopic simulation results. The ring simulation was performed for the same conditions as above (base case 0), but the following parameters were changed as shown in Table 6.5 for the scenarios 1 through 7:

Table 6. 5: Sensitivity analysis scenario parameters

Scenario	τ **(s)**	***mean*** v_{des} **m/s (kph)**	***s.d.*** v_{des} **m/s (kph)**	F	t_h **(s)**
0	**1.0**	**30.0 (108.0)**	2.5 (9.0)	**1.0**	4.0
1	**0.5**	30.0 (108.0)	2.5 (9.0)	1.0	4.0
2	**1.5**	30.0 (108.0)	2.5 (9.0)	1.0	4.0
3	1.0	**35.0 (126.0)**	2.5 (9.0)	1.0	4.0
4	1.0	**25.0 (90.0)**	2.5 (9.0)	1.0	4.0
5	1.0	30.0 (108.0)	2.5 (9.0)	**0.5**	4.0
6	1.0	30.0 (108.0)	2.5 (9.0)	**1.5**	4.0
7	1.0	30.0 (108.0)	2.5 (9.0)	1.0	**2.0**

Because the purpose of this sensitivity analysis is to examine the sensitivity of the proposed sequential planning model, the simulations were performed using the sequential planning lane change model only and not the basic lane change model. In the base case scenario 0, both the sequential planning and basic model were simulated as described in the previous section.

In this analysis, the sensitivity to changes in each of the four parameters (τ, v_{des}, F, t_h) is considered. Figure 6.12 shows the macroscopic q,u curves of scenarios 0, 1 and 2. The influence of the τ parameter on the macroscopic performance of the simulator with the proposed sequential planning lane change model can be seen. The rightmost point on each curve can be considered as the capacity. As in many conventional traffic simulators, the value of τ is inversely related to the car following headway, which determines capacity (in vehicles per hour per lane). Specifically, doubling of the τ parameter would cut the capacity in half, and so on. The results of the investigation were as expected. Table 6.6 shows the capacity values found in the simulation results, which have good accordance with the expected inverse relationship with τ.

Table 6. 6: Simulation capacity values by reaction time lag parameter

τ (s)	Capacity (vphpl)
0.5	3900
1.0	2100
1.5	1500

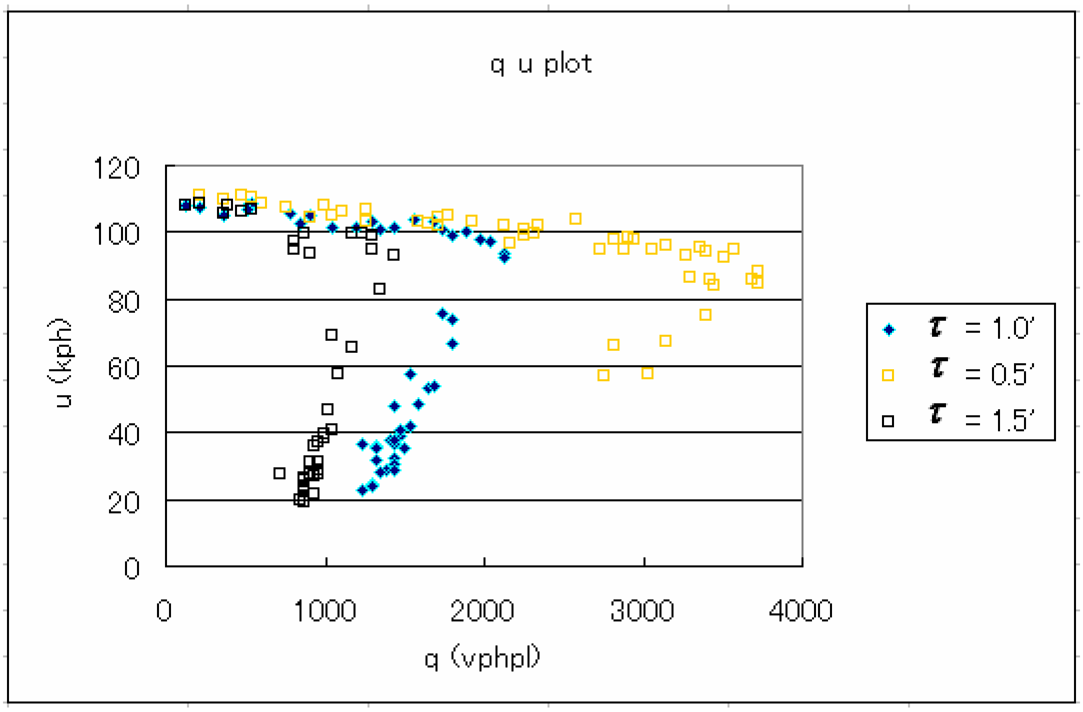


Figure 6. 12: Speed (u) - flow (q) curves by reaction time lag parameter

Figure 6.13 contains the plots of scenarios 0, 3, and 4. It shows the influence of changing the desired speed parameter v_{des},. The difference in the 3 macroscopic curves is seen in the free-flow portion of each, reflecting the free flow speed. The effect on the capacity (the rightmost extent of the q u curve) appears to be relatively small. This can be seen in Table 6.7 which shows the approximate values of the capacities found for each value of v_{des}:

Table 6. 7: Simulation capacity values by desired speed parameter

v_{des} *(m/s)*	Capacity (vphpl)
25 (90 kph)	2200
30 (108 kph)	2100
35 (126 kph)	2100

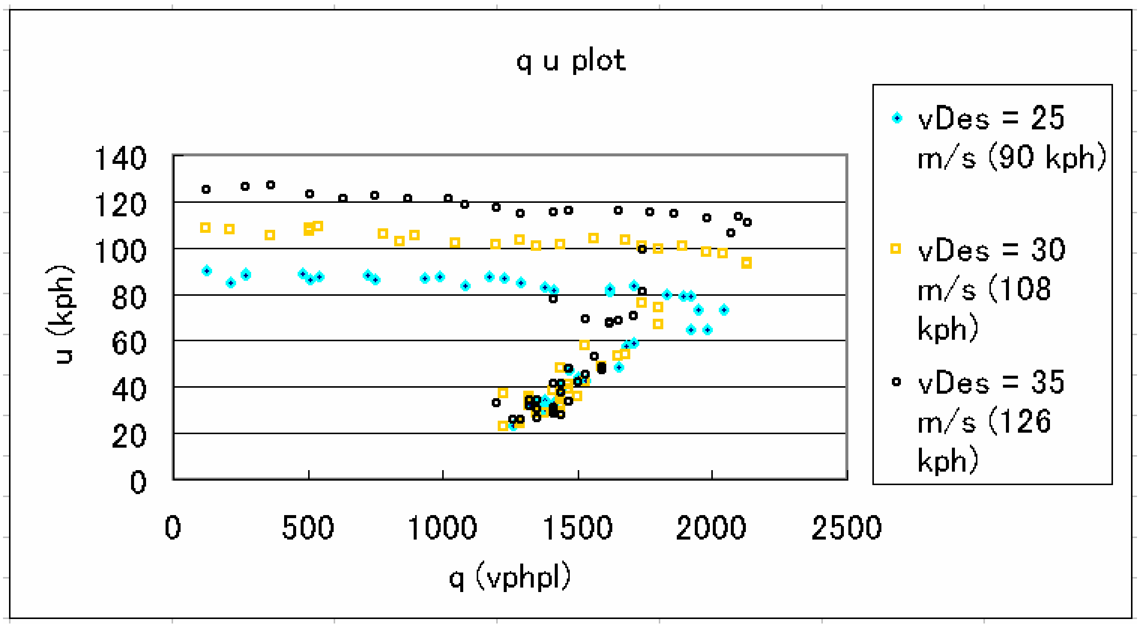


Figure 6. 13: Speed (u) - flow (q) curves by desired speed parameter

Also, the sensitivity to the gap acceptance parameter *F*, is considered. This time, the *q k* (speed vs. density) plot is shown in Figure 6.14, for simulations of scenarios 0, 5 and 6. There are several findings:

(1) In the congested queue-discharge portion of the curve (right-hand side), for a smaller *F* (*F = 0.5*), lower flow rates are achieved for a given density. Moreover, the breakdown of the traffic is much more abrupt than for the larger *F* parameter values. It is thought that the sudden breakdown for low *F* is caused during lane changes in which the subject vehicle accepts a small rear gap and thus forces the rear vehicle in the destination lane to suddenly brake, causing a backward propagating shockwave. For larger *F* values, the lane changing subject vehicle allows a larger gap to the rear vehicle and the shockwave is avoided.

(2) Capacity (as judged in terms of the upper-most extent of each *q k* curve) appears to be slightly lower for a smaller *F*. It is possible that the smaller *F* causes the breakdown conditions before the peak capacity is achieved, for the reasons given in (1) above.

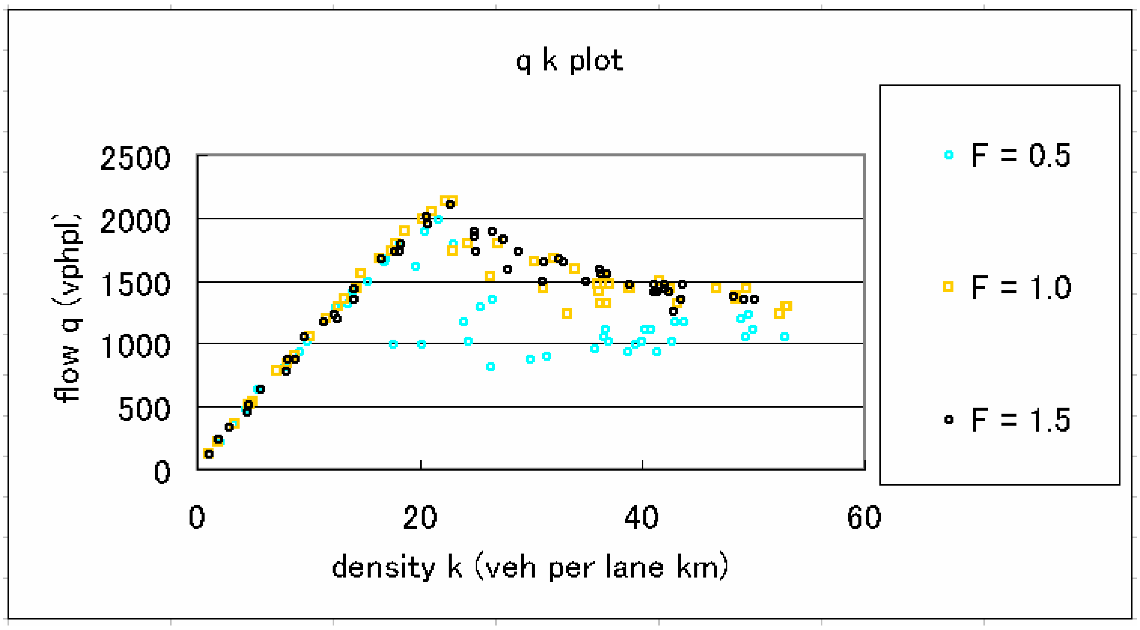


Figure 6. 14: Flow (*q*) vs. Density (*k*) curves by gap adjustment factor parameter

The difference in capacity and traffic flow performance using different *F* parameter values is confirmed by checking for differences in inter-vehicle interactions between the two scenarios. The individual trajectories on the left-most lane over the longitudinal position interval [500 m, 1000 m] in the simulated section are shown for the simulation time interval [600 s, 750 s] over which the maximum capacity was reached, and in the case of the $F = 0.5$ scenario, the severe breakdown in traffic flow occurred. Figure 6.15 shows the case of $F = 0.5$ and Figure 6.16 shows the case of $F = 1.5$. The difference can be seen. In $F = 0.5$, there is frequent occurrence of lane changing and shockwaves as the traffic flow quickly deteriorates into turbulent flow. In contrast, in the $F = 1.5$ scenario some shockwaves form as capacity is reached, and flow gently decreases as the shockwaves and stop-and-go traffic patterns continue to increase, but there is no breakdown into turbulent traffic flow.

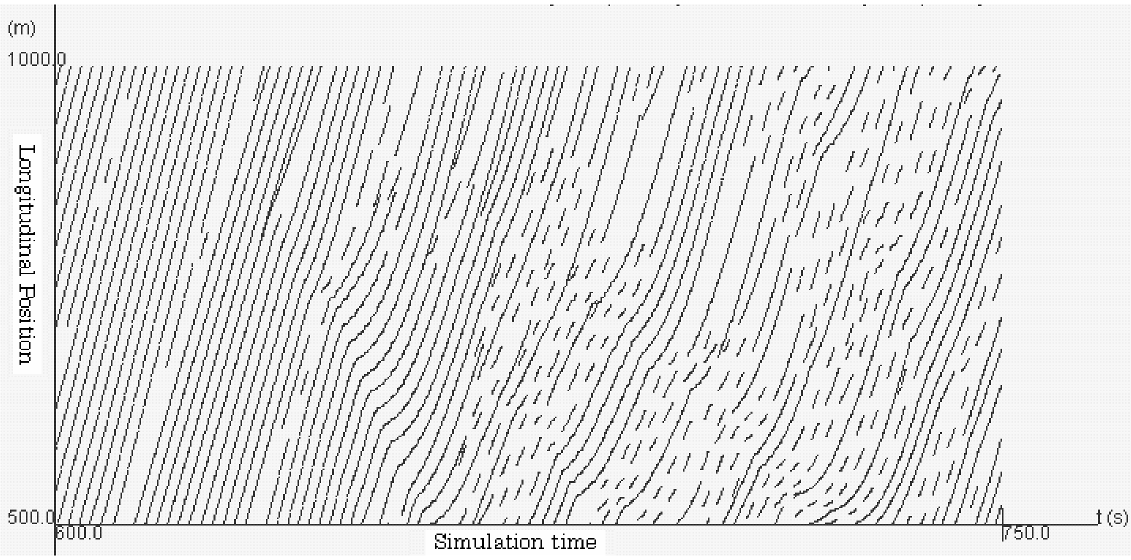


Figure 6. 15: Vehicle trajectories for small *F* parameter value (*F = 0.5*): breakdown into turbulent flow

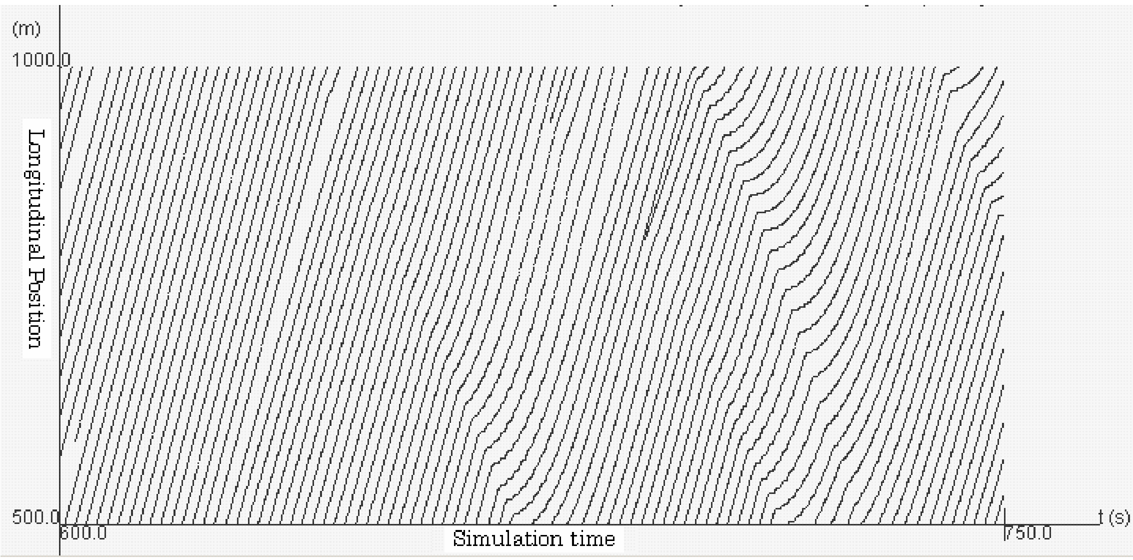


Figure 6. 16: Vehicle trajectories for large *F* parameter value (*F = 1.5*): gradual flow decrease with stop-and-go shockwaves

Finally, sensitivity to the planning time horizon parameter t_h is considered. A flow vs. speed plot is shown in Figure 6.17 for the sequential planning lane change model scenarios 0 and 7 as well as the basic lane change model scenario. The curves generally appear similar, thus there appears to be little or no sensitivity in the macroscopic traffic flow to the time horizon parameter over the ranges examined.

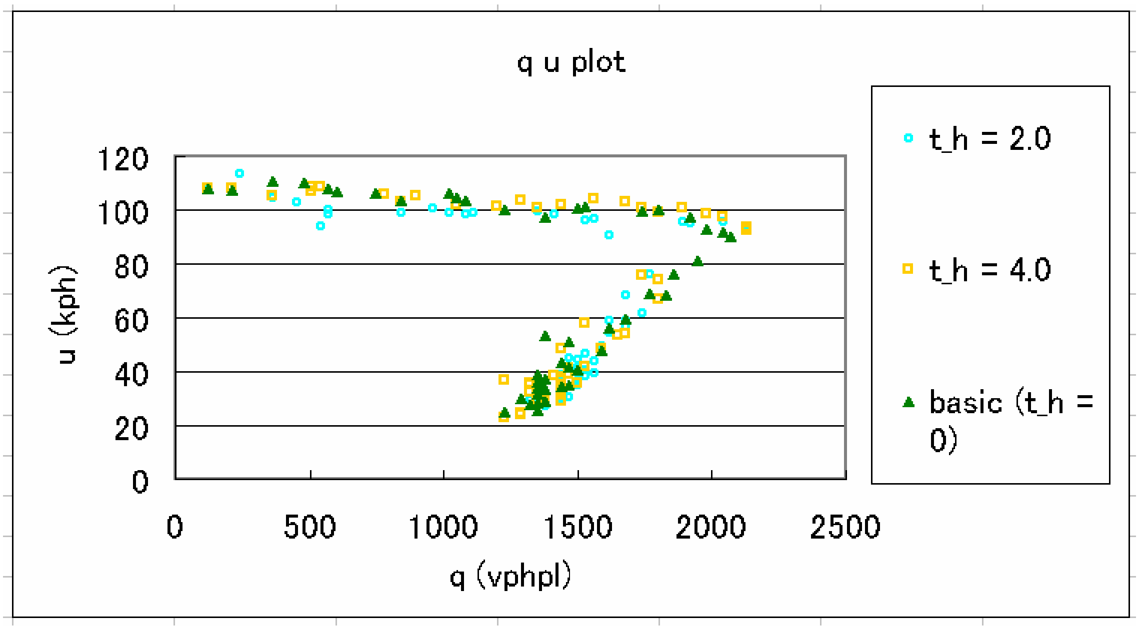


Figure 6. 17: Speed (u) - flow (q) curves by time horizon parameter

The lane change actions in either scenario differ only in a possibly small portion of the overall lane changes – those in which the subject vehicle is able to detect an advantage in a maneuver sequence with a different initial lane change action, which is only able to be seen by looking ahead to the longer time horizon. This is confirmed by checking for differences in inter-vehicle interactions between the $t_h=2.0$ and $t_h=4.0$ scenarios. The individual trajectories on the left-most lane in the over longitudinal position interval [500 m, 1000 m] in the simulated section are shown for the simulation time interval [600 s, 800 s] over which the maximum capacity was reached. There appears to be little difference in the simulated vehicle trajectories in either the $t_h=2.0$ and $t_h=4.0$ scenarios. Any difference in lane change behavior between the two scenarios is not large enough to exert a change in the macroscopic traffic flow patterns.

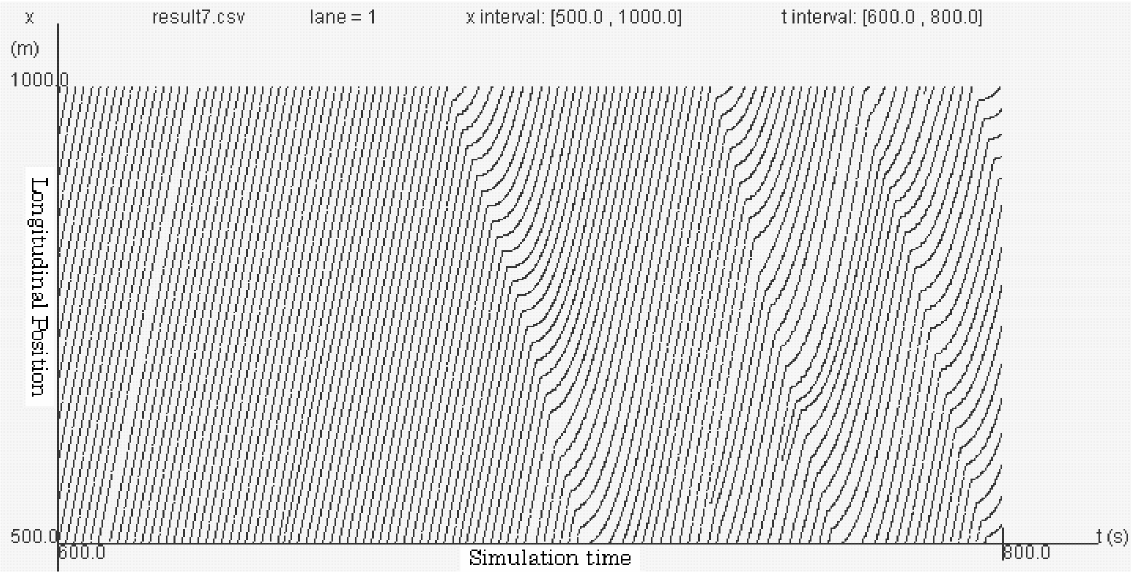


Figure 6. 18: **Vehicle trajectories for small t_h parameter value (t_h = *2.0)***

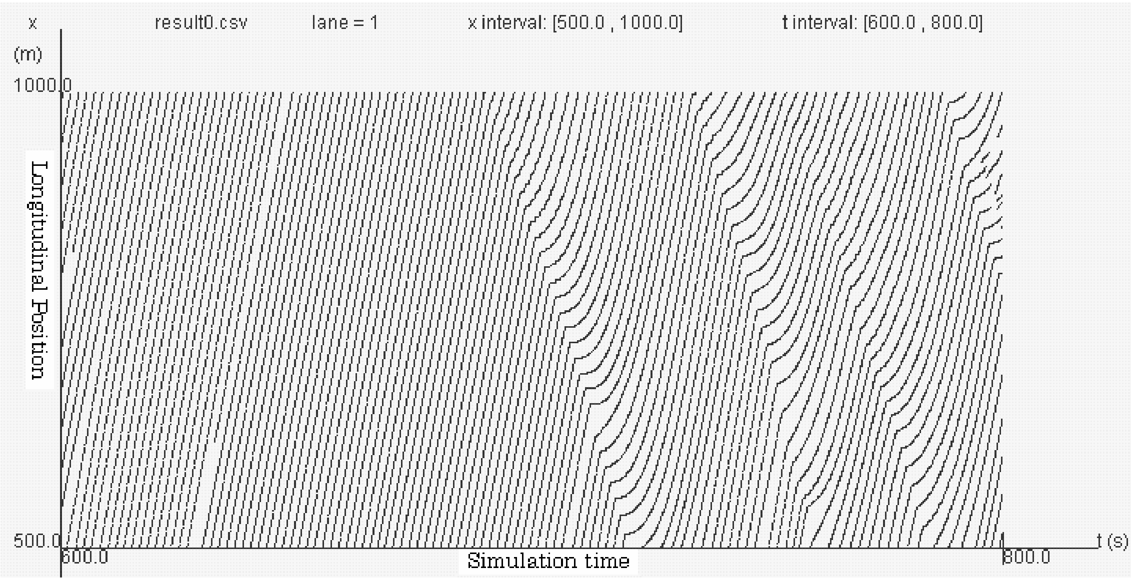


Figure 6. 19: **Vehicle trajectories for small t_h parameter value (t_h = *4.0)***

In conclusion, this section considered the sensitivity to the driver model parameters (τ, v_{des}, F, t_h) of the macroscopic flow relations to traffic simulated using the proposed sequential planning lane change model. The findings are generally as would be expected for a typical traffic simulator. A detailed consideration is beyond the scope of this thesis. Rather this section served to verify that the performance of the simulator was generally as expected through conventional traffic flow theory.

6.2 Description of data set

The NGSIM project (Cambridge Systematics, 2004) (Alexiadis et al, 2004) is a research project led by the US Department of Transportation to provide a core set of driver behavior data and algorithms for verification and validation purposes. Vehicle trajectory data from video image processing is provided free to the research user community. The data set consists of a *900 m* long *6*-lane section of the I-80 freeway in Oakland, California. The data set was collected from 2:35 to 3:05 p.m. on April 22, 2004. The traffic conditions range from moderate to congested flow conditions. The section contains an upstream single-lane entry ramp, and a downstream single-lane exit ramp. The data has a spatial resolution within *1.0* meters, and the time resolution is *1/15 s*. The time duration of the data set is approximately *30* minutes. This data set has been treated in detail by other researchers such as Ni and Leonard (2006). Vehicles to be used for the calibration were selected at random from the passenger cars or small trucks both beginning and ending on the mainline.

6.3 Selection of vehicles for analysis

A variety of driving maneuvers were found in the vehicle trajectory data set. Some vehicles made no lane changes, while a few made the maximum observed *6* lane changes. Figure 6.20 shows the frequency distribution of number of lane changes by vehicle in the trajectory data set.

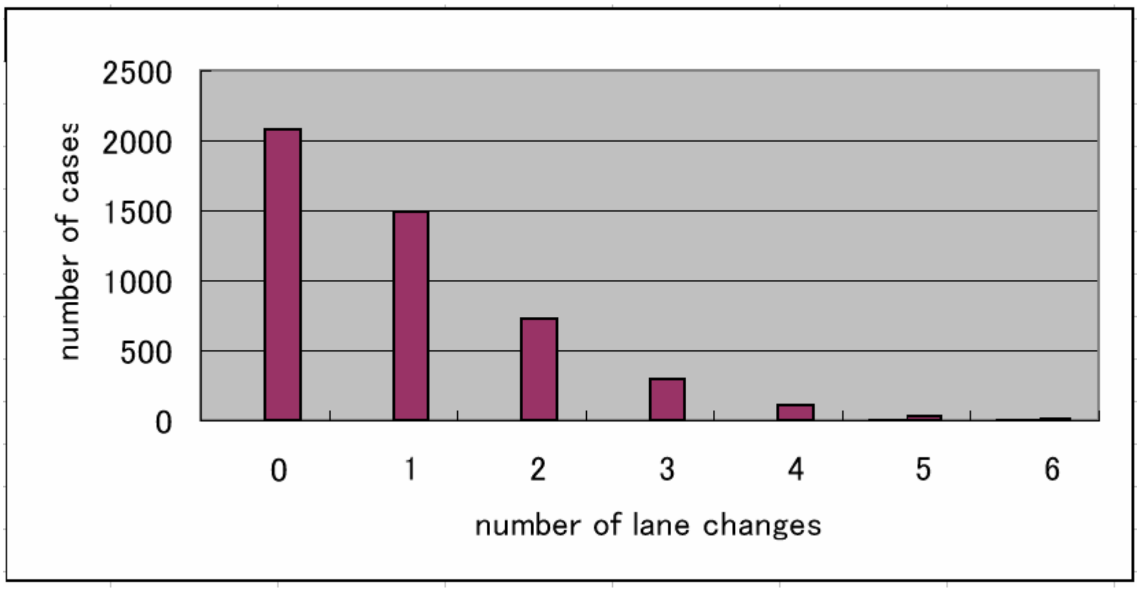


Figure 6. 20: **Frequency distribution of number of lane changes by vehicle in trajectory data set**

Not all vehicles in the trajectory show the tactical lane changing behavior which the proposed model has the potential to represent. For this dissertation, rather than show that the proposed lane change model outperforms the basic lane change model in the entire population of vehicles in the trajectory data, the comparison will be performed over a subset of the vehicle population which has the greater number of lane changes and relatively higher speeds, which will hereon be referred to as the aggressive drivers. Through this screening, the tactical driving behavior of weaving across several lanes, such as to access the high-occupancy vehicle (HOV) lane, can be focused upon.

The search process for selecting the most aggressive drivers is described here. Over the entire data set (*4733* vehicles), the following values were obtained for each vehicle:

- "Entry Ramp" (Conditional: *0* for *false*, *1* for *true*): Vehicle using the entry ramp continuing on the mainline. This condition was used to isolate vehicles merging into traffic, rather than out of traffic. Because downstream destination information was not known for the vehicles (exit ramps further downstream from the camera view area), and mandatory lane changes are affected by the downstream destination, it is hoped that the influence of mandatory lane change behavior on the selected vehicles will be negligible. As explained in a previous chapter, the proposed model in this dissertation as implemented in the prototype considers discretionary lane changes only and not mandatory lane changes. The lane changes made by the selected vehicles are expected to be motivated to a greater degree by their travel time improvement, which the proposed lane change model explicitly represents. Although there could be an influence of downstream destination outside the camera view area. *301* vehicles were found meeting this condition.
- "Passenger Car" (Conditional: *0* for *false, 1* for *true*): Vehicle is the size of a passenger car ($3m < length < 8m$) Large and heavy vehicles such as trucks and buses have different performance characteristics, so it is better to avoid considering these in the analysis. *4526* vehicles were found meeting this condition.

In the observation data set, an HOV rule is in effect for the final *5* minutes of the *25*-minute data set. When the rule is in effect, the innermost lane is reserved for HOVs only, and high-occupancy vehicles are considered as those with two or more people inside. In the analysis performed, attractiveness of the HOV lane to HOVs is not explicitly modeled. Instead, the vehicles will naturally decide a trajectory using the HOV lane if it offers them travel time savings.

The number of vehicles found meeting the "entry ramp" and "passenger car" conditions was: *297* vehicles. To pick the most aggressive vehicles of this group, this set of vehicles was further restricted in terms of two measures: (1) the number of lane changes $n_{LC}(i)$ and (2) the relative speed to the surrounding traffic $S(i)$. These two measures were quantified for each vehicle and the vehicles best meeting a combination of these measures were selected for the performance comparison.

The relative speed to the surrounding traffic was considered in terms of a speed index S_k of each vehicle which is the ratio was calculated as described here:

$$S_k = \frac{\sum_{\forall t}\left[\left(\frac{v_k(t)}{\sum_{\forall i} v_i \delta_i(t)}\right)\delta_k(t)\right]}{\sum_{\forall t}\delta_k(t)}$$

S_k	=	Speed index of vehicle k
i	=	Index of vehicle in trajectory data
t	=	A time instant in the trajectory data
$v_i(t)$	=	Speed of vehicle i at time t in the trajectory data
$\delta_i(t)$	=	1 if vehicle i was present at time t in the trajectory data, 0 otherwise

In the above equation, the relative speed index of each vehicle is calculated using only the trajectory data covering the time interval in which that vehicle is present in the data. For this reason, the values of $\delta_i(t)$ and $\delta_k(t)$ are used, to account for the presence of the subject vehicle and surrounding vehicles, respectively.

The scores of n_{LC} and S were normalized, and the set was finally reduced to *36* vehicles which met both of the following criteria.

- $nLC(i) \geq 3$ (*140* vehs)
- $S(i) > mean\ (S(i)) + 0.5\ s.d.$ (*86* vehicles)

This sample size was selected because it is thought to be reasonably large to capture the diversity in driver behavior, but small enough to be analyzed on a desktop computer. These vehicles were used for the best-fit parameter estimation as well as performance comparison.

6.4 Model best-fit parameter estimation overview

In this research, model parameters to be used in the driver behavior models are calibrated for each selected vehicle. The objective is to find the parameter vector which gives the best-fit of the simulated vehicle's driver behavior exhibited by the actual vehicle in the trajectory data. This section lists the various parameters to be calibrated as well as an overview of the stages in the calibration process.

Table 6.8 shows each parameter and the model components in which it is used.

Table 6. 8: Calibration parameters overview

Parameter	Used in longitudinal control model	Used in basic lane change model	Used in sequential planning lane change model	Fixed	Longitudinal model calibration stage	Lane change model calibration stage
max acceleration (m/s^2), a	●	●	●	●		
max deceleration (m/s^2), b	●	●	●	●		
Reaction time delay (s), τ	●	●	●		●	
Desired speed (s), v_{des}	●	●	●		●	
Gap adjustment factor, F		●	●			●
Search time horizon (s), t_h			●			●
Lane change penalty, c_l			●			●

Acceleration and deceleration values were assumed constant for all vehicles and appropriate values were taken from the literature references (Koppa, 2002):

- a, 3.0 m/s^2
- b,: -4.6 m/s^2

The remaining parameters were calibrated in a two-stage calibration process: first the longitudinal model calibration, and second the lane change model calibration. It should be noted that there is some degree of interaction between the longitudinal and lateral control actions (Toledo, 2003), and therefore the longitudinal and lateral parameter calibration should ideally be performed simultaneously, in a single step. However, in order to simplify the parameter search problem, the longitudinal and lateral calibrations are performed in separate steps.

In the longitudinal model calibration stage the parameters most directly related to longitudinal control behavior are adjusted. These are:

- τ, reaction time (s)
- v_{des}, desired speed (m/s)

In the lane change model calibration stage the best-fit parameters already found in the longitudinal model calibration stage (τ and v_{des}) are fixed, and the parameters used only in the lane change model are calibrated. The parameters calibrated are:

- F, critical gap adjustment factor (unitless)

- t_h, search time horizon (s) (sequential planning model only)
- c_l, lane change penalty (sequential planning model only, only for selected vehicles)

In the simulator, all vehicles were assigned to their actually-traveled trajectories except for the subject vehicle, which was put under the control of the selected driver behavior models. The next section describes the search algorithms used to find the optimal parameters.

The range and grid search interval of longitudinal control and lane change model parameters are shown in Table 6.9. These values were selected so as to provide a adequate range as well as coverage density of appropriate values. The search range of reaction time lag τ was selected to adequately cover the range of this value, as reported in a number of studies on driver reaction time reviewed in Koppa (2002). The desired speed v_{des} search range was selected to adequately cover a range of speeds from well below to well above the average time-mean speed in non-congested flow (100 km/h) found in the reference describing the data set (Cambridge Systematics. NGSIM BHL Data Analysis, 2004).

Table 6. 9: Parameter search range and grid spacing

Parameter	Description	Minimum	Maximum	Interval
τ	Reaction time lag (s)	0.2	2.0	0.2
v_{des}	Desired speed (m/s)	25.0 (90 km/h)	40.0 (144 km/h)	2.5 (9 km/h)
F	Gap adjustment factor	0.4	1.6	0.2
t_h	Planning time horizon (s)	1.0	8.0	1.0

Although through tuning of the parameters, a close correspondence of real and simulated vehicle trajectories can sometimes be obtained, in general there are many unobservable influencing factors to the driver longitudinal and lateral behavior. Important influencing factors which are not included in this model are the downstream destination and its influence on mandatory lane change behavior, as well as various other characteristics and behavior which vary over the driver population and over time for an individual driver.

The following subsections describe:

- the search process used to find the best fit parameter vectors
- car following calibration and sensitivity analysis
- lane change model calibration and sensitivity analysis

6.4.1 Parameter search algorithms

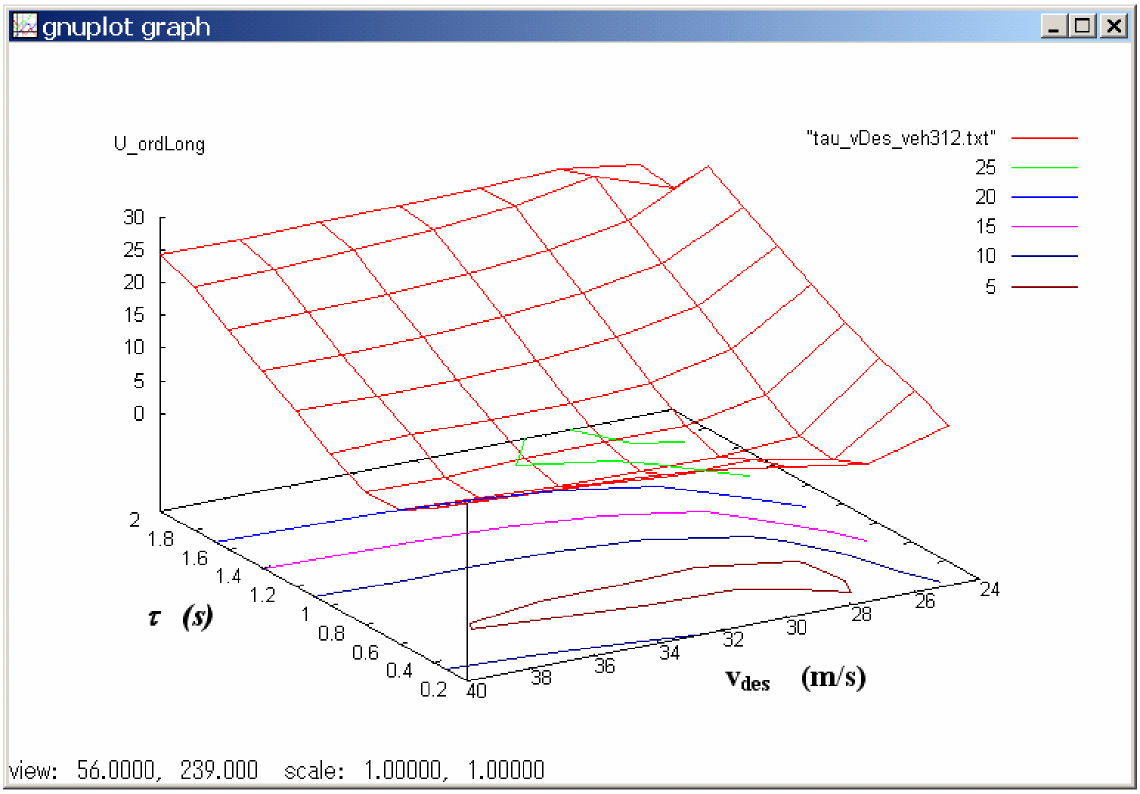
When searching for a parameter vector $\{x_1, \ldots, x_n\}$ which minimizes function $U(x_1, \ldots, x_n)$, a grid search, with a fine enough grid size, allows good coverage of the search area and ensures that the global optimum can be found. However, for surfaces which are convex, computation time could be saved by limiting the points searched somehow. Russell (2003) describes various search techniques, including stochastic search methods of simulated annealing and genetic algorithms, as well as mathematical programming methods such as gradient search and nearest neighbor hillclimbing.

In this research, the search strategy is to use a grid search for surfaces which are thought to be non-convex, and to use hillclimbing otherwise. Hillclimbing is a relatively simple approach, because it is able to be developed and implemented quickly without relying on external software or algorithms. A hillclimbing search algorithm was implemented in the Java programming language, allowing interoperability with the traffic simulator. For a detailed description of the hill climbing and other algorithms, the reader is directed to Russell (2003), chapter 4.

In the application of hill climbing implemented in this research, an initial grid is searched and the best point is selected as the starting point. Then, the score of each of the point's neighbors is evaluated, and if an improvement can be found, the search is moved to this point. The search stops when no improvement can be found in any direction. This approach allows computation time savings of approximately *90%*, compared to the grid search, but it is vulnerable to mistaking a local optimum point for the global optimum for non-convex surfaces.

Consider an example of a search space of $U_{ordLong}(\tau, v_{des})$ for a selected vehicle (vehicle no. *312*) which was applied in the best-fit parameter vector estimation for car following calibration. In Figure 6.21, all the grid points have been evaluated.

Instead, if an initial 3 x 3 grid were searched and hill climbing algorithm were applied, then the descent path in Figure 6.22 would be followed, realizing a considerable savings in computation time. Grid search as in Figure 6.21 searches $\tau = 0.2$ to *2.0* step *0.1 = 19* points and v_{des} = *25.0* to *40.0* step *1.0 = 16*. This is a total of *19 x 16 = 304* points. In contrast, the Hillclimb search takes the original 9 grid points, plus 6 along the descent path to reach the final point at 15 steps.



gnuplot graph
U_ordLong
"tau_vDes_veh312.txt"
25
20
15
10
5
30
25
20
15
10
5
0
2
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
τ (s)
40
38
36
34
32
30
28
26
24
vdes (m/s)
view: 56.0000, 239.000 scale: 1.00000, 1.00000

Figure 6. 21

6.5 Longitudinal control model calibration

The objective function $U_{ordLong}(\tau, v_{des})$ is computed over a range of values and estimate (τ^{*}, v_{des}^{*}) which minimizes U_{CF}. The search domain is $(0.2 <= \tau <= 2.0$ to the nearest $0.1)$ and $(25 <= v_{des} <= 40$ to the nearest $1)$. A hill climbing algorithm, with a *2x2* grid of initial starting points, is used. To evaluate each $U_{ordLong}(\tau, v_{des})$, the simulator is executed with the selected parameters as input arguments, in an automated fashion. The traffic simulator is run in *MIXED* mode using the real vehicle trajectories for the surrounding vehicles and the subject vehicle under the simulator model control. The lane change action is disabled for the subject vehicle. For each time step in the simulation, if the subject vehicle has a different lead vehicle than the real NGSIM dataset vehicle, then the subject vehicle is reset to the real vehicle's position and velocity. The simulator writes the trajectory of all simulated vehicles to an output data file, which is then read and the root-mean-squared (RMS) difference of the subject vehicle's longitudinal position to the actual position in the real data is calculated for every time step in which the simulated vehicle and real vehicle are both present.

The objective function is as follows:

$$U_{ordLong} = RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_{i|sim} - x_{i|realData})^2}$$

where:

$U_{ordLong}$	=	Objective function based on longitudinal difference between simulated subject vehicle and its real course
i	=	Index number of time step over the duration of the simulation
n	=	Total number of time steps

In Figure 6.21, an example of the search for minimum of $U_{ordLong}(\tau, v_{des})$ is shown. For display purposes, a full grid search was conducted. In this case, the values of τ and v_{des} which minimize $U_{ordLong}(\tau, v_{des})$ form a valley in the grid.

In Figure 6.23, the longitudinal course is shown for the vehicle running in the simulation according to its optimized longitudinal control parameters $\{\tau^{*}, v_{des}^{*}\}$, together with the actual vehicle trajectory.

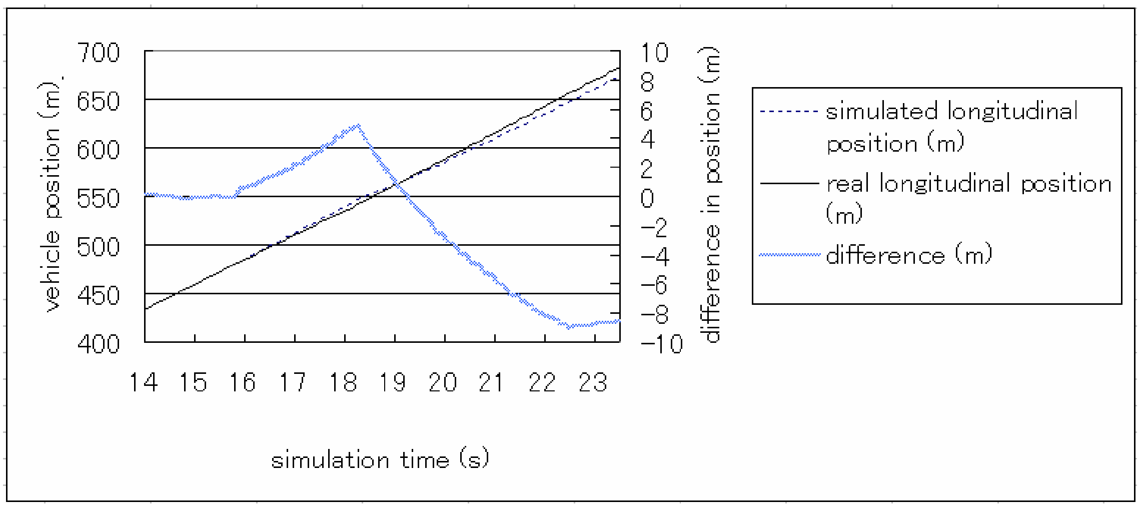


Figure 6. 23: Example of the optimized longitudinal control simulated trajectory compared to the real vehicle trajectory (veh. no. 312)

In the following subsections, special cases of sensitivity analysis are considered, and issues of parameter overestimation are addressed.

6.5.1 Sensitivity analysis of acceleration and deceleration

As explained above in the beginning of Section 6.2.2, the values of maximum acceleration and deceleration were assumed to be constant for all simulated vehicles. This subsection describes a sensitivity analysis of the longitudinal model performance to different values of maximum acceleration and deceleration. For a selected vehicle for which (τ^*, v_{des}^*) had already been estimated using the default maximum acceleration and deceleration values, the $U_{ordLong}\ (\tau^*, v_{des}, accel_{max})$ and $U_{ordLong}(\tau^*, v_{des}, decel4_{max})$ function was estimated, and the surface is shown in Figures 6.24 and 6.25. For the selected vehicle (vehicle id no. *342*) examined, as can be seen below by visual inspection, there appears to be very little sensitivity to the values.

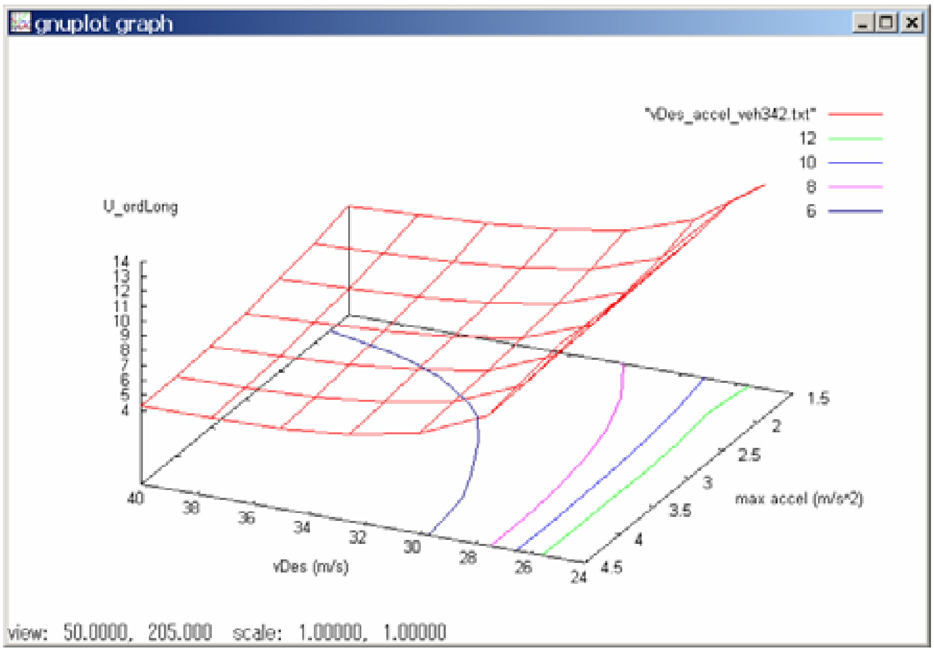


Figure 6. 24: **Sensitivity to maximum acceleration (veh. no. 342)**

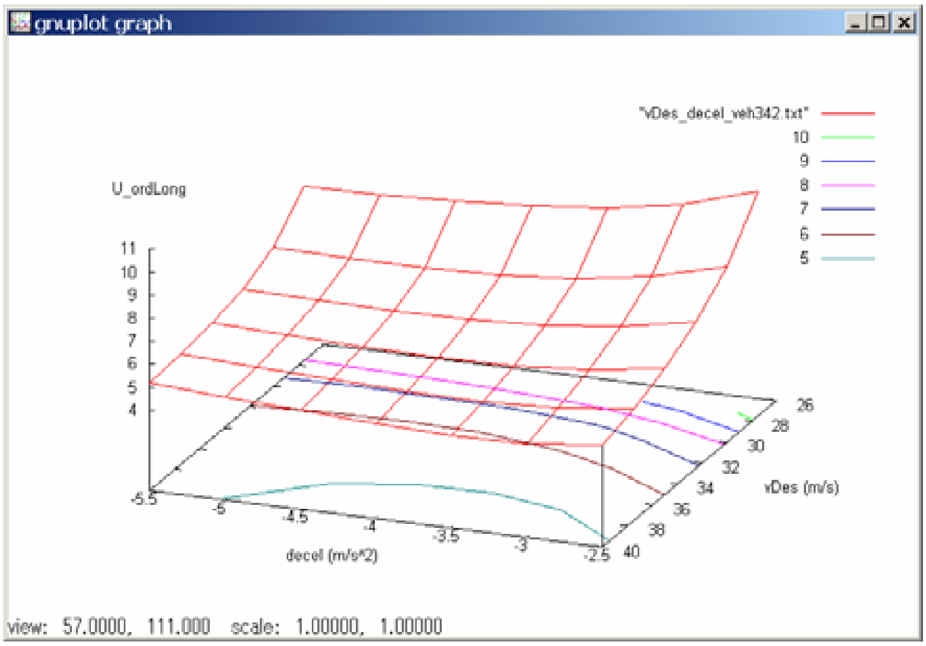


Figure 6. 25: **Sensitivity to maximum deceleration (veh. no. 342)**

6.5.2 Estimation of desired speed

For certain subject vehicles, using the search procedure described in the beginning of Section 6.5, unreasonably high estimates of desired speed occur. An example is shown in Figure 6.26: the grid search of $U_{ordLong}(\tau, v_{des})$ for vehicle number *253* from the trajectory data set is shown. In these cases, the score $U_{ordLong}$ asymptotically converges to a minimum with a high desired speed. The cause of this overestimation is complex and it allows arbitrarily small but progressively higher desired speed values to offer a slightly closer resemblance of the simulated to real-world trajectories.

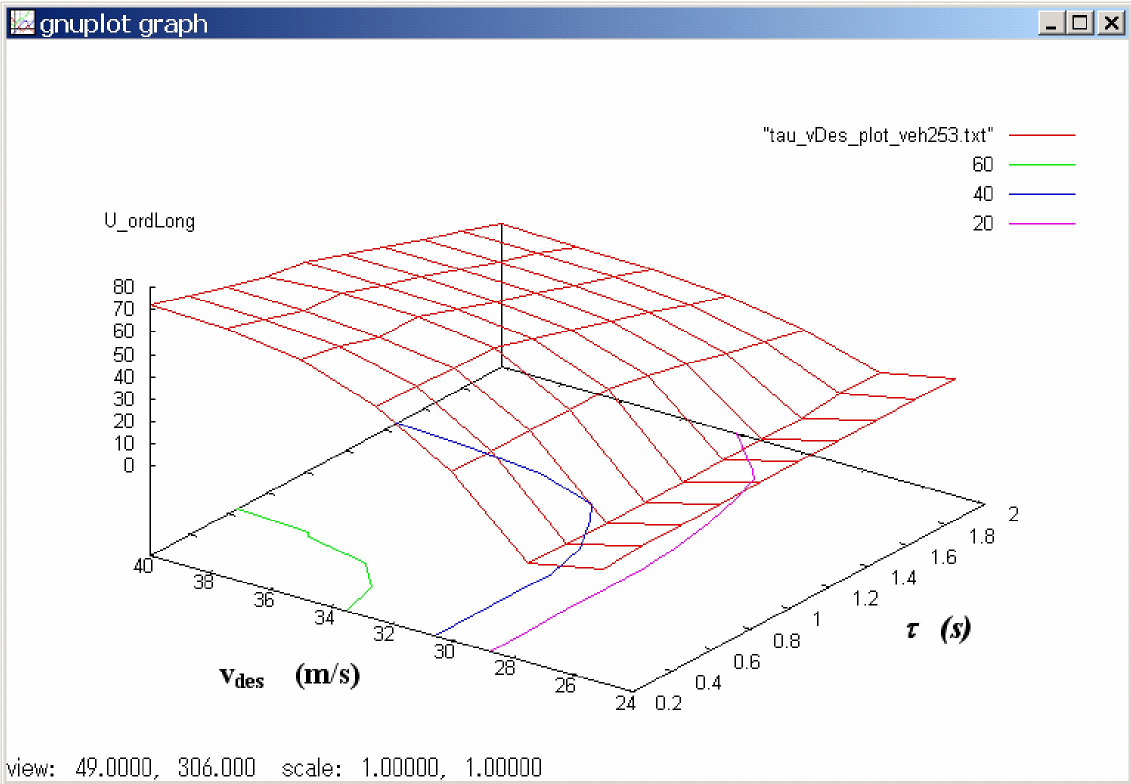


Figure 6. 26: Grid search for best-fit longitudinal control model parameters (veh. no. 253)

In this study, the estimated desired speed shows good convergence to a minimum for vehicles which undergo at least some driving in free driving conditions. However, for vehicles which are in heavy traffic or congested conditions, the free drive portion of the car following model is never used, therefore the desired speed has little or no influence on the subject vehicle's longitudinal control (see Equation (1) in Chapter 4 describing the Gipps Car Following model) and therefore there is little or no sensitivity to the desired speed in the cases where it has been overestimated.

In summary, the estimation of desired speed will be limited in these cases to the maximum of the searched values, that is *40* m/s (144 kph), which is sufficiently above the speed limit of the road: 105 kph (65 miles per hour) to cover even the fastest drivers. However, in these cases, the estimated value of desired speed will not be attained in these simulated cases because the vehicle is in heavy congestion and always under the car following control. And the vehicles which are in light traffic will have desired speed values which are reasonably stable in the estimation.

Likewise it should be noted that the car following reaction time lag parameter, which is estimated in the car following estimation step, but is used in the lane change model estimation step, shows good performance in the search for the global minimum.

6.6 Lane change model calibration

This section describes the parameter calibration for the lane change models. This includes both the basic lane change model, as well as the sequential planning lane change model. For both types of lane change models, the best-fit parameters were estimated independently.

For the selected subject vehicle, the parameters for this stage were searched to find the parameter vector which gives the best match of simulated to observed behavior. For the basic model calibration, the parameter search vector was $\{F\}$ and for the sequential planning model, the search vector was $\{F,t_h\}$ and a special case considering $\{F,t_h,c_l\}$ is considered in section 6.6.6. The overview of the parameter search vectors in the overall calibration process was explained at the beginning of section 6.4.

For some analyzed vehicles, multiple points in the search space were found to give the best performance. In this case, the values reported in the results as the best-fit parameter were selected according to tie-breaking rules. The tie-breaking rules were selected to apply the principle that, when selecting between multiple candidate models with equal performance, the simplest is preferred. The best-fitting F value nearest to 1.0 was selected. $F = 1.0$ represents the simplest and unmodified application of the lane change gap acceptance because this would allow the subject vehicle's critical gap size to be exactly equal to the critical gap according to safe stopping distance as described in Section 4.3.1 Eqs. 20-22. The best-fitting t_h value which was smallest was selected. This represents the simplest application of the model by building a shallower Forward Search Tree with fewer enumerations, fewer calculations, but nonetheless giving the same model performance. The best-fitting c_l value which was smallest was selected. This represents the simplest application of the model by eliminating the consideration of the lane change penalty entirely, by completely removing the $10^{c_l} n_{LC}(k)$ term from Section 5.5.1 Eq. 3.

For the lane change model calibration, two candidate fitness measures were considered. The measures are the (1) based on comparison every time step, and (2) based on comparison every *gap session*. To select the most effective and accurate measure, a comparison the two measures was performed. First, the two measures are described. Afterward, the performance comparison is described.

6.6.1 Lane change model performance by time step

When this performance measure is used, the simulated subject vehicle's longitudinal control action is disabled so that the only values returned from the driver model are the lane change actions. The subject vehicle is simulated with its longitudinal position fixed to the real vehicle's position at every time step. At each time step, the lane change action resulting from the simulator given the selected vector of parameters (*{F , t_h }* for the sequential planning lane change model calibration, *{F}* for the basic model), is used to compute the objective function to be minimized:

$$U_{LC} = \frac{\sum_{\forall i} \delta_i}{n}$$

where:

U_{LC}	=	lane change model performance index
i	=	Index number of time step over the duration of the simulation
n	=	Total number of time steps
δ_i	=	*0* if the simulated lane change action: *{left, right, or no lane change}* equals the real vehicle's lane change action at time step *i*, *1* otherwise

If the lane change control actions of the simulated vehicle at each time were identical to those of the real vehicle, then the objective function would evaluate to *0*. The worst possible score is *1*. A range of values over the parameter vectors is searched, U_{LC} is evaluated, and the parameter vector which minimizes U_{LC} is found.

6.6.2 Lane change model performance by gap session

A *gap session* is a time period over which the subject vehicle has the same set of vehicles in the relative positions around it, specifically the *{lead, rear, left lead, left rear, right lead, right rear}* positions, and the same gap availability.The concept of gap session is illustrated in an example below which shows how one gap session transitions into another.

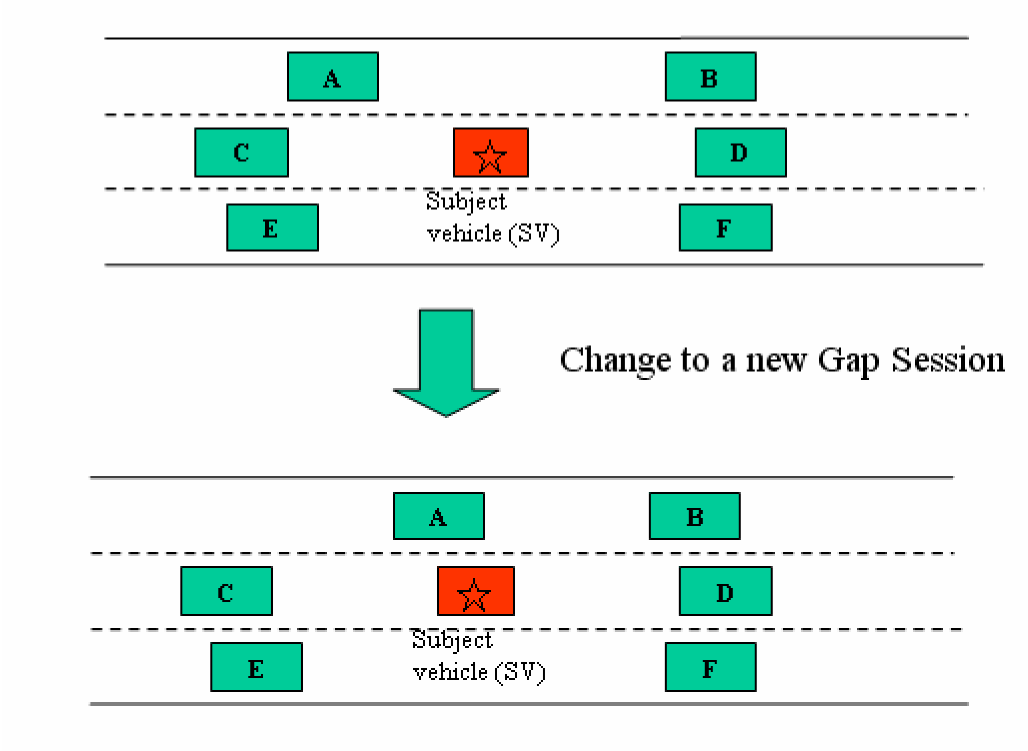


Figure 6. 27: Transition between gap sessions

The gap session shown at the top of Figure 6.27 has lead vehicle D, rear vehicle C, a left gap with lead vehicle B and rear vehicle A, and right gap with lead vehicle F and rear vehicle E. This gap session transitions to that shown at the bottom of Figure 6.27, when vehicle A in the left lane pulls alongside the subject vehicle, ending the availability of a left gap.

In the lane change calibration using gap sessions, the simulated subject vehicle (SV) is set at initial conditions and history of the real vehicle (RSV) for the beginning of the gap session. Then the SV is simulated through to the end of the gap session. If, during the simulated gap session i, the SV performed the same lane change as the RSV, δ_i is 0; otherwise it is *1*. The score U_{LC} is computed as:

$$U_{LC} = \frac{\sum_{\forall i}\left[L_{x|i} L_{t|i} \delta_i\right]}{\sum_{\forall i}\left[L_{x|i} L_{t|i}\right]} \qquad (6\text{-}1)$$

U_{LC} = Performance evaluation of lane change model. *0* is perfect, *1* is the very worst.

i = Index number of Gap Session i

$L_{x|i}$ = Spatial size of Gap Session i at its start. For example, in Figure 6.27, "Gap Session 1" has a spatial length in meters which is the distance from the back bumper of Vehicle D to the front bumper of Vehicle C.

$L_{t|i}$ = The time duration of Gap Session i

δ_i = *1* if the SV has a different lane control action from the RSV in Gap Session i, *0* otherwise.

As seen in the above equation, the contribution of each gap session i is given by its weight: $(L_{x|i}) * (L_{t|i})$. This weighting strategy allows gap sessions which have a bigger size and a longer duration to get a greater influence on the computation of the measure of correctness U_{LC}.

6.6.3 Selection of lane change model performance measure

It is thought that the time step based performance measure has a disadvantage because if the real and simulated vehicles make a lane change but at slightly different times or the real vehicle does not make a lane change and the simulated vehicle does, then the score will be heavily penalized. Conversely, if the real vehicle makes a lane change but the simulated vehicle does not, then the penalty occurs only for one time step. This is an imbalance in the treatment of these two types of errors. However, more important than the relative time of the lane change is whether the lane change action was made at all.

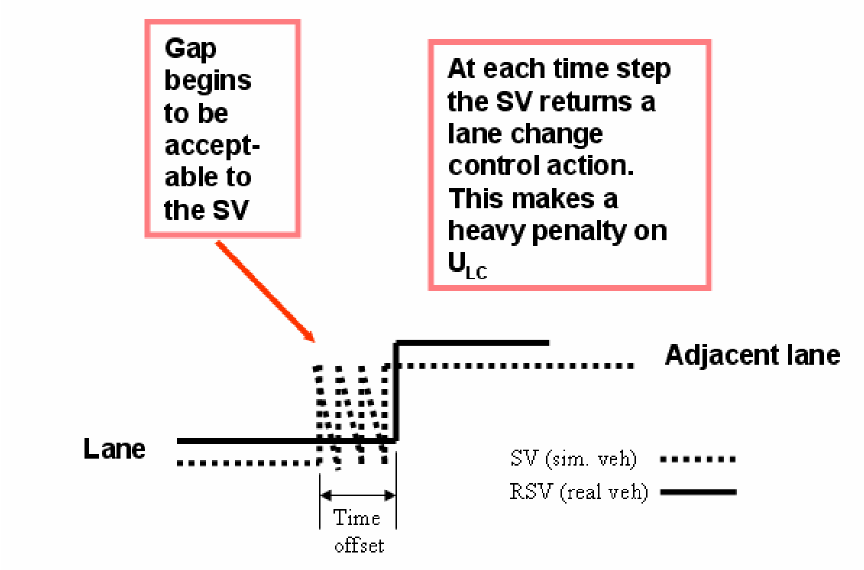


Figure 6. 28: Errors in time step performance method

The above two measures were evaluated on a test set of 10 vehicles, arbitrarily selected from the 36 "aggressive drivers" (explained in Section 6.3). The optimized (τ^*, v_{des}^*) parameter vectors from the longitudinal calibration stage were used. For both the basic and sequential planning models, the optimum (minimum) values of U_{LC} were computed over the range of F ($U_{LC}(F)$). For the sequential model, the range of t_h were considered and that giving the minimum U_{LC} was used. ($U_{LC}(F,t_h^*|F)$).

For the ten analyzed vehicles it was found that the gap session method allowed greater variation over the range of F values, and in 70% of the cases, it reduced the occurrence of decreasing asymptotic trends compared to the time step method. As an example, for one of the analyzed vehicles, Figure 6.29 shows these trends. These characteristics are desirable for a performance estimation method because they can serve to better highlight the differences in performance between the basic and sequential planning lane change models, and the differences in model performance over a range of F values. For these reasons, the gap session method is selected hereon for use in computing U_{LC} in the remainder of the work described in this document.

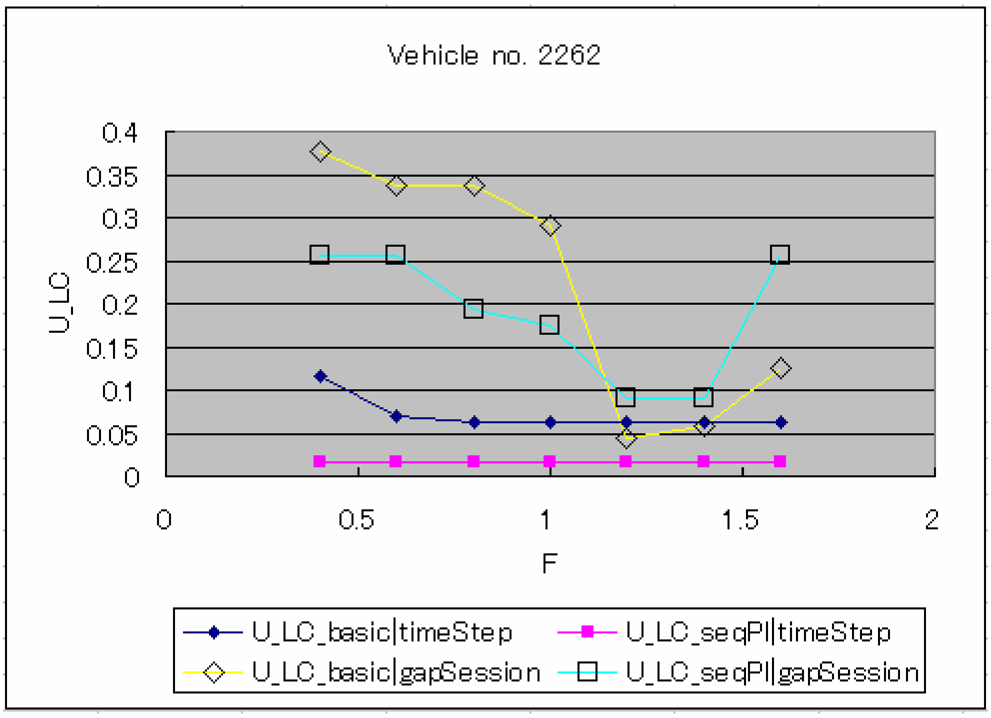


Figure 6. 29: Performance comparison of time step and gap session evaluation methods

6.6.4 Lane change model performance sensitivity analysis to *(τ,v_{des})*

Although the values of parameters (τ,v_{des}) have already been determined in the longitudinal model calibration stage, these values are used in the lane change model as well. Therefore it is of interest to examine the sensitivity of the lane change model performance to these variables. In order to adequately consider the range of possible cases, several vehicles are analyzed. The vehicle-specific best-fit longitudinal control model and sequential planning lane change model parameters are shown in Table 6.10.

Table 6. 10: Best-fit model parameters for selected vehicles for *(τ,v_{des})* sensitivity analysis

svID	*τ (s)*	*v_{des} (m/s)*	*F*	*t_h (s)*
2451	0.8	40	0.4	6.0
266	0.4	40	1.0	3.0
1875	0.4	39	1.2	5.0
2262	0.5	38	1.2	5.0

The following performance relations are investigated:

(1) $U_{LC}(\tau) / v_{des}*$, that is, allowing the re-estimation of τ (Figure 6.30):

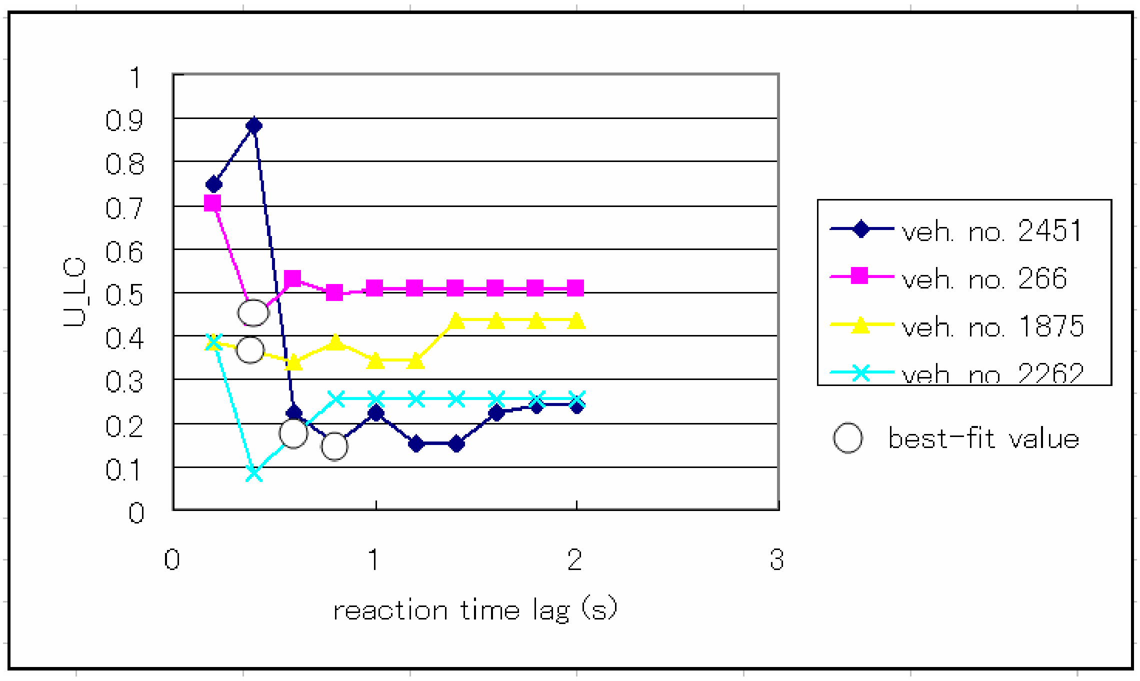


Figure 6. 30: Sequential planning lane change model sensitivity to reaction time lag: *$U_{LC}(\tau) / v_{des}*$*

(2) $U_{LC}(v_{des}) / \tau*$, that is, allowing the re-estimation of v_{des} (Figure 6.31):

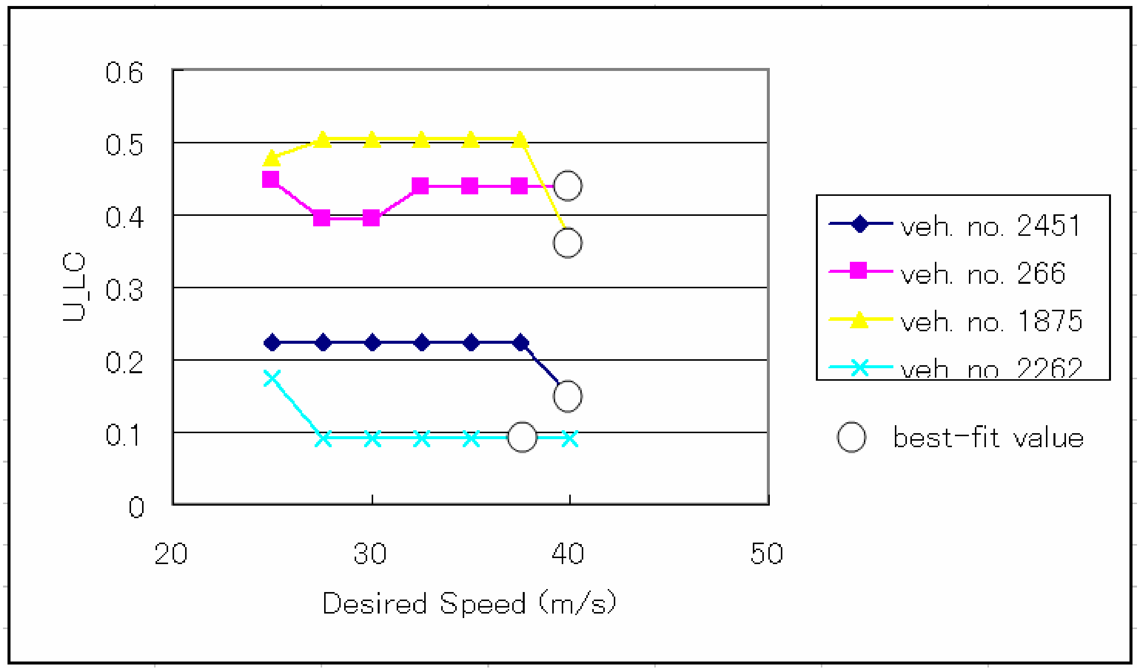


Figure 6. 31: Sequential planning lane change model sensitivity to desired speed $U_{LC}(v_{des}) / \tau^*$

The best-fit values are marked. By visual inspection, it can be seen that the lane change model performance is clearly sensitive to both τ and v_{des}. Although in most of the cases analyzed, there is no improvement to be found by changing τ and v_{des}, for a few cases (vehicles no. 1875 and 2262 in the τ sensitivity analysis, and vehicle no. 266 in the v_{des} sensitivity analysis) there is the possibility for a slight improvement to the performance could be realized by allowing for their adjustment. However, because this would require additional specification of model variables, inducing greater model complexity, such efforts are left for further research.

6.6.5 Lane change model performance sensitivity analysis to gap adjustment factor and time horizon

In this section, the sensitivity of the lane change model to the two lane change model parameters: gap adjustment factor F and time horizon parameter, t_h, is considered.

Sensitivity to gap adjustment factor F

For 5 selected vehicles, the optimum values of $U_{LC}(F)$were computed over the range of F values. A range of t_h values was considered and that giving the minimum U_{LC} was used: $(U_{LC}(F,t_h^*|F))$. Figure 6.32 shows the sensitivity of the lane change model performance to F for the selected vehicles, with the best-fit value marked by a circular symbol. In cases of multiple values of F giving identical performance, the best-fit value was selected according to the tie-breaking rule, which was described in Section 6.6, in which values closest to $F = 1.0$ are selected.

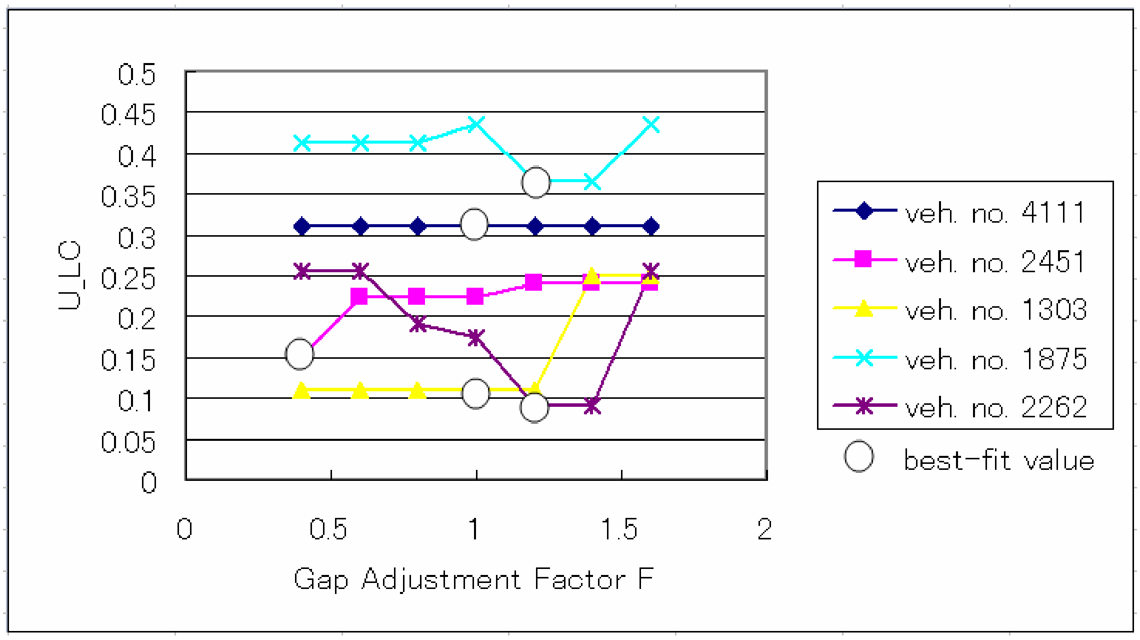


Figure 6. 32: Sequential planning lane change model sensitivity to gap adjustment factor *F*

The best-fit lane change model performance sensitivity can be seen to vary according to the analyzed vehicle. This is due to the fact that each vehicle observed in the trajectory data has a unique experience in terms of the lane changing opportunities and lane change actions performed by the real vehicle.

Sensitivity to planning time horizon t_h

In the real driving situation, it is likely that the a driver's planning time horizon may vary depending on the complexity of the situation: for example when driving on a straight freeway section with no ramps nearby, the planning-ahead time may be short, perhaps only *2-3* seconds. For a certain driver, it is also possible that the planning-ahead time may vary depending on the degree of congestion, that is, congested or non-congested conditions. If so, then it may be necessary to assign not a single value but rather two or more values of the planning-ahead time parameter in terms of the congestion-level, in a traffic simulator during vehicle generation.

Although the driver's actual thought process cannot be observed, it may be possible to infer the time horizon (t_h) parameter value for a driver. If the driver takes a particular lane change action which shows a short-term advantage looking ahead as far as t_{short}, however were he to be able to anticipate further into the future to time t_{long}, then he would have taken a different lane change action; then we know that his search time horizon is in between t_{short} and t_{long}.

In this section the sensitivity of the performance to the time horizon parameter t_h is examined for several selected vehicles. The selected vehicles and their best-fit sequential planning lane change model parameters are shown in Table 6.11. The performance sensitivity $U_{LC}(t_h)$ of the selected vehicles is shown in Figure 6.33. A high degree of sensitivity can be seen by visual inspection.

Table 6. 11: Best-fit model parameters for selected vehicles for time horizon parameter sensitivity analysis

svID	*F*	t_h *(s)*
266	**1.0**	**3**
1303	**1.0**	**3**
135	**1.0**	**1**
68	**1.0**	**1**

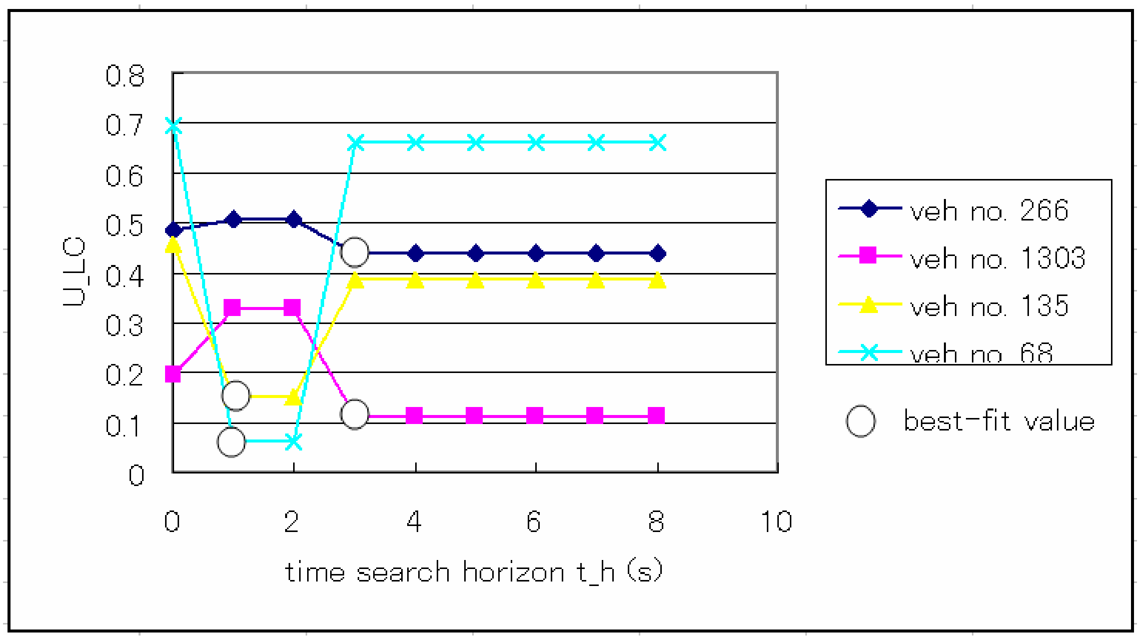


Figure 6. 33: Sequential planning lane change model performance sensitivity to time horizon parameter

The sensitivity varies by vehicle, as each vehicle's experience driving in the surveyed study area is unique in terms of the lane changing opportunities and lane change actions performed by the real vehicle. Next, for two selected vehicles, the simulated vehicle lane change actions for selected gap sessions are considered for their impact on the overall performance $U_{LC.}$ In the first example (veh. no. 1303) the driver's planning time horizon is inferred to be *at least* a specified duration, while in the second example (veh. no. 68) the driver's planning time horizon is inferred to be *at most* a specified duration.

The $U_{LC}(F,t_h)$ surface for vehicle no. *1303* is shown in Figure 6.34. The basic lane change model, which is shown in the plot at $t_h = 0$ is also included. In this and subsequent figures of the lane change model performance, the U_{LC} surfaces are not smooth; rather they contain discrete jumps. A change from one point in the parameter search space to an adjacent point results in a change in the performance of the model in correctly reproducing the lane change action of the analyzed vehicle in a gap session. This causes a step difference between the two points in the parameter space. Because it represents a crossing of a boundary in the parameter search space for which on one side the model gives the correct result and on the other an incorrect result, the discrete step in the performance surface would be present even if the grid search density were increased.

Also, because of the finite and relatively small number of gap sessions available from the vehicle trajectory data for each analyzed vehicle, it is likely that multiple values in the parameter search space may perform identically for all the gap sessions. This results in a flat surface on the portion of the parameter space as seen here. If more gap sessions were available for analysis, a greater number of possible combinations of gap session performance values would be available for each parameter search point, likely resulting in a surface with more transitions and fewer flat areas.

Nonetheless, it is recognized that in this work the U_{LC} lane change model performance evaluation based on the gap session can be insensitive over a wide range of the $\{F,t_h\}$ parameter vector space. Perhaps a greater sensitivity could be found by incorporating other information about each lane change action, such as lane change timing and/or the distance relative to adjacent vehicles, rather than evaluating the subject vehicle lane change action in each gap session on a simple yes/no basis, as in the current method. However, it is always a point of caution to avoid over-specification of a model based on limited data. For example, even for the same conditions of the subject and surrounding vehicles, the subject vehicle might take a different lane change action in another instance. In light of this, incorporating probabilistic elements into the model might also be considered. It is recommended that such improvements to the model performance estimation be considered in further works.

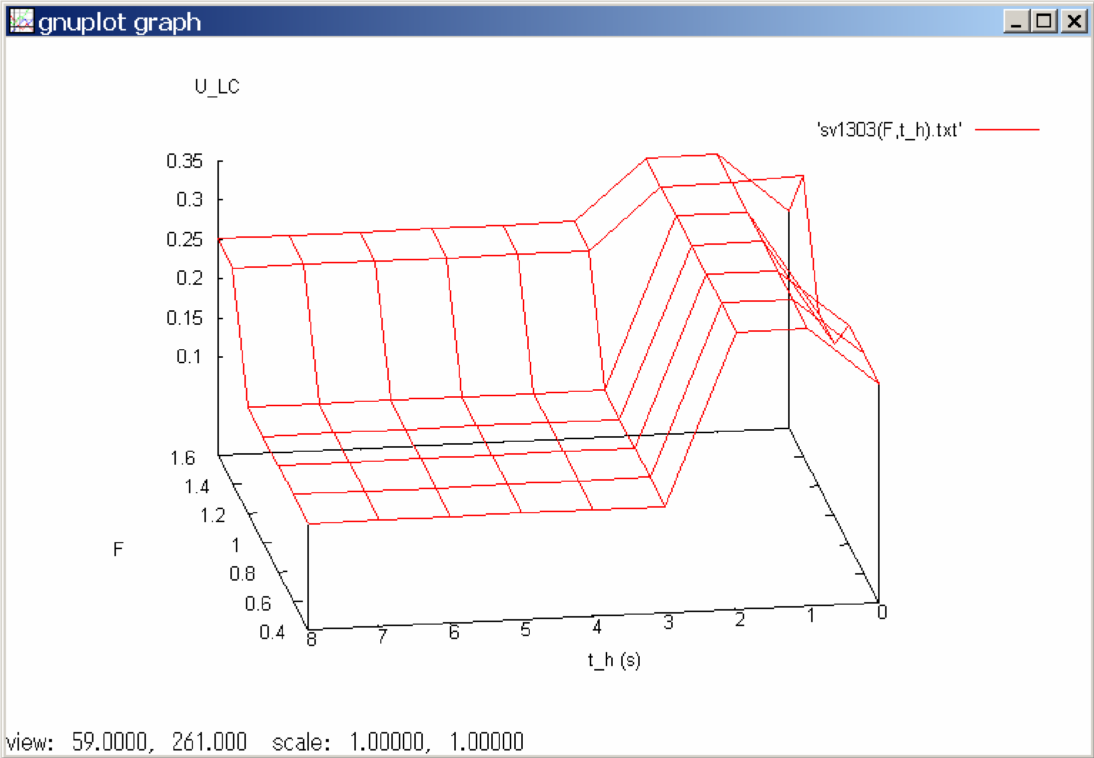


Figure 6. 34: Sequential planning lane change model performance sensitivity to gap adjustment and time horizon parameters $U_{LC}(F,t_h)$ for veh. no. 1303

It can be seen that there is a strong sensitivity to t_h and in this case $t_h \geq 3.0$ seconds gives the best result. Also, in this case for $t_h \geq 3.0$ and $F \leq 1.4$, there is no sensitivity in performance to F. Therefore the tie-breaking rule described in Section 6.6 is applied in the values of F closest to 1.0 is selected and $t_h = 3.0$ is selected. Considering the case of $F = 1.0$, which is included in Figure 6.33, it can be seen that the simulated vehicle performs lane change actions most similarly to the real vehicle for parameter values $t_h \geq 3\ s$. Examining the performance of the simulated vehicle at particular gap sessions experienced in the trajectory data or simulation, the causes of the difference in scores can be identified. Table 6.12 shows the performance of the simulated vehicle in being the same ($\delta = 0$ in Section 6.6.2) or different ($\delta = 1$) from the real vehicle's lane change action. For the various gap sessions, this value may change as t_h changes, indicating the simulated subject vehicle becomes aware of a tactical advantage that was not evident until planning this far ahead in time.

Table 6. 12: **Performance of simulated vehicle by gap session (veh. no. 1303)**

delta_i_for_t_h (0 = correct) (1 = incorrect)									
gsBeginTime (s)	weight_i	1	2	3	4	5	6	7	8
538.333	217.9489	0	0	0	0	0	0	0	0
539.733	399.1113	0	0	1	1	1	1	1	1
542.267	70.75575	1	1	0	0	0	0	0	0
542.867	**833.24**	**1**	**1**	**0**	**0**	**0**	**0**	**0**	**0**
546.933	298.89	0	0	0	0	0	0	0	0
548.8	277.9905	1	1	0	0	0	0	0	0
550.6	1144.66	0	0	0	0	0	0	0	0
557.533	273.4635	0	0	0	0	0	0	0	0
559.667	87.00686	0	0	0	0	0	0	0	0

In Table 6.12, some of the gap sessions are correct for all values of t_h. This indicates that the model gave the same response (lane change or not) as the real subject vehicle in the trajectory data, regardless of the t_h parameter values used. For others, the value of δ_i becomes correct for larger values of t, while still others it is correct for the smaller values. The optimum (minimum) score of U_{LC} is reached at the overlap where the most, especially the heavily weighted, gap sessions have the correct response by the model vehicle. The gap session which is heavily weighted ((L_x L_t in Eq. 6-1 in Section 6.6.2 is very large) and differing over the range of t_h values, has been marked in bold.

Cases in which the resulting value of δ_i remains constant at 1 over the range of parameters suggest the possibility of an improvement in the model such as an added feature describing the lane changing behavior could result in the simulated vehicle getting the correct response, over a subset of the parameter vector space. For example, in the analyzed data set, destination information for further downstream lanes was not available, and it is possible that this could be influencing the lane change decisions of the analyzed vehicles.

Considering the gap sessions which have an effect on the $U_{LC}(t_h)$ surface, the difference in the subject vehicle lane change actions can be examined. Figure 6.35 shows a gap session with the real vehicle (RSV) and the subject vehicle (SV) lane choices depending on the value of the t_h parameter. The simulated subject vehicle with $t_h < 3\ s$ does not predict far enough ahead to notice that he will incur slightly greater delay behind the slower vehicle in the current lane. However for $t_h \geq 3\ s$, as well as for the real vehicle, the simulated subject vehicle predicts that a left lane change will allow getting further ahead by avoiding the slower vehicle in the current lane. Therefore it can be inferred that the time horizon of the real vehicle is at least 3 seconds, for this analyzed vehicle.

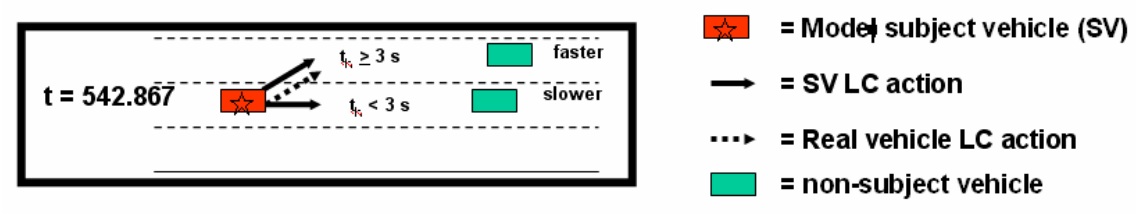


Figure 6. 35: Real vehicle lane change actions and simulated vehicle's lane change actions depending on time horizon (Vehicle no. 1303)

Next, vehicle no. 68 is analyzed. The $U_{LC}(F,t_h)$ surface is shown in Figure 6.36.

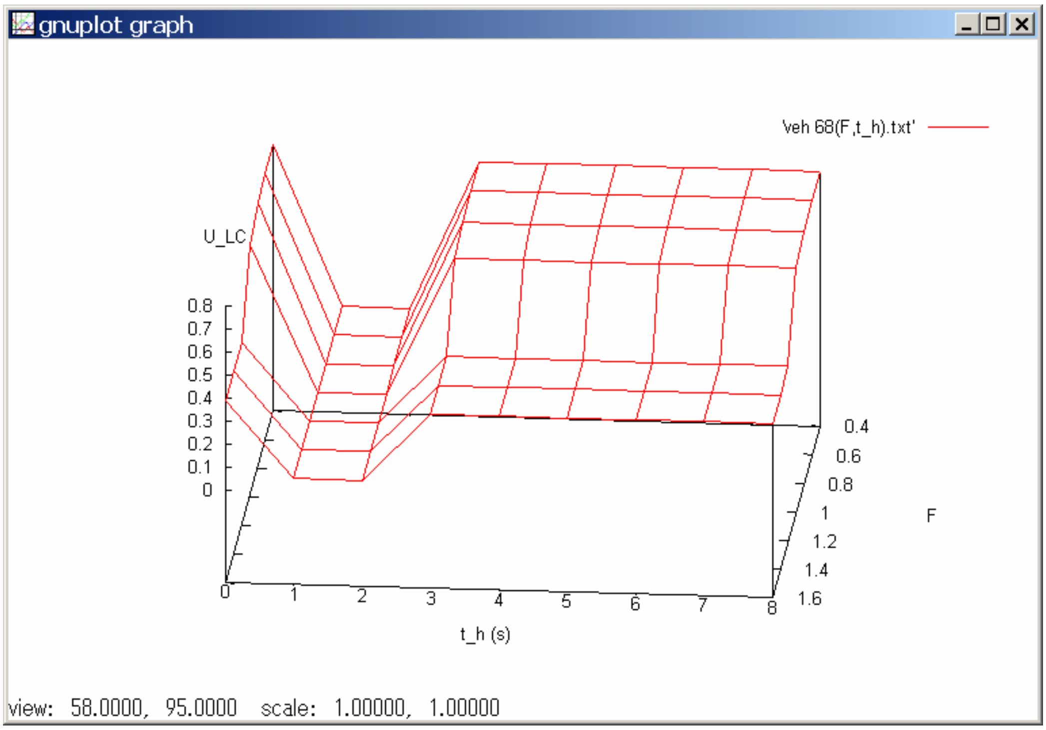


Figure 6. 36: Sequential planning lane change model performance sensitivity to gap adjustment and time horizon parameters $U_{LC}(F,t_h)$ for veh. no. 68

It can be seen that there is a strong sensitivity to t_h and in this case $t_h \leq 2.0$ seconds gives the best result. On the other hand, in this case for $1.0 \leq t_h \leq 2.0$, there is no sensitivity in performance to F. Therefore the tie-breaking rule described in Section 6.6 is applied in the values of F closest to 1.0 is selected. Considering the case of $F = 1.0$, which is included in Figure 6.33, it can be seen that the simulated vehicle performs lane change actions most similarly to the real vehicle for parameter values $t_h \leq 2\ s$. Table 6.13 shows the performance of the simulated vehicle in being the same ($\delta = 0$

in Section 6.6.2) or different ($\delta = 1$) from the real vehicle's lane change action. For the various gap sessions, this value may change as t_h changes, indicating the simulated subject vehicle becomes aware of a tactical advantage that was not evident until planning this far ahead in time.

Table 6. 13: Performance of simulated vehicle by gap session (veh. no. 68)

		delta_i_for_t_h (0 = correct) (1 = incorrect)							
gsBeginTime (s)	weight_i	1	2	3	4	5	6	7	8
20.733	28.45898	0	0	0	0	0	0	0	0
21.733	27.96582	0	0	0	0	0	0	0	0
22.133	27.38554	0	0	0	0	0	0	0	0
22.933	0	0	0	0	0	0	0	0	0
23	39.97737	0	0	0	0	0	0	0	0
23.933	0	0	0	0	0	0	0	0	0
24	50.11699	0	0	0	0	0	0	0	0
25.133	101.0022	0	0	0	0	0	0	0	0
26.267	23.98256	0	0	0	0	0	0	0	0
26.6	47.48497	0	0	0	0	0	0	0	0
27.2	53.39988	1	1	1	1	1	1	1	1
27.6	91.554	0	0	0	0	0	0	0	0
28.267	202.164	0	0	1	1	1	1	1	1
29.533	**427.3748**	**0**	**0**	**1**	**1**	**1**	**1**	**1**	**1**
31.867	26.62	1	1	1	1	1	1	1	1
32.333	136.6304	0	0	0	0	0	0	0	0
35.067	72.25062	0	0	0	0	0	0	0	0
36.4	49.5954	1	1	1	1	1	1	1	1
36.933	6.34557	0	0	0	0	0	0	0	0
37.067	308.0818	0	0	1	1	1	1	1	1
40.4	177.32	0	0	1	1	1	1	1	1
42.667	128.3806	0	0	1	1	1	1	1	1
44.467	50.98748	0	0	0	0	0	0	0	0

Considering the gap session beginning at $t = 29.533$, which has a very high weight ($L_x L_t$ in Eq. 6-1 in Section 6.6.2 is very large), the simulated subject vehicle with $t_h \le 2\ s$ takes the correct lane change action while $t_h > 2\ s$ does not. Figure 6.37 shows the real vehicle lane change action and simulated vehicle lane change action by t_h. In this case, if the time horizon is longer than 2 seconds, then the simulated vehicle infers an advantage in the lane to the left because the faster vehicle in that lane is assumed to move ahead, thus giving the subject vehicle more distance gained at the time horizon. But if the time horizon is 2 seconds or less, then there is no advantage seen in moving to the left lane. Therefore it can be inferred that the time horizon of the real vehicle is at most 2 seconds, for this analyzed vehicle.

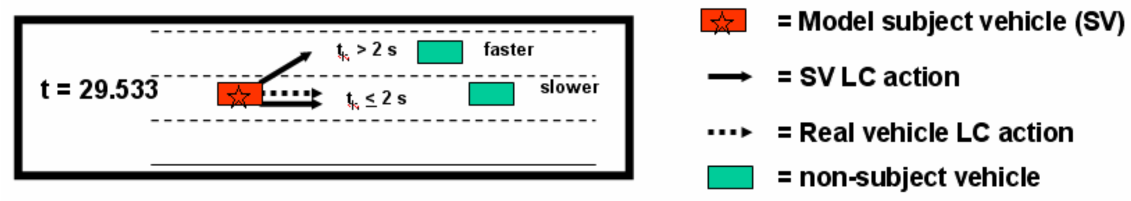


Figure 6. 37: **Real vehicle lane change actions and simulated vehicle's lane change actions depending on time horizon (Vehicle no. 68)**

The findings from this sensitivity analysis are that the search horizon parameter has a significant effect on the performance of the sequential planning lane change model. In Figure 6.33 it can be seen evidence that the best-fit t_h parameter also varies by driver. Therefore it is decided that for the forthcoming analysis, the t_h parameter will be best-fit estimated for each vehicle.

The results shown in Table 6.14 were found for the 36 selected aggressive drivers, calibrated in the two stages with $(\tau,\ v_{des})$ estimated in the car following model calibration, and $(F,\ t_h)$ for the sequential planning model estimated in the lane change model calibration stage, using the gap session method. There can be seen a wide variation of resulting optimal t_h parameters over the selected vehicles.

Table 6. 14: **Optimal lane change parameters for 36 selected vehicles** $U_{LC}(F,t_h)$

svID	τ (s)	v_{des} (m/s)	F	t_h	U_{LC}
4111	1.9	25	1.0	1	0.310
2451	0.8	40	0.4	6	0.151
266	0.4	40	1.0	3	0.438
1875	0.4	39	1.2	5	0.366
2262	0.5	38	1.2	5	0.091
1303	1.3	30	1.0	3	0.111
135	0.6	40	1.0	1	0.152
3920	1.2	25	1.0	1	0.236
2633	1	40	0.6	3	0.124
68	0.4	39	1.0	1	0.062
3136	1.6	40	1.0	1	0.077
99	0.3	29	1.0	1	0.199
4236	0.8	32	1.0	1	0.238
1609	0.4	26	1.0	1	0.185
69	1.3	40	1.0	1	0.154
133	0.8	30	1.0	1	0.079
45513	1.1	25	1.0	1	0.055
2552	0.2	27	1.0	1	0.000
1715	0.6	31	1.6	3	0.114
2679	1.6	28	1.0	1	0.184
14012	0.6	33	1.0	1	0.099
3327	0.6	25	1.0	1	0.313
1975	0.3	37	1.0	5	0.000
1702	0.9	26	1.0	1	0.000
264	0.4	40	1.0	1	0.089
551	0.4	31	1.0	3	0.000
2109	0.9	29	1.0	1	0.070
459	0.6	31	1.0	4	0.201
4135	0.6	40	1.0	3	0.111
2014	0.9	40	1.0	3	0.280
224	0.6	30	0.4	3	0.036
3094	0.8	33	1.0	1	0.096
89	0.5	33	1.0	1	0.104
2636	1.1	25	1.0	1	0.097
3688	1.1	26	1.0	1	0.253
3006	1.5	25	1.0	1	0.000

Also, it should be kept in mind that for the trajectory data used in this experiment, the vehicles were each observed over only a limited period of time: approximately 30 seconds. Therefore, to a greater or lesser degree depending on the analyzed vehicle, the vehicle may not have experienced a set of gap sessions with sufficient variation to capture the range of influencing factors. If a longer observation time duration of the individual analyzed vehicles were possible, such as using an instrumented vehicle to monitor the behavior of an individual driver, a richer and more accurate representation of the driver lane changing behavior could be obtained. (However, the instrumented vehicle data may have limited or inaccurate information about the positions of surrounding vehicles.)

Sensitivity to t_h *for multiple lane change maneuver*

An additional analysis was also performed on the influence of the time horizon parameter on sequential planning and lane change behavior for a lane change maneuver which is part of a sequence of multiple lane changes. Consider again the real observed vehicle 1161 from the NGSIM trajectory data set (Cambridge Systematics, 2004) which was introduced in Chapter 2. The situation is shown again here in Figure 6.38.

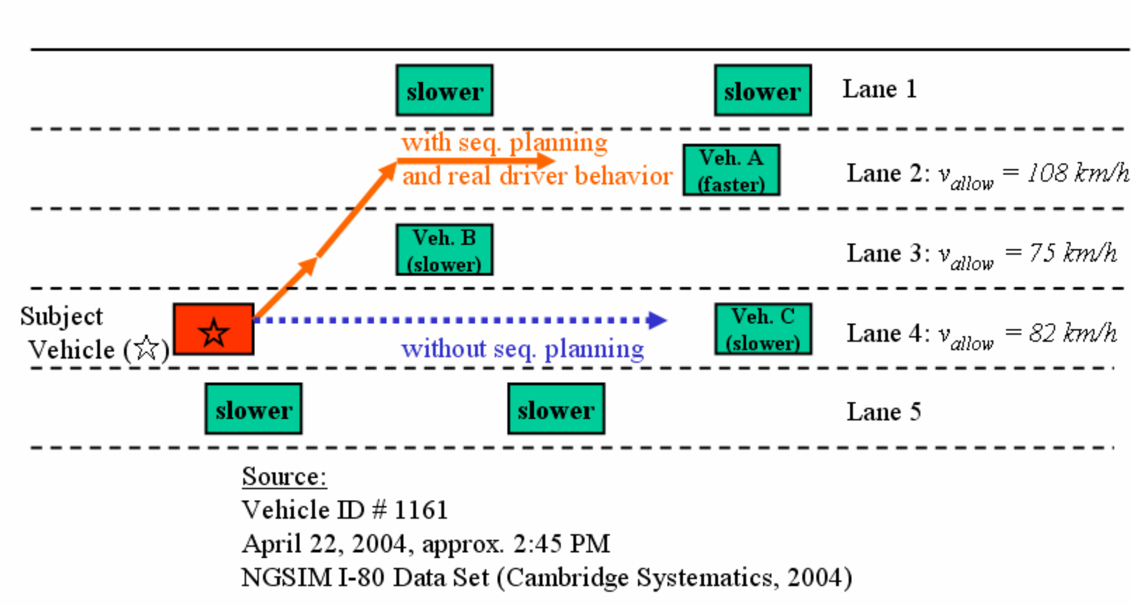


Figure 6. 38: Sequential planning of multiple lane change maneuver, example reconsidered (veh. no. 1161)

In order for the subject vehicle to recognize the long term advantage of moving to Lane 2, he must be able to see past the short-term disadvantage of moving into Lane 3 which causes a reduction in the allowable speed, which can be considered as a kind of lane utility. The effect of the time horizon t_h on the enumerated sequential plans and selected lane change action considered.

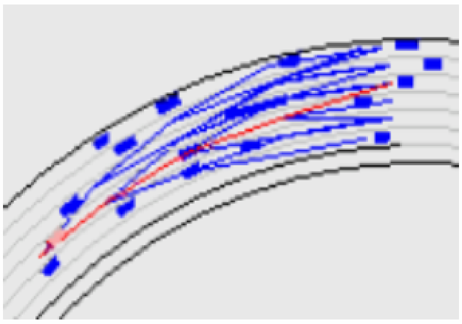
For the examined vehicle, the subject vehicle best-fit parameters $\tau = 1.0\ s$ and $v_{des} = 40\ m/s$ were estimated using the procedure as described in Section 6.5. The lane change gap adjustment factor $F = 0.1$ was obtained though trial-and-error by continually reducing the F value until the subject vehicle was able to accept the same gap as that by the real driver.

The examined situation was simulated using the sequential planning model with time horizon t_h of 1.0 to 8.0 with 1.0 step size. Because the best-fit value of reaction time lag for the analyzed vehicle is $\tau = 1.0\ s$ and this is also the planning time step size, the value of t_h can also be thought of as the number of planning steps included in the subject vehicle's plan. The enumerated plans and resulting lane change actions under the different values are shown in Table 6.15.

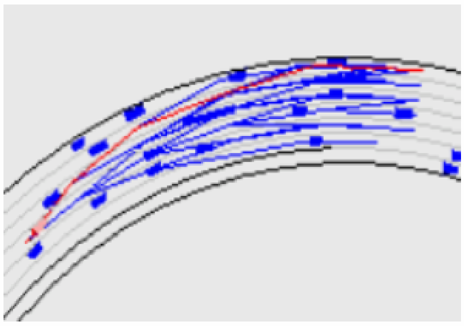
Table 6. 15: Lane change action by time horizon, subject vehicle 1161

Time horizon t_h (s)	Lane change action: -1 = left, 0 = no lane change, +1 = right lane change
1	0
2	0
3	0
4	0
5	0
6	-1
7	-1
8	-1

The difference in the lane change action is seen between $t_h = 5\ s$ and $t_h = 6\ s$. Because the real vehicle's lane change behavior was to make a left lane change, then it can be inferred that the real driver, at least in this gap situation, has a time horizon of $t_h \geq 6\ s$. The enumerated plans for $t_h = 5\ s$ and $t_h = 6\ s$ are shown in Figure 6.39.



$t_h = 5\ s$



$t_h = 6\ s$

Figure 6. 39: Enumerated sequential lane change plans (veh. no. 1161)

In the Figure 6.39, the subject vehicle is red. The subject vehicle projected trajectories for each enumerated maneuver plan are shown: red for the selected plan (best utility to the subject vehicle) and blue for others. The difference due to increasing the search time horizon to 6 s can be seen clearly by comparing the left and right-hand of the figure. In $t_h = 5\ s$, the best plan is to make no lane change. However, for $t_h = 6\ s$, the best plan is a sequence of two lane changes to the left.

Note that in the figure the lines showing the maneuver plans are drawn on the road at the present time, not the projected time. For this reason, positions of the vehicles at the later time are further ahead than shown.

In summary, in this subsection it was shown that the both the time horizon parameter t_h and the gap adjustment factor F have a significant effect on the model lane change action. For an example vehicle making two lane changes, the value of time horizon parameter was inferred. For some analyzed vehicles, there were multiple points in the lane change model parameter vector search space giving the best model performance. It should be noted, that for comparing the performance for different lane change models in which only the performance measure, not the best-fit parameter vector, is used, this is not a problem. However, in applications in which the model is used in a traffic simulator, it is important to obtain more precise values of the lane change model parameters for individual vehicles. Ways to improve this have been discussed in this section, and are recommended for further research. Specifically, the lane change model performance measure could be expanded to include not only the lane change action (yes/no) but also information about relative position of vehicles at the time of lane change. Also, additional observations of lane change behavior are recommended to provide more complete coverage over the range of explanatory factors.

6.6.6 Lane change model performance sensitivity analysis to c_l

A sensitivity analysis of the lane change model performance to the lane change penalty parameter, c_l, was conducted. This is the tactical lane change model in which an additional feature has been added to penalize planned maneuver sequences which have a higher number of lane changes, which is explained in Section 5.5.1.

To see if an improvement in performance could be realized, the lane change model was evaluated for the selected vehicles by searching in a grid over the following variables: $\{F, t_h, c_l\}$. For vehicle no. 1875, the best $U_{LC} = 0.152$ was found when $F = 1.2$, $t_h = [5.0 \text{ to } 6.0]$, and $c_l = [-1.5 \text{ to } -0.5]$ (very low). The performance surface for F fixed at 1.2 is shown in Figure 6.40. For this vehicle, there is no performance improvement using the lane change penalty. Other vehicles investigated are described below.

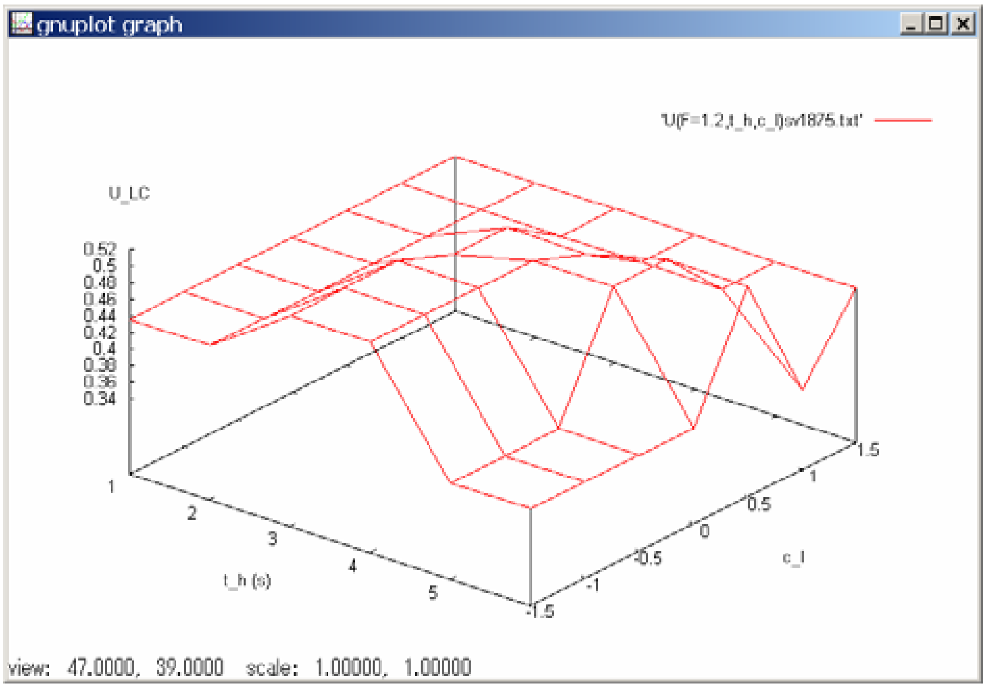


Figure 6. 40: Performance sensitivity for lane change penalty coefficient (Vehicle no. 1875)

Vehicle no. *4111*:

Best $U_{LC} = 0.310$ when $F = 1.0$, $t_h = [1.0,2.0]$ and $c_l = [-1.5 \text{ to } 1.5]$ (full range).

The performance surface for $F = 1.0$ is shown in Figure 6.41:

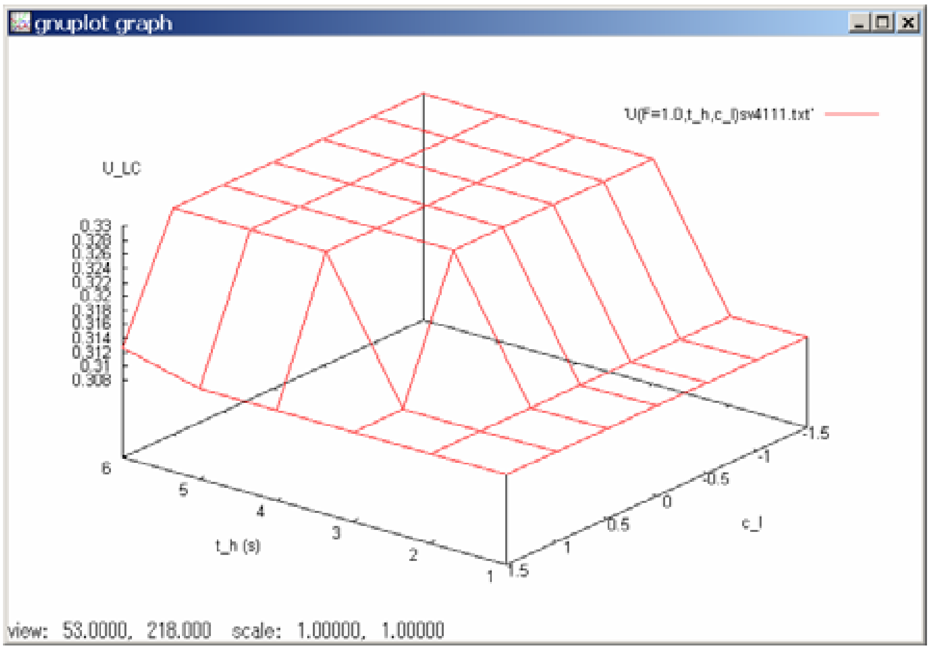


Figure 6. 41: Performance sensitivity for lane change penalty coefficient (Vehicle no. 4111)

In this case as well, the lane change penalty does not offer better performance.

For vehicle no. *135,* the optimum performance is found $F = 1.0$, $t_h = [1.0,2.0]$ and $c_l = [-1.5 \text{ to } 1.5]$ (full range).. The surface is shown here for $F = 1.0$: (Figure 6.42)

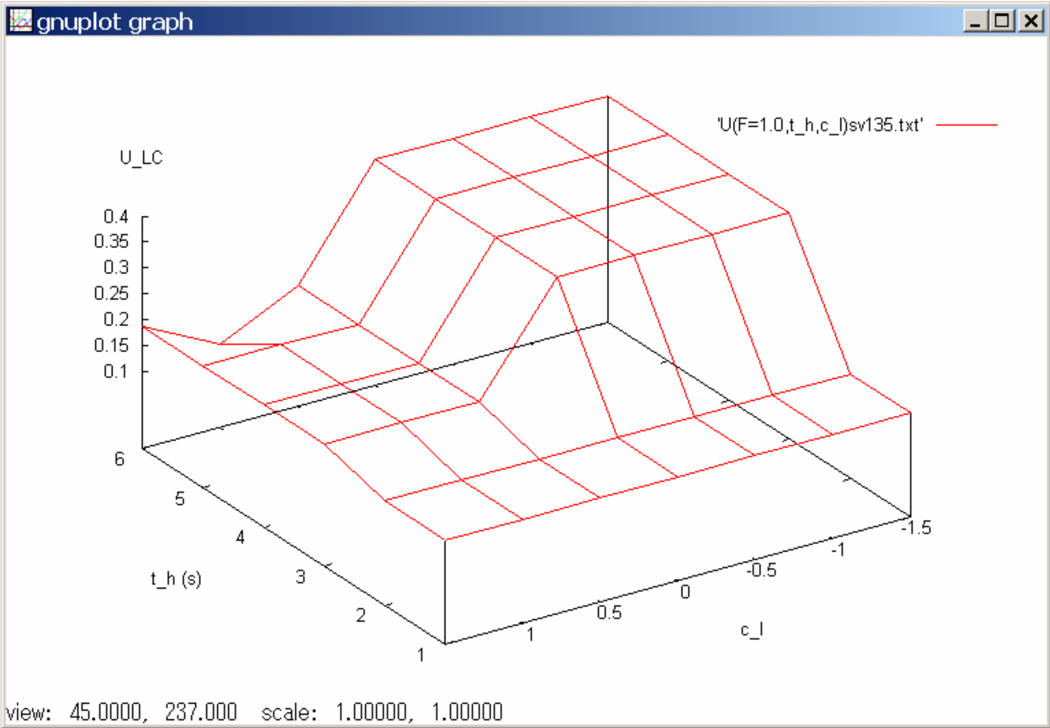


Figure 6. 42: Performance sensitivity for lane change penalty coefficient (Vehicle no. 135)

The performance tends to be better for longer time horizons and smaller lane change penalty.

In summary, in this subsection, the sensitivity of the lane change model performance U_{LC} to the lane change penalty parameter c_l was tested for three vehicles, and it was found not to improve the performance.

6.7 Lane change model performance comparison

The performance of the proposed tactical lane changing model is compared to that of the basic lane change model, in terms of the ability to realistically represent the behavior of an individual vehicle in its traffic environment. A real-world trajectory data set is used. The performance of either lane changing model is judged by how well it reproduces the driver behavior (longitudinal control actions: acceleration / deceleration, lateral control actions: lane change or no lane change) of individual drivers actually observed in the trajectory data set, in response to the conditions of the surrounding vehicles and road geometry.

For all *36* selected vehicles from the aggressive group of drivers (as described in section 6.2.1.2), the longitudinal and lane change model calibration stages were performed. As mentioned, the lane change calibration was performed using the gap session method. Before describing the comparison, first the justification for selection of the basic lane change model will be revisited. The following subsections describe the selection of the baseline model, and the comparison procedure, respectively.

6.7.1 Baseline model selection

To make the comparison of the sequential planning lane change model performance to a baseline lane change model, first the baseline model must be decided. The baseline lane change model is one which is considered to have a similar level of functioning to those of many present-day traffic simulators. Specifically, the baseline lane change model should determine the lane change action based only on the utility of the immediate next lane change action, and does not consider the utility of subsequent situations.

This section describes the selection of the baseline model. Several options were considered. One was to use the proposed sequential planning model, but with its scope truncated to one planning time step. Such a *truncated sequential planning model* would develop a plan from present time t until time $t + \tau$. The second option is to use the basic lane change model which is described in Chapter 4. The two options and their consideration are described here.

Although seemingly straightforward, the use of the *truncated sequential planning model* as a baseline would be inadequate because it's objective function would be based only on the distance gained over the planning time interval, which would be the same regardless of the lane change action, as explained here: Consider a situation in which the subject vehicle is under control of the *truncated sequential planning model* and has gaps available in both adjacent lanes; then three one-step maneuver plans would be generated, as shown in Figure 6.43.

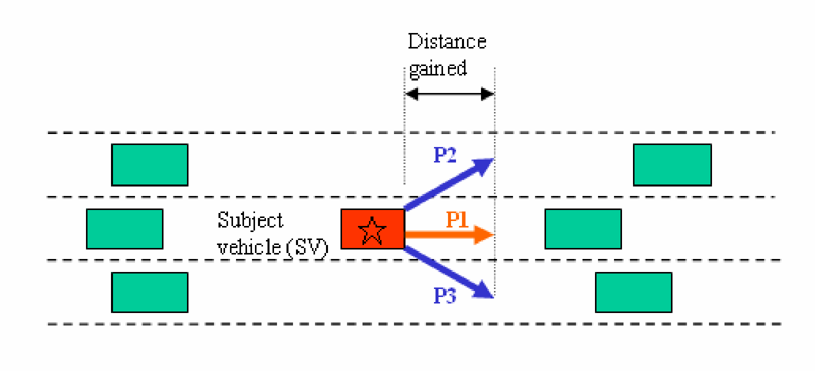


Figure 6. 43: Inadequacy of model with one-step maneuver plans

In the *truncated sequential planning model* implementation, the Forward Search Tree nodes are extended by decomposing the planned action into two components: longitudinal control and lane change actions. A maneuver plan is generated in the Forward Search Tree for each possible lane change action, in this case *{left lane change, no lane change, right lane change}*. For each maneuver plan, the longitudinal control action is computed for the subject vehicle's current lane in terms of the longitudinal control model described in Chapter 4. Therefore all three maneuver plans will be given the same longitudinal control action, longitudinal distance gained, and utility. As described in Section 5.3, the model deals with cases of equal utility by selecting the plan with the fewest number of lane changes, which in this case is the *no lane change* option. Therefore, the *truncated sequential planning model* will always give a *no lane change* action.

Obviously this would not serve as a fair representation of the status quo model, as it would give a lane change action different from the real vehicle in all cases when the real vehicle makes a lane change. Thus, the utility function used for the tactical lane change model is suitable for planning maneuvers over a relatively longer duration, but is less useful in evaluating the relative utility of lane change actions to be performed at the present simulation time.

Another option is to use the basic lane change model, which is described in Chapter 4. This model contains a utility function which is based on the allowable speed, v_{allow}, which is a function of the subject vehicle and lead vehicle speeds and positions in the destination lane as described fully in that chapter. This utility function is better at ascertaining the situation at a particular time. This is in contrast to the sequential planning model's utility function which is more suitable for quantifying how a vehicle's situation is changing over a time interval.

In conclusion, of the two options, the basic lane change model, as described in Chapter 4, was selected as the baseline model for use in the comparison, because it allows a fairer comparison, and is the best representation of a lane change model such as those used in many of today's traffic simulators.

6.7.2 Performance Comparison Method

The overall performance of both the basic and sequential planning lane change models was computed for each vehicle. For the selected vehicles, the summary values of the estimated parameters: $\{\tau^*, v_{des}^*, F^*_{basic}, F^*_{seqPl}, t_h^*_{seqPl}\}$ as well as their goodness-of-fit values $\{U_{ordLong}, U_{LC|basic}, U_{LC|seqPl}\}$ are shown in Table 6.16. For an analyzed vehicle, in the case of multiple equal-performing lane change model parameter vectors, the best-fit values shown in Table 6.16 of the lane change model parameters $\{F^*_{basic}, F^*_{seqPl}, t_h^*_{seqPl}\}$ shown are decided through the tie-breaking rules described in Section 6.6.2, in which F nearest to 1.0 and the lowest t_h are selected. The full range of best-performing parameters are shown in Table 6.18. If multiple points in the search space resulted in the optimum U_{LC} lane change model performance measure, the *[ ]* square brackets represent inclusive intervals over a range of parameter values.

Table 6. 16: Estimated parameters for selected vehicles

svID	τ^*(s)	v_{des}^* (m/s)	$U_{ordLong}$	F_{basic}^*	$U_{LC\|basic}$	F_{seqPl}^*	$t_h{}^*{}_{seqPl}$	$U_{LC\|seqPl}$
4111	1.9	25	12.861	1.0	0.329	1.0	1	0.310
2451	0.8	40	4.225	1.6	0.241	0.4	6	0.151
266	0.4	40	3.335	1.0	0.485	1.0	3	0.438
1875	0.4	39	4.599	1.0	0.619	1.2	5	0.366
2262	0.5	38	2.024	1.0	0.168	1.2	5	0.091
1303	1.3	30	4.091	1.0	0.194	1.0	3	0.111
135	0.6	40	7.518	1.6	0.392	1.0	1	0.152
3920	1.2	25	7.336	1.0	0.236	1.0	1	0.236
2633	1	40	4.187	1.0	0.209	0.6	3	0.124
68	0.4	39	3.291	1.2	0.393	1.0	1	0.062
3136	1.6	40	5.573	1.0	0.077	1.0	1	0.077
99	0.3	29	1.729	1.6	0.241	1.0	1	0.199
4236	0.8	32	3.381	1.6	0.310	1.0	1	0.238
1609	0.4	26	2.480	1.0	0.052	1.0	1	0.185
69	1.3	40	4.373	1.4	0.154	1.0	1	0.154
133	0.8	30	1.650	1.4	0.079	1.0	1	0.079
45513	1.1	25	23.971	1.6	0.069	1.0	1	0.055
2552	0.2	27	5.514	1.0	0.104	1.0	1	0.000
1715	0.6	31	5.609	1.6	0.114	1.6	3	0.114
2679	1.6	28	2.506	1.0	0.184	1.0	1	0.184
14012	0.6	33	3.861	1.0	0.821	1.0	1	0.099
3327	0.6	25	5.781	1.0	0.423	1.0	1	0.313
1975	0.3	37	2.684	1.0	0.034	1.0	5	0.000
1702	0.9	26	8.910	1.0	0.000	1.0	1	0.000
264	0.4	40	3.993	0.4	0.910	1.0	1	0.089
551	0.4	31	3.900	1.0	0.015	1.0	3	0.000
2109	0.9	29	6.637	1.0	0.015	1.0	1	0.070
459	0.6	31	4.346	1.0	0.201	1.0	4	0.201
4135	0.6	40	5.435	1.0	0.167	1.0	3	0.111
2014	0.9	40	3.945	1.0	0.285	1.0	3	0.280
224	0.6	30	4.369	0.4	0.036	0.4	3	0.036
3094	0.8	33	4.937	1.6	0.178	1.0	1	0.096
89	0.5	33	2.209	1.2	0.577	1.0	1	0.104
2636	1.1	25	5.471	0.6	0.053	1.0	1	0.097
3688	1.1	26	3.020	1.6	0.386	1.0	1	0.253
3006	1.5	25	5.591	1.0	0.000	1.0	1	0.000

The summary statistics of the estimated parameters: *{τ*, v_{des}*, F^*_{basic}, F^*_{seqPl}, $t_h{}^*{}_{seqPl}$}* as well as their goodness-of-fit values *{$U_{ordLong}$, $U_{LC|basic}$, $U_{LC|seqPl}$}* are shown in Table 6.17.

Table 6. 17: Summary statistics of vehicle parameter estimation

	τ^*(s)	v_{des}^* (m/s)	$U_{ordLong}$	F_{basic}^*	$U_{LC\|basic}$	F_{seqPl}^*	$t_h{}^*{}_{seqPl}$	$U_{LC\|seqPl}$
mean	0.806	32.4	5.1483	1.122	0.243	0.983	2.000	0.141
st.dev.	0.423	5.9	3.8908	0.322	0.223	0.193	1.493	0.108
median	0.700	31.0	4.2857	1.000	0.189	1.000	1.000	0.111
min	0.2	25.0	1.6499	0.400	0.000	0.400	1	0.000
max	1.9	40.0	23.9708	1.600	0.910	1.600	6	0.438

Table 6. 18: **Range of best-performing parameters**

svID	Range of best-performing lane change model parameters		
	Basic lane change model	Sequential Planning Lane Change Model	
	F	F	t_h (s)
4111	[0.6,1.6]	[0.4,1.6]	[1,2]
2451	1.6	0.4	[6,8]
266	[0.8,1.0]	[0.8,1.0]	[3,8]
1875	[0.8,1.6]	[1.2,1.4]	[5,6]
2262	[1.0,1.4]	1.2	[5,7]
		1.4	[5,6]
		1.4	8
1303	[1.0,1.2]	[0.4,1.2]	[3,8]
135	1.6	[0.4,1.6]	[1,2]
3920	[0.6,1.6]	0.4	[1,2]
		[0.6,1.6]	[1,8]
2633	0.6	0.6	[3,8]
68	[1.2,1.6]	[0.4,1.6]	[1,2]
3136	[1.0,1.6]	[0.4,0.8]	[1,2]
		[1.0,1.6]	[1,8]
99	1.6	[0.4,1.6]	[1,2]
4236	1.6	[0.4,1.6]	[1,2]
1609	[0.4,1.4]	[0.4,1.6]	[1,2]
69	[1.4,1.6]	[0.4,1.2]	[1,2]
		1.2	[6,8]
		[1.4,1.6]	[1,8]
133	[1.4,1.6]	[0.4,1.0]	[1,2]
		[1.2,1.6]	[1,8]
45513	1.6	[0.4,1.4]	[1,2]
		[1.6]	[1,8]
2552	[0.4,1.6]	[0.4,1.6]	[1,2]
		0.4	[7,8]
1715	1.6	1.6	[3,8]
2679	[1.0,1.6]	[0.4,0.8]	[1,2]
		[1.0,1.6]	[1,8]
14012	[1.4,1.6]	[0.4,1.6]	[1,2]
3327	1.6	[0.4,1.6]	[1,2]
		1.6	[3,4]
		[1.4,1.6]	[5,8]
1975	[1.2,1.6]	[1.2,1.6]	[3,4]
		[1.0,1.6]	[5,7]
		[1.0,1.4]	8
1702	[0.4,1.6]	[0.4,1.6]	[1,8]
264	0.4	[0.4,1.6]	[1,2]
551	[1.0,1.2]	[1.0,1.2]	[3,5]
2109	[0.4,1.6]	[0.4,1.6]	[1,2]
459	[0.4,1.4]	0.4	[3,4]
		[0.6,0.8]	3
		[0.6,1.2]	[4,8]
4135	1	1	[3,8]
2014	[0.6,1.0]	0.6	[3,5]
		[0.8,1.0]	[3,8]
224	0.4	0.4	[3,4]
3094	1.6	[0.4,1.6]	[1,2]
89	[1.2,1.6]	[0.4,1.6]	[1,2]
2636	[0.6,0.8]	[0.4,1.6]	[1,2]
3688	1.6	[0.4,1.6]	[1,2]
3006	[1.0,1.6]	[0.4,0.8]	[1,2]
		[1.0,1.6]	[1,8]

In the model calibration, there are two indicators of the goodness of fit: $U_{ordLong}$ for the longitudinal control model and U_{LC} for the lane change model, as were described previously. If the simulator were to perfectly match the real-world vehicle trajectory, then both of these would be zero. The summary statistics of the goodness-of-fit of the estimated basic and sequential planning lane change model parameters, $U_{LC|basic}$ and $U_{LC|seqPl}$ respectively, are shown in Table 6.17. The median value of U_{LC} is lower for the sequential planning model.

The best-fit result of gap acceptance parameter F in Table 6.17 is also of interest. The mean and st. dev. terms $F = 0.983 \pm 0.193$ for the sequential planning model indicate that many vehicles have a best-fit value of $F < 1.0$. These vehicles would accept smaller gaps than that which would allow a safe stop if the lead vehicle were to brake at maximum deceleration. This implies that the drivers are anticipating that the lead vehicles will not undertake such quick decelerations.

Over the set of vehicles analyzed, the overall performance of the two lane change models can be judged by the number of vehicles in which the performance was better by either model. Figure 6.44 shows the performance improvement (decrease in U_{LC}) by using the Sequential Planning lane change model compared to the Basic lane change model. In 23 of the 36 analyzed vehicles (64%), the proposed sequential lane change model performed better than the basic lane change model ($U_{LC|seqPl} < U_{LC|basic}$). Only 8% (3 out of 36) of the analyzed vehicles showed the Tactical lane change model giving an inferior performance ($U_{LC|seqPl} > U_{LC|basic}$). For the remaining 10 cases (28 %) both models gave an equal performance.

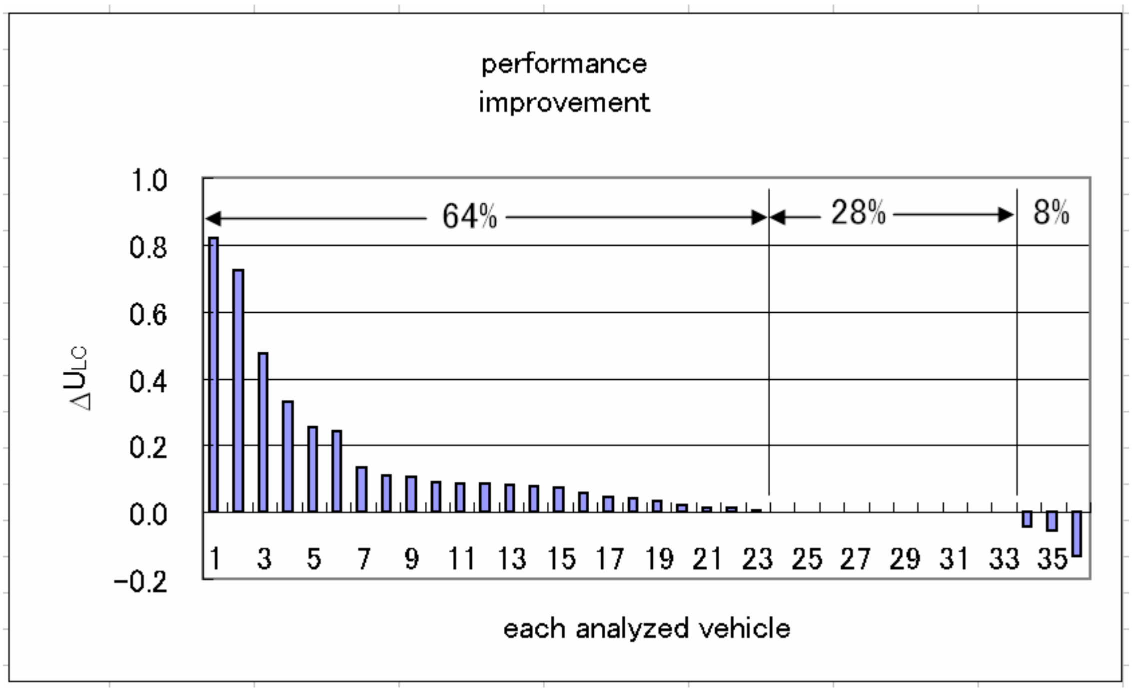


Figure 6. 44: Comparison of performance of lane change models.

6.8 Complexity and stability investigation

In this test, the effect of simulating the surrounding vehicles on the subject vehicle's simulated behavior is considered. The subject vehicle is simulated as traveling among the surrounding vehicles which are traveling as in the real-world trajectory data. It is of interest to consider the effect on the realism of the simulated subject vehicle as well as the stability of the system, of adding an increasing number of surrounding vehicles to the control of the simulator.

This section describes an investigation to observe such effects. One trial is described here.

In the initial case, the subject vehicle was simulated among the real vehicles. Then succeeding cases one, two, up to *4* surrounding vehicles were simulated (up to 5 total vehicles simulated at one time) and the simulation realism performance of the subject vehicle in each of the cases was compared.

To select the vehicles to use for the investigation, the trajectory data set was searched for a platoon of vehicles traveling close together. Platoons of vehicles would be expected to be in close proximity in terms of longitudinal position, lane, and also common time duration. Based on these characteristics, the following search technique was used: Every pair of vehicles in the initial 5 minute period of the trajectory data were compared for similarity in terms of the following measures:

- T = the length of the time interval in which they are both present in the trajectory data
- $U_{ordLong}$ = the root mean squared difference in longitudinal position of the two vehicles, over the time interval T
- U_{lane} = the absolute difference in lanes averaged over the time interval T

The vehicles to use in this investigation were selected as those which had a very long interval T, and very small displacements $U_{ordLong}$ and U_{lane}. From the trajectory data set, five vehicles were selected which have a very good trajectory similarity in terms of the measures described above. The selected vehicles are shown with their relative positions during their running, in Figure 6.45. The red vehicle is the main (anchor) subject vehicle.

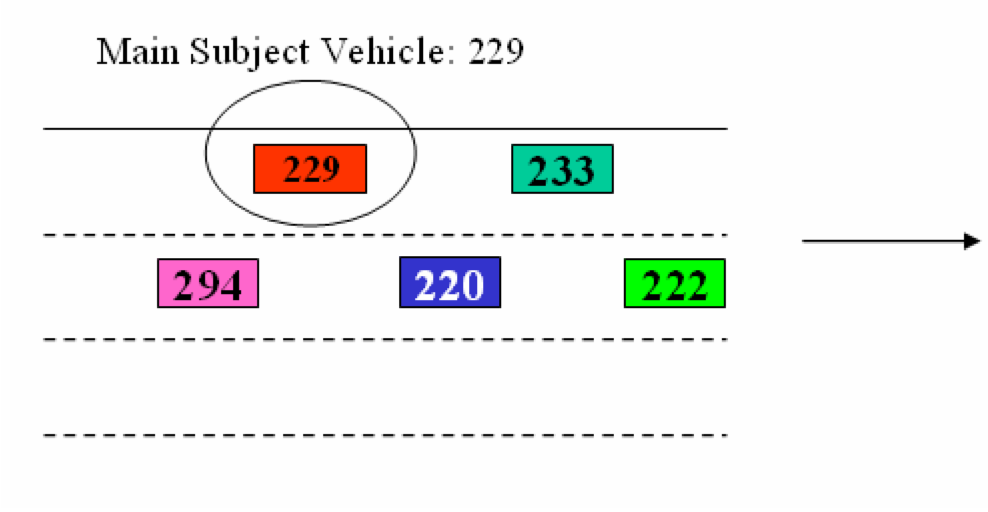


Figure 6. 45: Complexity and stability investigation: relative positions of vehicles in platoon

The optimal car following and lane changing parameters were then estimated for the selected vehicles through a two-stage best-fit search as previously described in sections 6.5 and 6.6. Table 6.19 shows the best-fit parameters for the vehicles used in the investigation.

Table 6. 19: Complexity and stability investigation: best-fit parameters

svID	τ *(s)*	v_{des} *(m/s)*	*F*	t_h *(s)*
229 (anchor vehicle)	0.5	40	0.4	4
220	0.5	38	0.4	2
294	0.5	40	0.4	2
222	0.7	36	0.4	4
233	0.9	27	0.4	4

It should be noted that in this investigation only, the best-fit estimation process was modified as follows: if multiple values of F were found which gave minimum U_{LC}, then the *lowest* searched value of F was used. This modification was implemented in order to allow the simulated vehicles a greater chance of accepting available gaps, thereby allowing greater sensitivity to conditions. The choice of the tie breaking rule is arbitrary in that any parameter value which gives the best fit could be considered equally reasonable.

Next, each of the cases was simulated. The first case is the anchor vehicle alone under the control of the driver models, and the other vehicles traveling as observed in the vehicle trajectory data. For the succeeding cases, one by one, other vehicles are added to the simulator's control. For each case, the realism of the simulation in terms of the following two measures is shown:

- $U_{ordLong}$ = the root mean squared difference in longitudinal position of the two vehicles, over the time interval T
- U_{lane} = the absolute difference in lanes averaged over the time interval T

Two trials were performed, using the same group of vehicles, but slightly rearranging the order in which the vehicles were introduced. The results of the trials are shown in Tables 6.20 and 6.21.

In trial 1, as the first vehicle (no. 220) was added to control by the simulator, there was a reduction in the realism performance: subject vehicle U_{lane} increases from 0 to 0.436. This finding is as would be expected because allowing additional vehicles to be simulated adds to the variation in the system, both by individual vehicles, and through their mutual interactions. However, thereafter, as additional nearby vehicles (nos. 294, 222, 233) were added to simulator control, the complex interactive dynamics resulted in stabilization or slight improvement in the realism of the anchor vehicle representation.

Table 6. 20: Complexity and stability investigation: trial 1

Case	**Subject Vehicle $U_{ordLong}$**	**Subject Vehicle U_{lane}**
Subject vehicle 229 (anchor vehicle) alone	8.555	0
Subject vehicle 229 with vehicle 220	6.429	0.436
Subject vehicle 229 with vehicles 220 and 294	8.829	0.049
Subject vehicle 229 with vehicles 220, 294, and 222	8.554	0
Subject vehicle 229 with vehicles 220, 294, 222, and 233	7.926	0

Table 6. 21: Complexity and stability investigation: trial 2

Case	**Subject Vehicle $U_{ordLong}$**	**Subject Vehicle U_{lane}**
Subject vehicle 229 (anchor vehicle) alone	8.555	0
Subject vehicle 229 with vehicle 233	7.876	0
Subject vehicle 229 with vehicles 233 and 220	6.157	0.365
Subject vehicle 229 with vehicles 233, 220, and 294	8.079	0.103
Subject vehicle 229 with vehicles 233, 220, 294, and 222	7.926	0

In trial 2, addition of the first vehicle (no. 233) does not negatively affect the performance, however, adding the next two vehicles (nos. 220 and 294) show a drop in the performance as seen in the U_{lane} value. But the addition of the last vehicle (no. 222) somehow causes the realism to improve.

In this investigation, although only one group of vehicles was considered, by just changing the order of vehicle introduction, through the complexity of the simulated system dynamics, a difference in realism performance was seen. Further investigation about the extent of the complexity, how it grows or decreases as influenced by the order of vehicle introduction would be an interesting topic for further research. For the purposes of the model development and performance comparison carried out in this thesis, which focuses on the realism of driver behavior of the individual vehicle, the possible decrease in realism performance due to addition of simulated vehicles does not have an impact.

6._Summary

In this chapter, the performance of the proposed tactical lane change model was examined. First, the model realism in terms of vehicle kinematics was examined. Next the real world vehicle trajectory data set was described. The rationale and procedure for selecting a subset of the vehicles to analyze was given. Specifically, rather than considering all vehicles, this analysis considers the vehicles which make many lane changes and have a relatively higher speed.

Next, an overview of the best-fit model parameter estimation was described, including parameter search techniques and selection of variables for estimation. The longitudinal and lane change model best fit estimation procedures were explained. For the longitudinal control model, the sensitivity analysis of acceleration and deceleration, as well as the considerations of desired speed estimation were described.

For the lane change model, a comparison was performed between two alternative methods for evaluating the model performance, and the gap session method was selected. This method considers the performance of the lane change model based on whether or not the simulated vehicle performed the same lane change action *{left lane change, no lane change,* or *right lane change}* as the real vehicle during a time period in which surrounding vehicles were in the same relative position with the same gap situation. Several other sensitivity analyses were performed including sensitivity to the time horizon parameter. It was found that this parameter can vary for the analyzed vehicles, and that it is possible to infer an individual vehicle's time horizon parameter value by considering the observed lane change actions in the context of hypothetical sequential maneuver plans. The lane change penalty coefficient, introduced in the Chapter 5, was also considered in a sensitivity analysis.

The performance of the tactical lane change model was compared to that of a basic lane change model which did not include sequential maneuver planning. It was found that the tactical lane change model gave a better performance than the basic lane change model for a greater number of analyzed vehicles.

Finally an investigation considering the complexity and stability of a simulation as the number of simulated vehicles is increased one by one.

7 CONCLUSIONS

7.1 Research Summary and Conclusion

The lane change models that have been developed until now, which are commonly used in today's traffic simulators, consider only the utility of the next lane change and do not consider the driver's planning of maneuver sequences. Representing this can be important in achieving realistic simulation of traffic which contains tactical weaving across several lanes such as at merging sections or freeways with high-occupancy vehicle (HOV) lanes.

This thesis presented a tactical lane change model which determines the current lane change action by developing a tree of potential sequential maneuver plans, and a model for selection of the current lane change action as part of the plan with the best utility for the driver. At each step in the simulation, for each modeled vehicle, the forward search algorithm generates a branching tree of sequential actions, taking into account the changes in the state of the subject vehicle and surrounding vehicles. The sequence of actions leading to the best outcome is then selected and the subject vehicle applies the first action of that sequence for this time step. This allows the driver model to select a current action for which the payoff is delayed.

A basic lane change model was also analyzed, which is intended to be representative of those used in present-day traffic simulators. The basic lane change model does not contain the sequential planning lane change behavior functionality. Instead, it considers the lane change actions in terms of the allowable travel speed in the adjacent lanes.

A traffic simulator was developed for use in this research to serve as the operating environment for developing and evaluating the tactical lane change model. Rudimentary tests of the simulation performance of the model have been performed, considering macroscopic traffic flow properties as well as complexity and stability effects on the realism of platoons through the tactical lane change model. Sensitivity analysis to the driver behavior model parameters was also conducted. These have been described in detail Chapter 6.

For selected real-world vehicles from the vehicle trajectory data, using best-fit estimated driver model parameters, the performance of the tactical lane change model was compared to that of a basic lane change model which did not include sequential maneuver planning. It was found that the tactical lane change model gave a better performance than the basic lane change model for a greater number of analyzed vehicles.

In conclusion, the method introduced for representing the sequential planning behavior in driver lane changing was shown to improve the simulation realism performance, compared to that of existing models. Because the proposed model can capture the tradeoffs in a driver’s decision to move to a slower adjacent lane in order to realize a longer-term advantage of reaching a faster lane two or more lanes away, it can capture this behavior which is not included in previous lane change models.

7.2 Contributions

The major contribution of this thesis is the application of a *forward search algorithm*, which has been widely used in artificial intelligence and robotics, as a heuristic for representing the human planning behavior leading to the lane change decisions. In this work, a framework is proposed and a prototype model is developed to improve the realism in driver lane changing by incorporating planning over a sequence of actions. This is an improvement over the lane change models used in present-day traffic simulators which consider only the utility of the next lane change and do not consider the planning behavior. Such a model is expected to contribute to the state of the art by improving the realism of traffic simulation especially in complex traffic situations in which consideration of a plan is necessary for correct modeling of lane changing behavior. The performance model is tested using a real vehicle trajectory data set.

By contributing to the improvement of lane change modeling, the quality traffic simulation applied to critical policy decision support functions such as infrastructure planning of freeway HOV systems, etc., can realize better decisions, resulting in more effective investment in infrastructure. Other directions for improvements and applications of the proposed model are given in the next section.

7.3 Model improvements

The following are possible approaches for expansion of the prototype model. By considering a detailed comparison of the simulated and actual lane changes, better model features and performance measures can be further developed.

Because this model has been developed to reflect discretionary but not mandatory lane changes, improving the model to reflect mandatory lane changes is recognized as an important next step in the development. To realize this, a vehicle data set which contains more complete information about vehicle destinations will be necessary. Representing mandatory lane changes as well as other driver behavior such as avoiding delay to a faster rear vehicle, longitudinal control planning, accepting risky short-term situations, and cooperative lane changes, have been recognized, and implementation approaches are described for each of these in Chapter 5.

Additionally, approaches for improving the computational efficiency can be considered further. Rather than completely enumerating a new forward search tree at every time step, maintaining the same tree and adjusting for changes in the present situation could offer more efficient computation. Also, the selection of the best alternative in this model could be replaced with a probabilistic behavior choice framework, recognizing that a driver does not always consider the very best choice in a set of alternatives.

The focus of this research is on the behavior of the individual vehicle. This is the fundamental element in a traffic simulation, but it is only the beginning. To fully implement traffic simulation for transportation management and operations applications requires the simulation of all the vehicles in the traffic stream. Each must be generated with an estimated joint distribution of driver behavior parameters. The greater the number of parameters, the more complex is the problem of representing the traffic population. This model has added at least one major parameter which is not found in the previous driver behavior models, namely the time horizon length, t_h. In adding this extra parameter, the benefit of improved simulation realism (as was highlighted in this thesis) should outweigh the complexity and data analysis costs of including it.

The improved simulation realism has been shown in terms of the individual vehicle, but depending on the application, this may or may not result in a difference in terms of macroscopic performance indicators such as average speed, flow, or travel time. In the case of HOV vehicles merging across the slower traffic streams, the travel time for these vehicles would be expected to be different.

In the next section, new technologies applications for the tactical lane change model are proposed.

7.3.2 New Applications

In this section, two new applications of the tactical lane change model are proposed. The first application serves to address the above-mentioned problem of estimation of driver behavior parameters in a traffic simulation.

(1) Real time control

Traffic simulation is already used in real time control of freeway ramp or urban street intersection traffic signals (Asano et al, 2004). The system is simulated under several candidate near-term control strategies, and the current control action is determined according to best performing strategy. Improving the vehicle lane changing in the simulation would naturally result in increased simulation accuracy and therefore improved control action decision making.

To improve the lane changing model in the simulation, a tactical lane change model with sequential planning behavior could be used. But models which are more complex also require more input parameters specifying the individual vehicles' behavioral characteristics. If it were possible to obtain the values of the parameters for the individual vehicles in the simulated control scenarios, a higher level of realism could be realized.

An example of such a system is shown in Figure 7.1. The control action at the ramp meter signal is determined through evaluation of the impact of alternative control strategies in a simulation.

In the simulation, the initial conditions and driver behavior parameters of the vehicles are specified. This input information is obtained through monitoring of the individual vehicles' prior observed behavior on an upstream monitoring section. The vehicles can be identified through an individual characteristic such as video feature vector containing information such as color, length and relative position of edges and points in the vehicle shapes, through the image processing system.

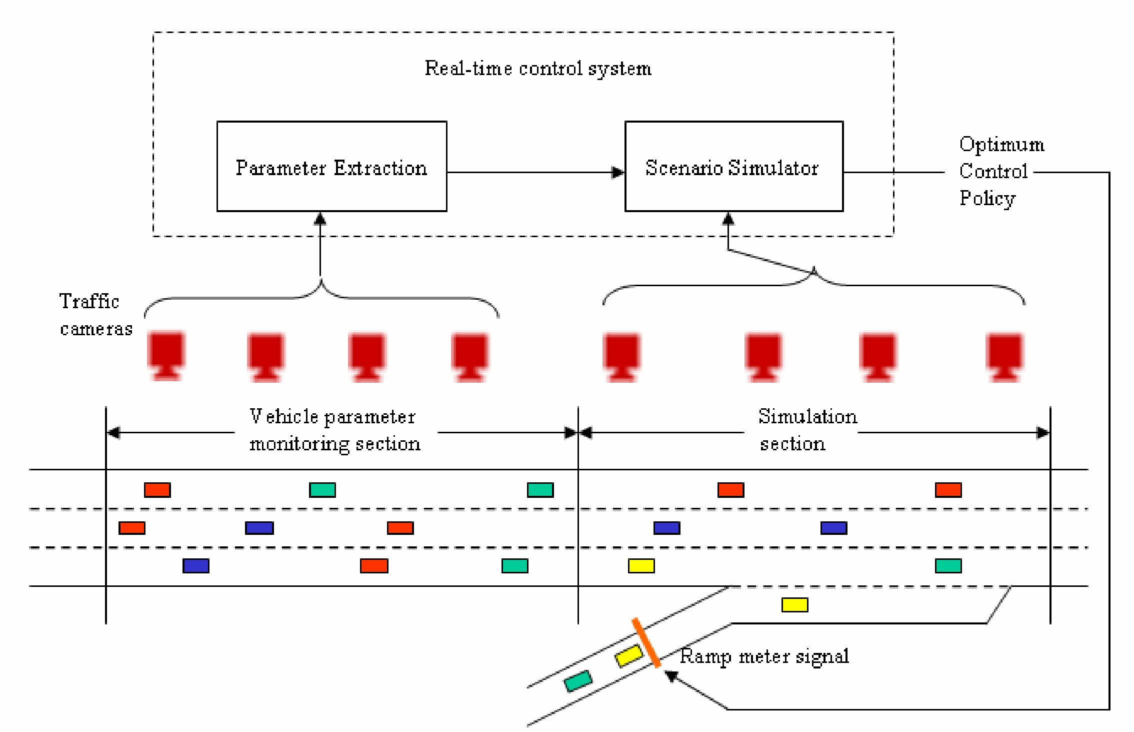


Figure 7. 1: **Real-time control system**

The parameter extraction would be performed for each vehicle after it has traversed the monitoring section, by searching over the range of parameters to find the parameter vector which gives the best fit of simulated to observed vehicle trajectory. Vehicle parameters could include reaction time lag, desired speed, gap acceptance factor, and search time horizon. The procedure would be similar to that which was carried out in Chapter 6 for best-fit parameter estimation of the individual vehicles. The scenario simulator could be executed at each time step, and would determine the set of candidate control actions, and then simulate the effect of each given the initial conditions in terms of the vehicle positions and speeds in the simulation section.

(2) Tactical lane change driver assistant

The application of traffic simulation could be extended beyond system control to user control. Some present-day driver assistance systems allow autonomous speed selection, that is, cruise control with car following, over the range of driving speeds including stop-and-go conditions. In addition, lane keeping and lateral collision warning systems have also been developed (Yamada et al., 2005). To take this concept further, a *tactical lane change assistant* function is proposed as shown in Figure 7.2.

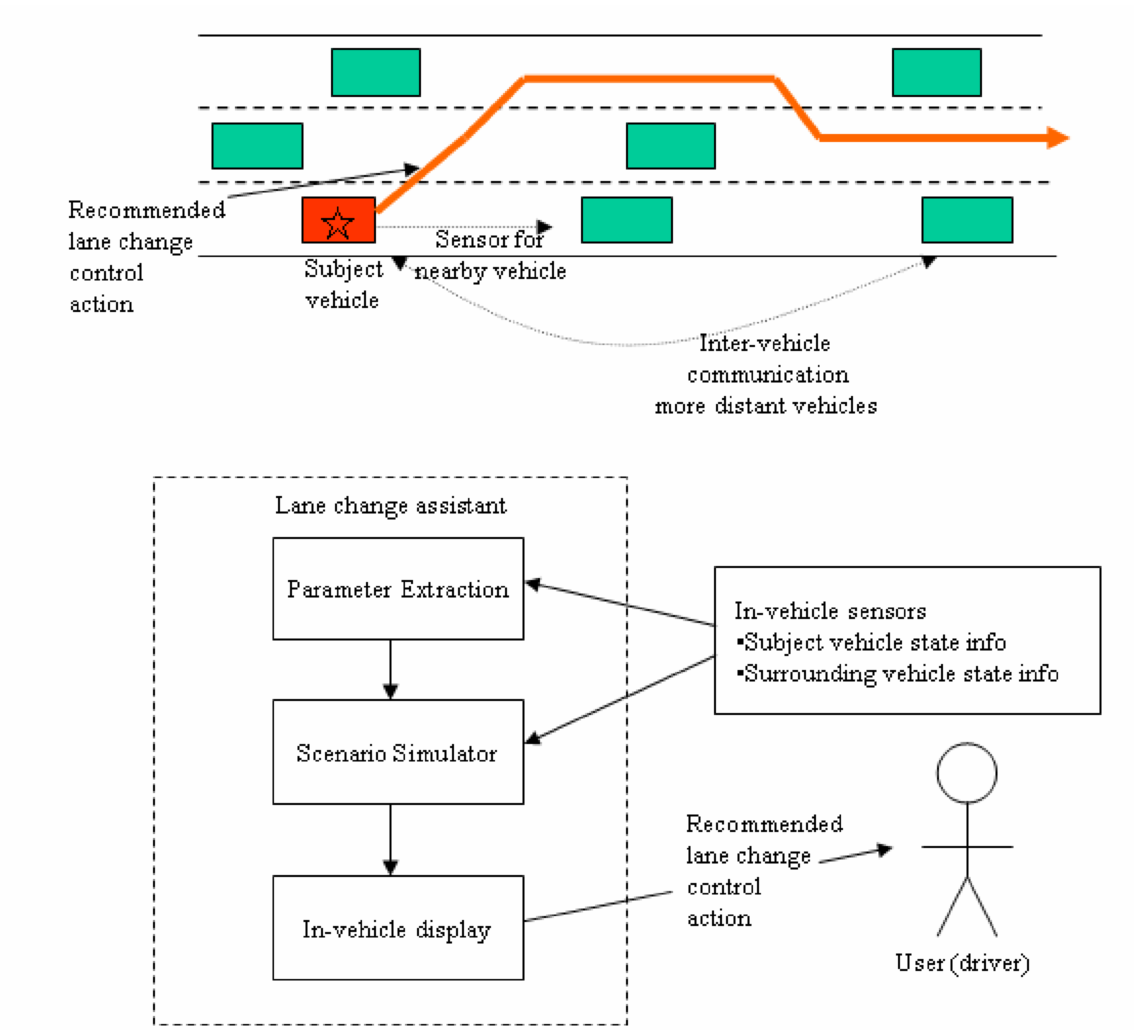


Figure 7. 2: Tactical lane change driver assistant

It would take in the information about the current state of the surrounding vehicles, and suggest to the driver to make a lane change at the most appropriate times. Such as system could employ real-time simulation to estimate or anticipate the movement of each of the surrounding vehicles, and then choose the best maneuver plan for the subject vehicle.

The usefulness of the real-time simulation and its result would depend on the sensor technologies used to obtain the surrounding vehicle state information. If video image processing or radar / laser sensors are used, the precise state information of only the very nearby vehicles (perhaps only in the adjacent lane) would be available. To expand on this, vehicle-to-vehicle communication systems could be used to communicate vehicle state information (position and speed) between the vehicles, either via an intermediate transmitter (for example roadside) or else vehicle-to-vehicle in an ad hoc network.

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