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Analysis and Modeling of Lane Changing Behavior

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ANALYSIS AND MODELING OF LANE CHANGING BEHAVIOR

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DEDICATION

This dissertation is dedicated to God and to my family, for all of their love, patience, kindness, and support.

The members of my dissertation committee have generously given their time and expertise to better my work. I thank them for their contribution and their good-natured support.

ANALYSIS AND MODELING OF LANE CHANGING BEHAVIOR

by

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ABSTRACT

Lane changing is one of the most basic activities when driving on freeways or arterials. A lane changing maneuver may be classified, depending on the driver's motivation, as mandatory or discretionary. A mandatory lane change occurs when a driver is trying to move his/her vehicle from its existing lane to the target lane in anticipation of the next turn or to avoid a lane closure downstream. On the contrary, a discretionary lane change occurs when a driver desires a faster speed or wants a greater following distance (i.e., at the driver's own discretion). Researchers have always assumed that drivers have different decision methodologies and/or risk-taking behavior for these two types of lane changes.

This dissertation answers four Research Questions based on analyses of field data: (i) do drivers have different risk-taking behavior when executing a discretionary lane changing maneuver on an arterial street at different times of the day?; (ii) do drivers have different risk-taking behavior between mandatory and discretionary lane changes on freeways?; (iii) do drivers have different risk-taking behavior when executing a mandatory lane changing maneuver at different freeway sites?; and (iv) if the answer to any of the above questions is "yes", can a lane changing decision model, which has been developed to meet a specific set of driving conditions, be customized to meet another set of driving conditions? To answer each of these questions, the Next Generation SIMulation (NGSIM) vehicle trajectory data sets were used to perform analyses.

For the first Research Question, there is enough statistical evidence to conclude that drivers have different risk-taking behavior at different times of the day when making a discretionary lane changing maneuver on an arterial street. The second Research Question asked if there is a statistically significant difference in drivers' behavior between discretionary and mandatory lane changes. Of the four risk taking parameters tested, there is not enough statistical evidence to suggest that there are significant differences in three of them; however, there is a statistically significant difference in the fourth parameter. As for the third Research Question,

again, there is statistical evidence to conclude that drivers have different risk-taking behavior when executing a mandatory lane changing maneuver at different freeway sites.

The answers of Research Questions 1 to 3 point to the need for a lane changing model to adapt to different driving environments (i.e. time of the day and locations). The answer to the fourth Research Question has shown that one existing discretionary lane changing model found in the literature does not perform as well when presented with mandatory lane changing data. Therefore, several models have been developed specifically for mandatory lane changes, as it has been proven as part of Research Question 2 that drivers behave differently between the two. An Adaptive Neuro-Fuzzy Inference System (ANFIS), developed as part of this dissertation, is recommended, as it outperforms the existing discretionary lane changing model found in the literature.

At a broad scale, the recommended ANFIS model may be incorporated into existing traffic simulation tools (software) to improve the modeling accuracy under different conditions. In the near future, there needs to be a better understanding of how drivers behave when changing lanes, specifically as it relates to automated vehicles. Most vehicles sold today are only partially automated, meaning that the vehicles may assist the driver with speed (e.g., adaptive cruise control), steering (e.g., lane departure warning) and lane changing (e.g., lane change advisory). The results from this dissertation have shown that drivers behave differently based on time-of-day and location. This demonstrates the need for semi- and fully automated vehicles to have a dynamic lane changing model that can adapt to different driving conditions.

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CHAPTER 1: INTRODUCTION

1.1: Background of Problem

A lane change is one of the basic activities when driving on a freeway or arterial. Drivers change lanes so as to, among other reasons, gain speed or move into the correct lane in anticipation of the next turning movement downstream (Balal et al., 2016; Pan et al., 2016; Zheng, 2014). A lane change that is not executed in a safe manner may result in a rear end, side swipe, or angled crash (Romo et al., 2014). With the advent of connected and automated vehicles, a good understanding of drivers' lane changing behavior and the ability to model it under different conditions has critical impacts on the design, safety, and capacity of automated driving on highways.

A lane change may be classified, depending on the driver's motivation, as mandatory or discretionary. A Mandatory Lane Change (MLC) usually occurs when the subject driver is trying to move his/her vehicle from its existing lane into the target lane in anticipation of the next left- or right-turn, or lane closure immediately downstream. A Discretionary Lane Change (DLC) usually occurs when a driver desires a faster speed, greater following distance, further line-of-sight, better ride quality, etc. in the target lane (Balal et al., 2016; Pan et al., 2016; Zheng, 2014). Because of the different motives, researchers have always assumed that the risk-taking behavior of a driver when executing MLCs and DLCs are different (Pan et al., 2016).

In microscopic traffic flow theory, a vehicle's two-dimensional motion on a continuous segment of highway surface may be decomposed into longitudinal and lateral movements. The longitudinal movement in the same lane, with the presence of a vehicle ahead (the preceding vehicle) and/or a vehicle behind (the following vehicle), is termed car-following. Additionally, the lateral movement, which is always accompanied with a longitudinal movement, is known as lane changing. Although car-following behavior has been studied by researchers for more than 50 years, relatively fewer investigations on lane changing behavior have been made. The reasons for this could be: (i) lane changing involves two-dimensional motions; and (ii) there are relatively more vehicles involved in a lane changing event.

The lane changing model is as important as the car-following model, as both are the fundamental building blocks in microscopic traffic simulation tools and in automated driving controllers. The microscopic driving behavior is also related to the macroscopic property of traffic flow. Therefore, accurate modeling of a driver's lane changing process is essential in producing realistic microscopic motions of vehicles and macroscopic output of traffic conditions.

A lane changing event involves up to five vehicles, the subject vehicle (*S*), the preceding vehicle before the lane change (*PB*), the following vehicle before the lane change (*FB*), the preceding vehicle after the lane change (*PA*), and the following vehicle after the lane change (*FA*). These vehicles may be seen in Figure 1.1. In coding the vehicles, *P* represents a preceding vehicle; *F* represents a following vehicle; *B* is before the lane change; and *A* is after the lane change. The longitudinal position of each vehicle may be seen in Figure 1.1 as the *Y*-value, using the front center of each vehicle as the reference point. The transverse position of each vehicle may be denoted as the *X*-value, again using the front center of each vehicle as the reference point. *X* may be an integer, with the value representing the lane number.

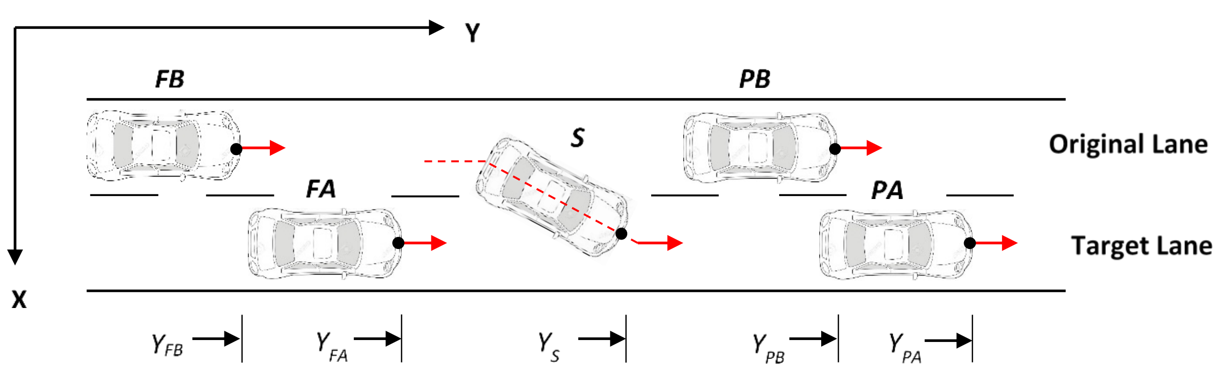
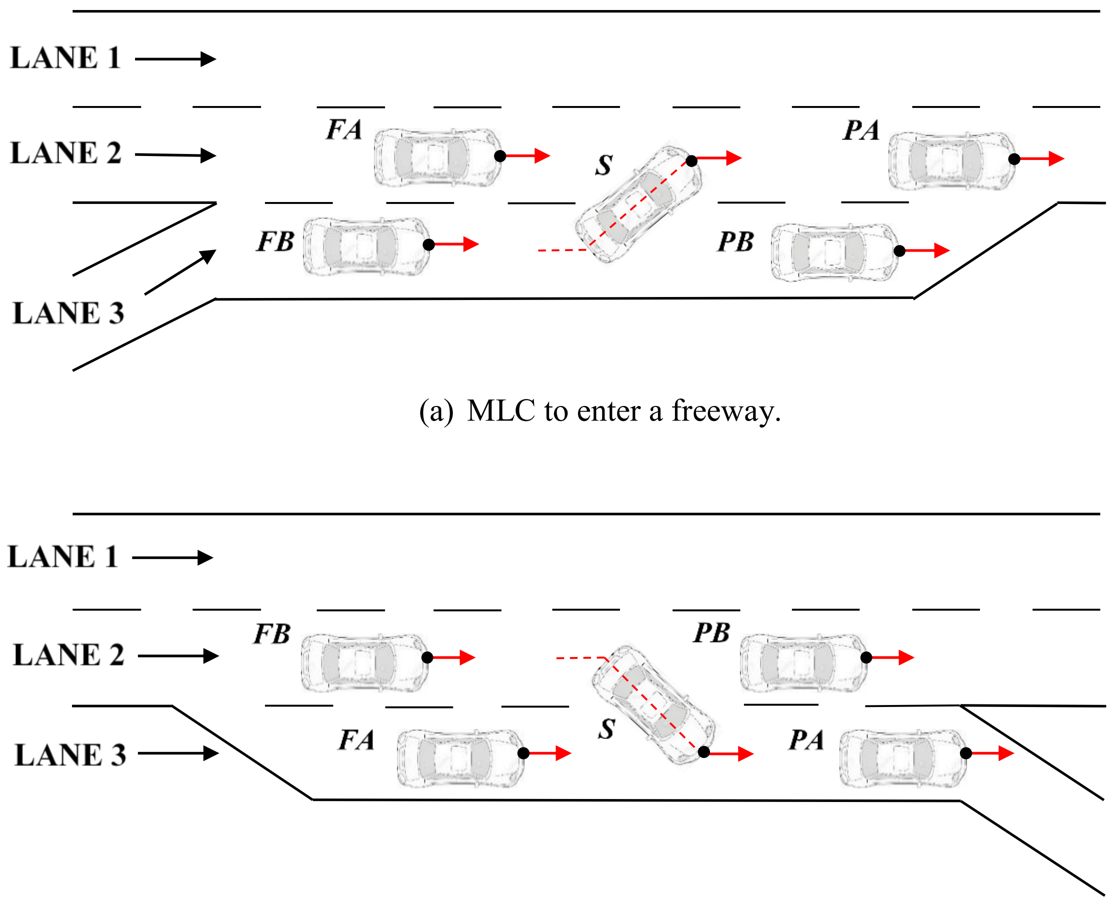


FIGURE 1.1. VEHICLES AND THEIR POSITIONS DURING A TYPICAL DLC.

A driver is expected to have different decision rules and/or risk-taking behavior for these two types of lane changes (i.e. MLCs and DLCs), on different highway facilities (i.e. freeways vs. arterials), and under different traffic congestion levels, the latter typically correlating with

different times during the day. Figure 1.1 may be viewed as a DLC, as there is no indication that there is an immediate need to change lanes to avoid a lane closure, exit the freeway, or avoid exiting the freeway. Figure 1.2 illustrates a typical MLC scenario, where the subject vehicle (*S*) must change lanes in order to continue on the freeway (in Figure 1.2(a)), or to exit the freeway (in Figure 1.2(b)).



(a) MLC to enter a freeway.

(b) MLC to exit a freeway.

FIGURE 1.2. VEHICLES AND THEIR POSITIONS DURING TYPICAL MLCS.

A lane change may be modeled as a four-step process (Moridpour et al., 2010):

(1) Motivation;

(2) Selection of target lane;

(3) Checking for the opportunity to move; and

(4) The actual move.

This research focuses on step (3), checking for the opportunity to move, which ends with a risk taking decision to proceed to step (4). Between steps (3) and (4), the driver decides whether to execute the lane change (i.e., starts to steer the subject vehicle towards the target lane) based on a set of decision parameters that represent his/her risk-taking behavior.

1.2: Research Questions

There are four Research Questions that this dissertation aims to answer:

1) Do drivers have different risk-taking behavior when executing a discretionary lane changing maneuver on an arterial street at different times of the day?

2) Do drivers have different risk-taking behavior between mandatory and discretionary lane changes on freeways?

3) Do drivers have different risk-taking behavior when executing a mandatory lane changing maneuver at different freeway sites?

4) If the answer to any of the above Research Questions is "yes", can a lane changing decision model, which has been developed to meet a specific set of driving conditions, be customized to meet another set of driving conditions?

Each of these questions will be answered in Chapters 5, 6, 8, and 9, of this dissertation, respectively. Prior to these, the literature reviewed for each Research Question will be explained in detail in Chapter 2, the research plan will be described in Chapter 3, and the data summarized in Chapter 4. To answer Research Questions 3 and 4 (Chapters 8 and 9), a survey on MLCs is necessary, and this survey will be reported in Chapter 7.

1.3: Outline

This dissertation is organized as follows. After this introduction, issues related to MLCs and DLCs are reviewed in Chapter 2, from the perspectives of the four Research Questions. This is followed by Chapter 3, which outlines the research plan, and then Chapter 4, a description of

the data. The next five chapters, which are the most important chapters of this dissertation, answer each of the four Research Questions in order, which includes a drivers' survey in Chapter 7. This dissertation concludes with Chapter 10 by highlighting the findings, limitations, and contributions of this research.

CHAPTER 2: LITERATURE REVIEW

2.1 Chapter Introduction

This chapter reviews literature on lane changes that are related to the Research Questions. The materials found in the literature search are organized according to lane changes on freeways and arterials. Then, lane changes for each road classification are further arranged into the two types of lane changes, namely MLCs and DLCs. In the next level, the respective MLCs or DLCs are further identified by the time-of-day or freeway sites. Figure 2.1 illustrates the organization this literature and its relations with the first three Research Questions. The next four sections in this chapter each discuss the earlier research that is concerned with Research Questions 1, 2, 3, and 4, respectively. The lane changing logics and models used in simulation tools may be found in Section 2.3.4.

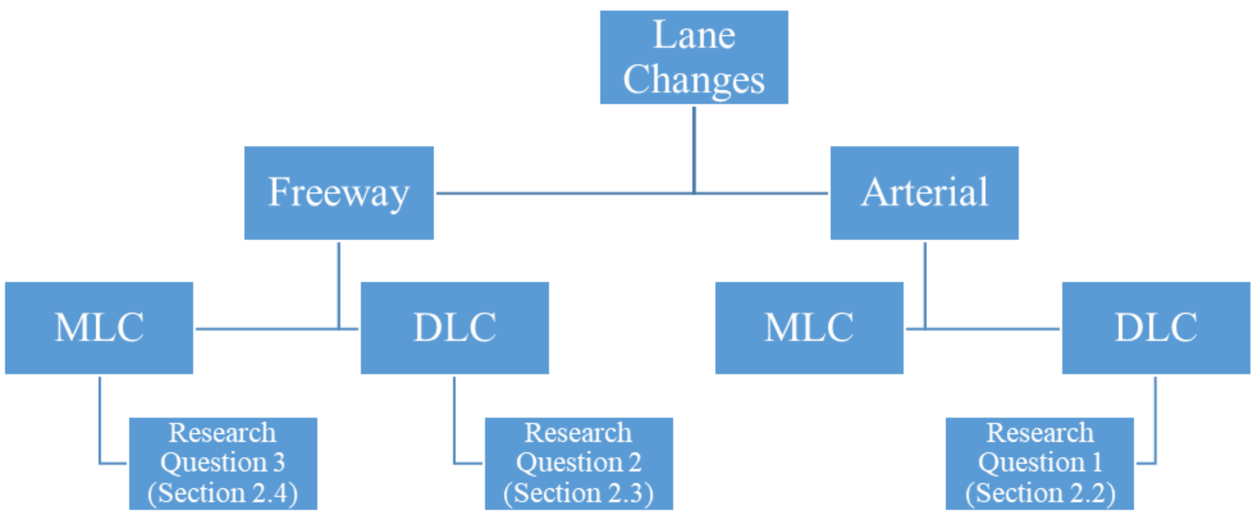


FIGURE 2.1. OVERVIEW OF LANE CHANGING LITERATURE.

2.2: Lane Changes on Arterials

The literature reviewed in this section is related to Research Question 1 (see Section 1.2) and is a comparison of arterial street DLCs in Figure 2.1. In order to answer this Research Question, the Next Generation Simulation (NGSIM) data was used to analyze discretionary lane

changing behavior on arterial streets. The Federal Highway Administration (FHWA) funded the NGSIM Project to collect vehicle trajectory data via eight cameras mounted on top of tall buildings for arterial streets and freeways (Cambridge Systematics Inc., 2007a, 2007b).

Any literature that has used NGSIM data was first reviewed to determine if other research has been conducted regarding lane changing behavior at similar arterial facilities. The NGSIM data has been used, for examples, to analyze the probability distribution of discretionary lane changing decision parameters in freeway driving (Balal et al., 2014); traffic relaxation, anticipation, and hysteresis (Deng and Zhang, 2015); and car-following (Hao et al., 2016; Rhoades et al., 2015). The NGSIM data has also been used to validate models such as the queue estimation method for signalized intersections (Hao et al., 2015).

Prior to the availability of the NGSIM data, Gipps (1986) is perhaps one of the earliest to document a lane changing study on a signalized street. The driver's decision-making framework consists of the possibility, necessity, and desirability to change lanes. He then proposed a lane changing model encompassing MLCs and DLCs. The decision-making framework was later used in the AIMSUN microscopic traffic simulation tool (TSS, 2002).

None of the above studies have considered the potential differences in gap acceptance behavior with regards to highway facilities (freeway vs. arterials) and driving conditions (traffic congestion levels and different times of the day). Furthermore, relatively little research has been conducted concerning lane changing on arterials. Most of the lane changing research has been conducted on freeways. These studies on lane changing on freeways will be described in the subsequent sections.

2.3: Lane Changes on Freeways

The literature reviewed in this section is related to Research Questions 2 and 3 (see Section 1.2 and Figure 2.1). Comprehensive reviews of lane changing models have been made by Moridpour et al. (2010) and Zheng (2014), and subsequently summarized by Balal et al. (2016).

2.3.1: DISCRETIONARY LANE CHANGES

The literature reviewed in this section is simply related to DLCs on freeways, and is specifically related to DLC studies as part of Research Question 2 (see Section 1.2). The literature that compares MLCs and DLCs are reviewed in Section 2.3.3.

Wilson and Best (1982) conducted a study regarding drivers' overtaking strategies that involve lane changes. Their research was related to drivers' gap acceptance during overtaking maneuvers on a two-lane highway in the United Kingdom. The authors used gap as the only risk-taking parameter. Naranjo et al. (2008) developed a lane changing fuzzy controller for automated vehicles during the overtaking maneuver. The subject vehicle will change to the target lane only if the target lane is free (i.e. there are no surrounding vehicles in the target lane). More recently, research on overtaking models that involve lane changes has been conducted by Barmpounakis et al. (2017), where they modeled the overtaking behavior of powered two wheelers.

2.3.2: MANDATORY LANE CHANGES

The literature reviewed in this section is related to Research Question 3 (see Section 1.2) and is a comparison of MLCs on freeways in Figure 2.1. This review focuses on MLCs and the parameters that are used to make a decision. It has been found that, in some models, it was impossible to distinguish MLCs from DLCs.

Recent research has revealed that lane changes have significant impacts on traffic safety, since accidents tend to happen in lane changing areas such as weaving sections and interchanges (Cassidy and Rudjanakanoknad, 2005; Golob et al., 2004; Pan et al., 2016). Jula et al. (2000) analyzed the velocities and accelerations of vehicles as they change lanes and merge on freeways. Their focus was on the minimum gaps at which crashes may be avoided.

Cao et al. (2017) determined the best position for providing MLC instruction to automated vehicles. Their proposed model was validated by a comparison with a simulation model in VISSIM and can be applied to guide automated vehicles to travel an optimal route.

2.3.3: Comparison of MLCs and DLCs

The literature reviewed in this section is related to Research Question 2 (see Section 1.2), as it considers the comparison of MLCs and DLCs from the literature. Research articles on lane changing behavior have mostly been focused on MLC and/or DLC model development and applications for freeway driving. Very few papers have compared the differences between MLCs and DLCs. Furthermore, no published literature has documented a quantitative study on the similarities and/or differences in driving behavior between MLCs and DLCs, with field data. The literature reviewed in this section focuses on the similarities and differences between MLC and DLC models.

Wu et al. (2000) described different motivations for changing lanes: pressure from the rear (fast approaching vehicle) and to gain speed. They did not distinguish between MLCs and DLCs. Zheng (2014) suggested the need to develop a framework that encompasses MLC and DLC decision-making processes. This is followed by Pan et al. (2016) who proposed a mesoscopic cell transmission multilane freeway model that incorporated MLC and DLC maneuvers. The multilane model has been calibrated and tested against field data collected at the State Route 241 (SR-241) in Orange County, California. Both Pan et al. (2016) and Zheng (2014) have suggested the need to model MLCs and DLCs separately.

After observing video recordings of 73 lane changing maneuvers in arterials in Sydney, Australia, Hidas (2002) classified lane changes into free, forced, and cooperative based on the front gap and rear gap in the target lane. Regardless of the type of lane change, the logic proposed by Hidas (2002) used a linear combination of accelerations of the subject vehicle as the decision parameter. Recently, machine learning algorithms have been applied to model lane changing behavior (e.g. genetic fuzzy (Hou et al., 2012), and Bayesian classification (Schlechtriemen et al., 2014)). Wang et al. (2017) used support vector machines to predict four merging behaviors at expressway on-ramp bottlenecks. None of the above studies have considered the potential differences in gap acceptance behavior with regards to different highway facilities under different traffic congestion levels.

A model by Kesting et al. (2007) was developed to measure both the attractiveness of a given lane and the risk associated with lane changes, specifically as it relates to accelerations in the car-following model. Laval and Leclercq (2008) highlighted the shortcomings faced by current traffic flow models by capturing the relaxation phenomena (i.e. vehicles are willing to accept very short gaps to enter a freeway but relax to more comfortable values thereafter) by using a macroscopic lane changing model.

Uno et al. (2003) found that there is a strong possibility that the following vehicle in the target lane may crash with the subject vehicle, should the subject vehicle encounter a situation where the emergency brakes be applied. More recently, Guo et al. (2018) investigated lane changing behavior on freeways in China. They found that lane changing has an impact, mainly in the target lane. When a driver changes lanes, it drastically reduces the time headway of the subject vehicle and the following vehicle in the target lane, which increases the risk of a rear-end crash.

A majority of the lane changing literature reviewed is related to the overtaking of a slower moving vehicle on both freeways and urban arterials. Other papers and reports have presented different lane changing models. They have been included in Moridpour et al. (2010) and Zheng (2014). The above representative articles have clearly highlighted that some modelers in recent years prefer to distinguish MLCs from DLCs, while others apply one model for both MLCs and DLCs. None of them have provided numerical evidence to support their decisions of using one or two separate models for MLCs and DLCs.

2.3.4: Microscopic Traffic Simulation Tools

The lane changing models found in popular microscopic traffic simulation tools have been included in the reviewed literature. The purpose of reviewing such tools is to identify the drivers' risk-taking decision parameters.

The lane changing model in FRESIM (FHWA, 1995) has been described in Wicks and Lieberman, (1980). There are two types of lane changes in FRESIM: free lane change and forced

lane change. A free lane change is sought when a subject vehicle is traveling below its desired speed and it can gain speed by moving to an adjacent lane. A binary decision to change lanes is generated according to a pre-defined probability and assigned to the subject vehicle. Once a decision has been made to change lanes, the subject vehicle must check that the lead time to collision and lag time to collision in the target lane satisfy their respective "non-collision constraint." VISSIM (PTV, 2007) classifies lane changes into free lane change and necessary lane change. PARAMICS (Quadstone, 2009) does not distinguish between MLCs and DLCs. A vehicle is allowed to move from its original lane to target lane if both (i) the front gap (in distance unit) between the subject vehicle and preceding vehicle in the target lane; and (ii) the rear gap between the subject vehicle and the following vehicle in the target lane exceed their respective threshold value. AIMSUN (TSS, 2002) describes a vehicle's lane changing decision-making process in terms of necessity, desirability, and possibility to change lanes. To distinguish between DLCs and MLCs, AIMSUN divides a freeway segment upstream of an off-ramp into three zones, where DLCs take place in the most upstream zone, and MLCs are in the two downstream zones. TransModeler (Caliper, 2011) uses the discrete choice approach to model a driver's lane changing decision. It considers three types of lane changes: discretionary, mandatory, and forced lane changes. These microscopic lane changing decision models contain a large number of parameters and cannot provide intuitive descriptions of system-level effects of lane changing traffic (Pan et al., 2016).

2.4: Applications of Fuzzy Logic in Modeling Lane Changing Decisions

The literature reviewed in this section is related to Research Question 4 (see Section 1.2), and considers the applications of fuzzy logic in the modeling of lane changing decisions.

2.4.1: Fuzzy Logic

The concept of fuzzy logic was originally developed by Zadeh (1965). Fuzzy logic makes use of a fuzzy set, which contain several linguistic terms, for example {*near*, *medium*, *far*} to describe a characteristic of an object or event. A fuzzy set does not contain a crisp boundary

between its linguistic terms, as do classical sets. Instead, the transition between two linguistic terms is represented more gradually.

An example of a crisp boundary in traffic engineering can be found in the gap acceptance theory, which gives a binary output of accepting or rejecting a gap. In the past, gap acceptance models were used to model lane changing decisions (Ahmed, 1999; Rahman et al., 2013; Toledo et al., 2007). Fuzzy logic has been used to represent human decision making since the 1980's (Abonyi et al., 1999; Kaur and Kaur, 2012a). The reason fuzzy logic has gained so much attention is its close relation in human thinking (Mohanadas and Karimulla, 2001). Therefore, fuzzy logic is a promising alternative method to model the drivers' lane changing decision process, as opposed to the traditional gap acceptance models used in the past.

2.4.2: Fuzzy Inference System

A Fuzzy Inference System (FIS) is a sequential decision making framework based on fuzzy logic, developed by Zadeh (1965). The FIS is a four-step process.

In the first step, crisp inputs are fuzzified (transferred or mapped), based on the user-defined membership functions, into fuzzy membership values, which fall within the range of [0,1]. Membership functions are associated with linguistic terms such as {*close, medium, far*} or {*small, large*}. A membership value describes to what degree an input parameter belongs to a linguistic term in a fuzzy set. For example, the gap between two vehicles has a crisp input value of 10.5 m (see Figure 2.2). This is mapped by fuzzy membership functions into 0.2 for *close* and 0.7 for *far*. These membership values describe the degree that 10.5 m belongs to each linguistic fuzzy set term.

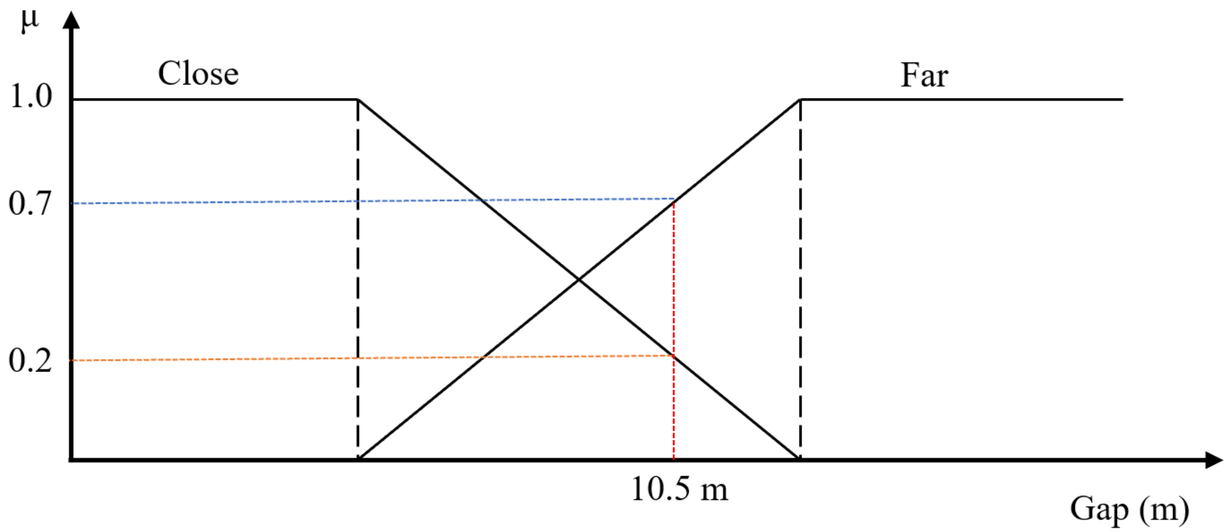


FIGURE 2.2. EXAMPLE OF TWO TRAPEZOIDAL MEMBERSHIP FUNCTIONS.

There are many different types of membership functions, depending on the application; however, the four most common types are triangular, trapezoidal, Gaussian, and the generalized bell membership function. The triangular and trapezoidal membership functions are the most widely used (Jang et al., 1997). The simplicity and computational efficiency of these membership functions make them ideal for fine-tuning. The Gaussian and generalized bell membership functions, on the other hand, are still commonly used; however the main drawback with them is that they are both unable to specify asymmetry (Jang et al., 1997).

The second step of FISs makes inferences regarding the membership values. Typically, after the first step, membership values are given to the linguistic terms. These linguistic terms are used as antecedents of IF-THEN rules to infer the outputs (Zadeh, 1965). The output of a rule is typically a linguistic term and its membership values.

The third step is composition, which compiles the outputs of all the rules into one fuzzified output. There are two commonly used composition methods: the max-min method and the max-product method (Jang et al., 1997).

The fourth and final step of the FIS is defuzzification. At this step, fuzzified outputs obtained from the composition step are defuzzified (converted or transformed) to a crisp output.

In general, there are two commonly used types of FISs: Mamdani and Sugeno, both differing in the inference (second) step (Jang et al., 1997).

2.4.2.1: *MAMDANI-TYPE FUZZY INFERENCE SYSTEM*

In the Mamdani type FIS, the rule's output membership functions follow the same format as the input membership functions (e.g. triangular, trapezoidal, etc.).

2.4.2.2: *SUGENO-TYPE FUZZY INFERENCE SYSTEM*

In the Sugeno type FIS, the rule's output is simply a deterministic mathematical function of the inputs (membership values). There are two sub-types of Sugeno type FIS: zero order and first order. In the zero order Sugeno sub-type FIS, the output is simply a constant value. In the first order Sugeno sub-type FIS, the output is a linear function of the inputs.

In both sub-types of Sugeno FISs, every rule has its own output value. First, the composite output value of the rules may be calculated by the weighted average method or the weighted sum method (Jang et al., 1997). Then, this composite value is used as an input to a linear (defuzzification) equation, which determines the final crisp output.

The main concern with the first order Sugeno sub-type FIS is determining the coefficients in the linear function. However, algorithms may be applied to optimize the values of these coefficients with given sample data.

2.4.2.3: *FUZZY INFERENCE SYSTEM TRAINING PROCESS*

Jang et al. (1997) recommends a three-step process when developing an FIS:

1. Choose appropriate fuzzy sets, linguistic terms, and membership functions;
2. Interview human experts with the target systems to determine rule base; and
3. Refine the parameters of the membership functions (for both the input and output) using optimization techniques.

In the discretionary lane changing research conducted by Balal et al. (2016), the authors stopped at the FIS Training Process Step 2. No optimization techniques were used in order to improve the system, as their results were deemed sufficiently accurate. Another shortcoming of

this FIS is that it was designed specifically for DLCs. No attempt was made to modify or adapt the FIS model for MLCs.

FISs have already been applied to both MLCs and DLCs. MLC research has been conducted by Hou et al. (2012), where they developed a fuzzy logic-based MLC model using NGSIM freeway data. Their fuzzy logic model was compared to a binary logit model, and the fuzzy logic model outperformed the binary logit model when using test data. The input parameters used were the speed of the subject vehicle, the speed difference between the lead vehicle in the target lane and subject vehicle, the speed difference between the lag vehicle in the target lane and subject vehicle, lead gap distance in the target lane, lag gap distance in the target lane, and the remaining distance to the end of the merge (original) lane. Later, Hou et al. (2014) used the same NGSIM data sets to develop a combined Bayes classifier and decision-tree models to predict an MLC event, using the same input parameters. One shortcoming of this research is that they did not report the motivation for using the six input parameters. No survey was conducted, nor were any drivers interviewed, so as to provide justification as to why these six parameters were used. Furthermore, the training and testing data was from the same site.

2.4.3: Adaptive Neuro-Fuzzy Inference System

One approach that may be applied to model and optimize an FIS is Artificial Neural Network (ANN). ANNs are modeled similarly to the human brain, with MultiLayer Feed-Forward (MLF) being the most commonly used. In an MLF, there are three layers: the input layer, hidden layer, and output layer. Each layer consists of neurons, and the synapses connect neurons from one layer with neurons in the next layer. In the MLF, neurons receive input signals from the preceding layer, and may only transmit an output to the subsequent layer. By structuring an FIS similarly to that of an MLF, the MLF's training techniques may be used to optimize the FIS in order improve its accuracy. The hybrid system is termed as a neuro-fuzzy system (more specifically Adaptive Neuro-Fuzzy Inference System, or ANFIS). An ANFIS combines the learning capabilities of neural networks with the human-like thinking of FISs.

In order to train an MLF, the input and output data must already be known (Haykin, 2001). This supervised training method allows the MLF to reduce the errors and improve the performance accuracy. First, the inputs are fed forward to the hidden layer. Each hidden layer's neuron receives an input from each of the neurons in the input layer. This combined strength of the input received by this hidden layer's neuron is the sum of all the inputs multiplied by their respective link weights. Once the input is received, an activation function is applied to provide nonlinear transformation between the neuron's input and output. There are several activation functions, with the sigmoid function being the most common (Haykin, 2001). The sigmoid function essentially compresses very large positive input signals to output of +1.0, and very large negative signals to output of 0.0. Then, these outputs are fed forward again from the hidden layer to the output layer. Each neuron in the output layer receives an input from all preceding nodes in the hidden layer. This total input received is the sum of all inputs, again, multiplied by their respective link weights. The output of the MLF is then compared to the actual output from the training data.

The cost function of the MLF is the root mean square error (RMSE) of all the training samples. The link weights are adjusted after each epoch (or iteration), in order to reduce the RMSE, through the backpropagation training process. The errors are backpropagated through the network, beginning with the output layer and working back towards the hidden layer, and then to the input layer. After many epochs of updating the link weights, the RMSE will converge to a "minimum". The main issue with the backpropagation training is that this so-called gradient descent (of RMSE) approach may reach a local minimum as opposed to the global minimum. Therefore, multiple MLFs should be conducted, all starting with various randomly generated link weights.

2.4.3.1: ARCHITECTURE

Jang et al. (1997) discovered that the Sugeno type FIS may be structured in such a way that the FIS parameters may be optimized similarly to how an MLF is optimized. The new system was termed an "Adaptive Neuro-Fuzzy Inference System," or ANFIS.

The architecture of a two input, one output ANFIS is presented in Figure 2.3.

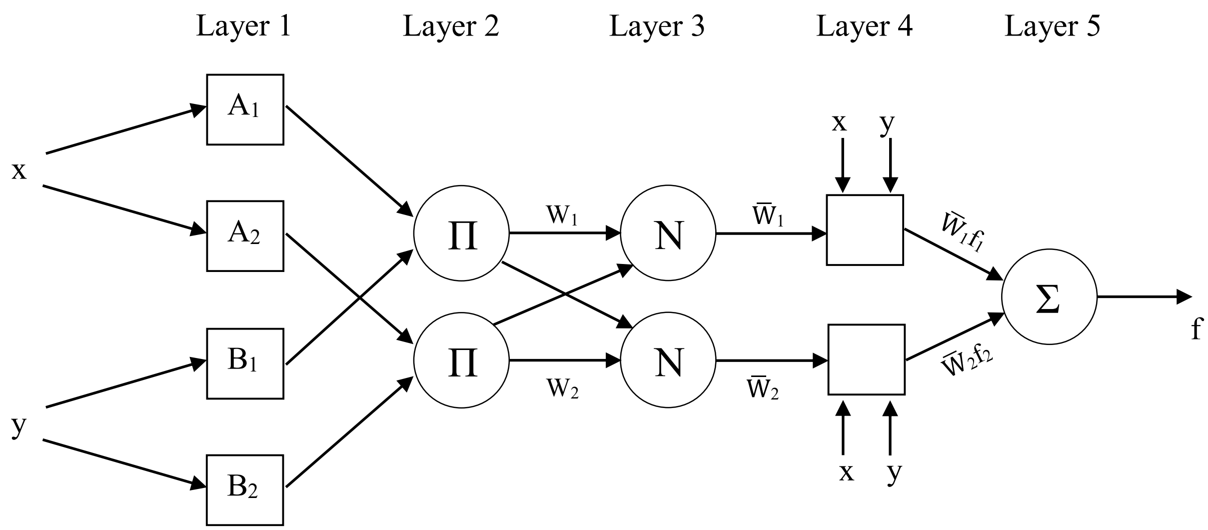


FIGURE 2.3. A TWO INPUT, ONE OUTPUT ANFIS ARCHITECTURE (JANG ET AL., 1997).

In Figure 2.3 the two crisp input values are *x* and *y*, and the ANFIS consists of five internal layers. Neurons that are square are adaptive neurons, which have internal parameters that may be optimized. Circular neurons simply apply some functions to the input signals to produce a single output signal.

In layer 1, each crisp input value, *x* and *y*, is fuzzified based on the preassigned membership functions built into the neurons. Note that there are two input membership functions for *x* and *y*, each, in Figure 2.3. That is, *x* and *y* each have a fuzzy set of two (linguistic values). These membership functions can be adjusted to improve the network's performance. Nodes in this layer are referred to as premise parameters. For example, the gaps between a subject vehicle and its preceding vehicle and following vehicle may be 10.5 and 14.5 m, respectively. These may be mapped by fuzzy membership functions to 0.7 for *close*, and 0.15 for *far* for the

preceding gap, and 0.6 for *close*, and 0.35 for *far* for the following gap (see Figure 2.2 as an example). These premise parameters may be viewed as the membership values.

In layer 2, each neuron represents one rule. In Figure 2.3, there are only two rules. For each neuron in layer 2, the inputs are the fuzzified outputs from layer 1. This layer considers all incoming input signals and outputs one fuzzified value based on the composition method defined (i.e. max-min or max-product). The weights of the links between layers 2 and 3 are known as the firing strengths for the rules.[1]

In layer 3, each neuron calculates the ratio of that rule's firing strength with respect to all rules. This is known as the normalized firing strengths. This is essentially the weighted average or weighted sum of the firing strength, depending on the user's preference.

The neurons in layer 4 are the second set of adaptive neurons. Notice that in Figure 2.3 the original crisp input values, x and y, are entered into neurons in the fourth layer. This is because in the Sugeno type FIS, the output is simply a constant or a linear function of the inputs (which can be a combination of x, y, and the outputs of the third layer). These adaptive neurons in the fourth layer are referred to as consequent parameters. For example, if the two crisp inputs, x and y, are 10.5 and 14.5 m, respectively, and the output is 1.0, the consequent parameters may be coefficients in a linear function using x and y, where the output is 1.0.

Lastly in layer 5, there is one fixed node that sums the output from every rule in layer 4, where the output of each rule in layer 4 is the normalized firing strength (from layer 3) multiplied by the linear function (from layer 4). This is thus considered the network's output after the feedforward propagation of the inputs x and y. The errors may then be backpropagated through the network in order to improve its accuracy.

2.4.3.2: Optimization

In the ANFIS architecture, there are two sets of adaptive neurons: the premise parameters in layer 1 and the consequent parameters in layer 4. The other three layers simply receive an

[1] When using the AND Boolean operator, the smallest of all incoming values is used as the firing strength.

input and provide an output, without adaptation. In order to optimize these two sets of parameters, there are two optimization techniques: backpropagation and the hybrid method.

The backpropagation method simply backpropagates the errors back through the network and updates all parameters based on the gradient descent approach. This method, however, takes much longer to converge to a minimum than the hybrid method.

The hybrid method is the preferred optimization method due to its computation efficiency. During a forward pass, the membership functions in layer 1 are held fixed. The linear function coefficients in layer 4 are updated via the least-squares estimation. On the backward pass, the linear function coefficients in layer 4 are now held fixed. The error signals are sent backwards through the network until layer 1, where the membership function parameter are updated.

In the field of transportation engineering, ANFISs have been used for traffic congestion prediction (Lu and Cao, 2003; Pongpaibool et al., 2007) and mode choice (Andrade et al., 2006). No such attempt has been made to use an ANFIS to model lane changing decisions.

2.5: Chapter Summary

Little research has been conducted concerning lane changes on arterials. Most of the lane changing research has been conducted on freeways. Therefore, further investigation into drivers' lane changing behavior on arterials, as part of Research Question 1, should be conducted.

For lane changes on freeways, very few papers compare the differences between MLCs and DLCs. Furthermore, no published literature has documented a quantitative study on the similarities and/or differences in driving behavior between MLCs and DLCs, with field data. Although some authors, such as Moridpour et al. (2010) and Zheng (2014), recommend modeling MLCs and DLCs separately, none of them provide numerical evidence to support their decisions of using one or two separate models for MLCs and DLCs. This should be investigated as part of Research Question 2.

Similar to the freeway lane changing literature as part of Research Question 2, no published literature has documented a comparison of MLCs based on location and/or time of day. Therefore, a comparison of drivers' MLC behavior from different sites and/or time of day should be conducted, as part of Research Question 3.

In order to model drivers' lane changing behavior, an ANFIS is recommended due to the ANFIS's adaptive training algorithm. In addition, these ANFIS rules have a learning capability to approximate nonlinear functions. Furthermore, none of the ANFIS literature reviewed has been applied to lane changes. Therefore, an ANFIS is ideal to answer Research Question 4.

CHAPTER 3: RESEARCH PLAN

3.1: Research Questions

There are four Research Questions that this dissertation aims to answer:

1) Do drivers have different risk-taking behavior when executing a discretionary lane changing maneuver on an arterial street at different times of the day?
2) Do drivers have different risk-taking behavior between mandatory and discretionary lane changes on freeways?
3) Do drivers have different risk-taking behavior when executing a mandatory lane changing maneuver at different freeway sites?
4) If the answer to any of the above Research Questions is "yes", can a lane changing decision model, which has been developed to meet a specific set of driving conditions, be customized to meet another set of driving conditions?

3.2: Research Approach

The data used to answer each of these four Research Questions will be described in detail in Chapter 4. Then, each Research Question will be answered in the subsequent chapters.

Research Question 1 will be answered in Chapter 5. It was determined in Section 2.2 that none of the literature reviewed, which used the NGSIM arterial data, considered the potential differences in gap acceptance behavior with regards to time-of-day and traffic congestion levels. This Research Question will be answered by the following approach consisting of four steps:

(i) For each lane changing decision (risk-taking) parameter, comparatively examine the descriptive statistics for DLCs at two different times during the day;

(ii) For each risk-taking parameter, conduct a hypothesis test on the difference between the means for DLCs at two different times during the day;

(iii) For each risk-taking parameter, apply the Kolmogorov-Smirnov test (Ang and Tang, 1975), to test the difference in the observed cumulative probability distributions between DLCs at two different times during the day; and

(iv) For each risk-taking parameter, fit the probability distributions to the DLC data at two different times during the day respectively, and use the Kolmogorov-Smirnov test to test the difference between the fitted probability distributions.

Research Question 2 will be answered in Chapter 6. It was determined in Section 2.3 that very few papers (Gipps, 1986; Pan et al., 2016; Zheng, 2014) compare the differences between MLCs and DLCs. Furthermore, no published literature has documented a quantitative study on the similarities and/or differences in driving behavior between MLCs and DLCs, with field data. Some researchers in recent years have suggested the need to model MLCs and DLCs separately (Pan et al., 2016; Zheng, 2014); however, none of them provided statistical evidence to support their decisions of using one or two separate models for MLCs and DLCs. Therefore, in this dissertation, statistical tests will be conducted, using two different NGSIM data sets, to determine if drivers have different risk-taking behavior when executing an MLC compared to a DLC. The answer to this Research Question will be analyzed by the following approach consisting of four steps:

(i) For each risk-taking parameter, comparatively examine the descriptive statistics between MLCs and DLCs;

(ii) For each risk-taking parameter, conduct a hypothesis test on the difference between the means of MLCs and DLCs;

(iii) For each risk-taking parameter, apply the Kolmogorov-Smirnov test (Ang and Tang, 1975), to test the difference in the observed cumulative probability distributions between MLCs and DLCs;

(iv) For each risk-taking parameter, fit the probability distributions to the MLC and DLC data, respectively, and use the Kolmogorov-Smirnov test to test the difference between the fitted probability distributions.

The first two Research Questions use risk-taking parameters based on a DLC survey conducted by Balal et al. (2016). These parameters will be described in greater detail in Chapter 4. Since Research Question 2 is a comparison of MLC and DLC behavior using the DLC

parameters from Balal et al. (2016), if there are any differences found from the four approaches, a different survey will be conducted in order to determine the most important parameters drivers consider when executing an MLC. The results from the survey will be reported in Chapter 7.

Research Question 3 will be answered in Chapter 8. It was determined in Section 2.4, and similar to the limitations described in Section 2.3, that none of the literature reviewed has considered the potential differences in gap acceptance behavior with regards to different highway sites, due to perhaps different driving cultures, congestion levels, time-of-day, or other factors. The purpose of Chapter 8 is to establish, through statistical tests, that there is a significant difference in the MLC behavior between two sites, without identifying the factors that contribute to the difference. The specific steps taken to answer this Research Question are:

(i) For each risk-taking parameter, comparatively examine the descriptive statistics for MLCs at two different freeway sites;

(ii) For each risk-taking parameter, conduct a hypothesis test on the difference between the means of MLCs at two different freeway sites;

(iii) For each risk-taking parameter, apply the Kolmogorov-Smirnov test (Ang and Tang, 1975), to test the difference in the observed cumulative probability distributions between MLCs at two different freeway sites; and

(iv) For each risk-taking parameter, fit the probability distributions to the MLC data at two different freeway sites, and use the Kolmogorov-Smirnov test to test the difference between the fitted probability distributions.

Research Question 4 will be answered in Chapter 9. Research Question 4 simply asks: *If the answer to any of the above Research Questions is "yes", can a lane changing decision model, which has been developed to meet a specific set of driving conditions, be customized to meet another set of driving conditions?* The approach taken to answer this question consists of five steps:

(i) Simply apply the existing FIS model, which has been developed for DLCs by Balal et al. (2016), to MLC test data;

(ii) Adapt the DLC FIS by Balal et al. (2016) to MLCs by optimizing the defuzzification threshold, τ, with MLC test data in order to determine the FIS's best performance when presented with MLC test data; and

(iii) Develop four different ANFISs using MLC training data and apply them to MLC test data.

Each of these abovementioned approaches will be conducted as part of one experiment (Experiment 1) using NGSIM data from one freeway site for training and another for testing. A second experiment (Experiment 2) will also be conducted where the data sets are reversed for a better understanding of the models' performances. Once both experiments have been conducted, then the last two steps may be performed:

(iv) Select the model between steps (ii) and (iii) that performs the best with the MLC test data for both experiments; and

(v) If there are any differences in the input parameters from the MLC survey in Chapter 7, when compared to those found from the DLC survey conducted by Balal et al. (2016), remove the input parameter from the best model in step (iv) and apply it to the MLC test data again to compare the differences. This step is known as Experiment 3.

3.3: Work Plan

In order to answer these four Research Questions, a detailed work plan has been developed, as presented in Figure 3.1. The work plan consists of seven tasks. Each task will be explained in more detail. The remaining work for this dissertation follows the flow shown in the work plan in Figure 3.1.

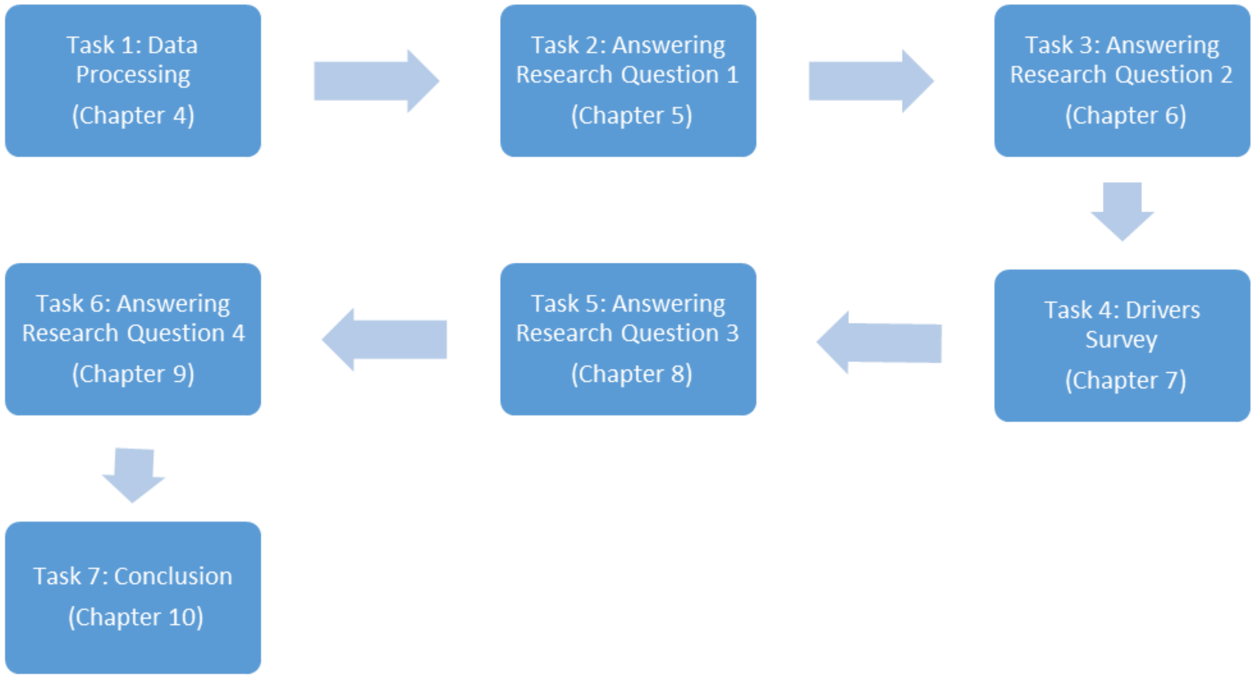


FIGURE 3.1. WORK PLAN.

Task 1 – Data Processing

The first task is to process the data in order to answer all four Research Questions. The data processing steps will be reported in Chapter 4 of this dissertation.

Task 2 - Answering Research Question 1

The second task is to answer Research Question 1. The answer to this Research Question will be reported in Chapter 5 of this dissertation.

Task 3 - Answering Research Question 2

The third task is to answer Research Question 2. The answer to this Research Question will be reported in Chapter 6 of this dissertation.

Task 4 - Drivers Survey

The fourth task is to conduct a survey in order to determine the parameters that describe the risk-taking behavior for an MLC. A DLC survey, conducted by Balal et al. (2016), revealed the most important parameters when executing a DLC; however no such survey has been

conducted for MLCs. The survey is similar to that conducted by Balal et al. (2016), and the survey results will be presented in Chapter 7 of this dissertation. The outcome of this survey helps to justify the selection of the risk-taking parameters to the MLC decision model, which may be different from those for the DLC model. The use of the correct parameters to describe the risk-taking behavior of MLCs is important in answering Research Questions 3 and 4.

Task 5 - Answering Research Question 3

The fifth task is to answer Research Question 3. The answer to this Research Question will be reported in Chapter 8 of this dissertation.

Task 6 - Answering Research Question 4

This sixth task is to answer Research Question 4, using a five-step approach. Each of the five steps will be described next. The answer to this Research Question will be reported in Chapter 9 of this dissertation.

The first step is to simply apply an existing lane changing FIS model, which has been developed for DLCs by Balal et al. (2016), to MLC test data. This is essentially the benchmark and do-nothing condition, which considers the transferability of a DLC model to MLC data.

The second step is to adapt the DLC FIS by Balal et al. (2016) by changing the defuzzification threshold. The output of the DLC FIS model is a crisp value, within the range of [0,1]. The defuzzification threshold, τ, is used to convert the output of [0,1] to the binary decision of "no, do not change lanes" or "yes, change lanes," respectively. Optimizing the defuzzification threshold is essentially the best that a DLC model can perform in predicting MLC decisions.

The third step is to develop four different ANFIS models using MLC training data to train the models. The models may then be tested with MLC test data. The difference with the four different ANFIS models are the membership function shapes, composition method, etc.

Each of the three aforementioned steps will be conducted as part of one experiment (i.e. Experiment 1). A second experiment (i.e. Experiment 2) will also be conducted by reversing the training and test data sets.

In the fourth step, the models from steps two and three will be evaluated based on their performance with the test data. This includes both Experiment 1 and Experiment 2. By selecting the model that performs the best from two experiments, this will essentially be the best transferable model, which may be used in various locations.

In the fifth and final step (i.e. Experiment 3), if the MLC survey results in a different risk-taking parameter when compared to the DLC survey conducted by Balal et al. (2016), one input parameter may be removed from the best model from step four, and reapplied to the MLC test data again. The differences in the model's performance, before and after the removal of an input parameter, will indicate the model's robustness.

Task 7 - Conclusions and Recommendations

This task is the seventh and final task, which will highlight the key findings of this dissertation. This chapter will also describe the significance of this research, specifically as it relates to the intellectual merit and broader impact, as well as the listing of publications derived from this dissertation. These results will be presented in Chapter 10.

CHAPTER 4: VEHICLE TRAJECTORY DATA AND METHODOLOGIES

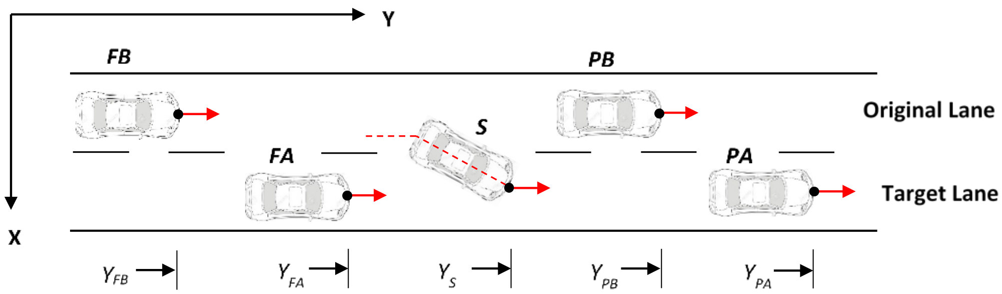
4.1 Chapter Introduction

The vehicle trajectory data used for this research is taken from the Federal Highway Administration's (FHWA) Next Generation SIMulation (NGSIM) database. This database contains vehicle trajectory data from arterial and freeway segments. The vehicle movements were captured using cameras mounted at high elevations (i.e. tall buildings). Videos recorded by these cameras tracked each vehicle in the study area every tenth of a second (Cambridge Systematics Inc., 2005a, 2005b, 2007a, 2007b).

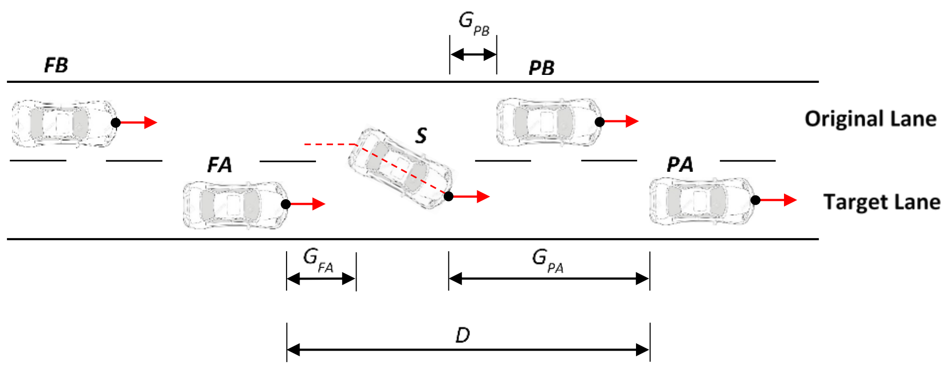
This chapter describes the data preparation and organization into the different data sets to be used in the subsequent chapters. Before these, the lane changing parameters that are used by drivers in making decision on DLCs are first defined. These parameters are also the same parameters used by drivers when making MLC decisions, as found in the MLC survey in Chapter 7. After the parameters have been defined, the subsequent sections in this chapter discuss the general methodology used to answer each Research Question. The results for these methodologies will be presented in Chapters 5 through 9, which includes the MLC survey in Chapter 7.

4.2 Lane Changing Parameters

A DLC survey was conducted by Balal et al. (2016), and the four most frequently used parameters were selected as the four input parameters for their FIS model. The vehicles involved in a typical lane changing event are presented in Figure 4.1a. The four input parameters used for DLCs, by Balal et al. (2016), is presented in Figure 4.1b. These are the four input parameters that will be used to answer Research Questions 1 and 2.



(a) Vehicle Positions



(b) Risk-Taking Parameters

FIGURE 4.1. VEHICLES AND RISK-TAKING PARAMETERS DURING A DLC (Balal et al., 2016).

The top four input parameters from Figure 4.1 are:

- *Front gap before lane change* (in meters):

$$G_{PB} = (Y_{PB} - L_{PB}) - (Y_S), \quad G_{PB} \geq 0 \tag{4.1}$$

- *Front gap after lane change* (in meters):

$$G_{PA} = (Y_{PA} - L_{PA}) - (Y_S), \quad G_{PA} \geq 0 \tag{4.2}$$

- *Rear gap after lane change* (in meters):

$$G_{FA} = (Y_S - L_S) - (Y_{FA}), \qquad G_{FA} \geq 0 \tag{4.3}$$

- *Distance* (in meters):

$$D = (Y_{PA} - L_{PA}) - (Y_{FA}), \qquad D \geq 0 \tag{4.4}$$

The formula used for calculating G_{PB} and G_{PA} was the longitudinal distance between the rear bumper of the preceding vehicle (before and after the lane change, respectively) and front bumper of the subject vehicle. Likewise, the formula used for calculating G_{FA} was the longitudinal distance between the rear bumper of the subject vehicle and the front bumper of the following vehicle after the lane change. The formula used for calculating D was the summation of G_{PA} and G_{FA}, which includes the length of the subject vehicle. These parameters are also referred to as risk-taking parameters in this dissertation, as they are the most frequently used parameters drivers consider when determining the risk when changing lanes. The survey conducted by Balal et al. (2016) considered six other risk-taking parameters; however, they were used relatively less often by drivers surveyed.

4.3: Arterial Data

This section describes the NGSIM data used for Chapter 5. The NGSIM data sets used were collected at Peachtree Street in Atlanta, Georgia (Cambridge Systematics Inc., 2007a, 2007b). The data collected between 4:00-4:15 p.m. (with traffic exposure[2] of 1,725 vehicles/15-minute) is denoted as Dataset P1. The data collected between 12:45-1:00 p.m. (with traffic exposure of 1,458 vehicles/15-minute) is named Dataset P2. The Peachtree Street site was

[2] The traffic exposure was calculated by the summation of all vehicles entering each intersection for all five intersections within the study area.

approximately 2,100 feet in length, with five intersections and two to three arterial through lanes in each direction. More details of these data sets will be discussed in Chapter 5.

A summary of the NGSIM data sets that were used to answer this Research Question 1, as well as the corresponding reference, is presented in Table 4.1.

TABLE 4.1. SUMMARY OF ARTERIAL STREET DATA SETS CONSTRUCTED FROM NGSIM DATABASE.

Research Question	Chapter	Data Used		Reference	Lane Change Type
1	5	Dataset P1	Peachtree St. (Atlanta, Georgia) November 8, 2006 **4:00–4:15 p.m.**	Cambridge Systematics Inc. (2007b)	DLC
		Dataset P2	Peachtree St. (Atlanta, Georgia) November 8, 2006 **12:45–1:00 p.m.**	Cambridge Systematics Inc. (2007a)	DLC

4.3.1: METHODOLOGY FOR ARTERIAL STREET DATASETS

Datasets P1 and P2 have been filtered to only include vehicles that changed lanes when traveling along Peachtree St. without making a turn, as to eliminate a possible MLC maneuver. Each dataset was then filtered based on vehicle class, as to only include passenger vehicles; and then filtered again based on lane identification number, as to eliminate vehicles in turn-bays. There were 134 and 135 subject vehicles after data screening for Datasets P1 and P2, respectively.

The remaining vehicles were then analyzed to determine which vehicles made exactly one lane change and which vehicles made more than one lane change. Any lane change that occurred in an intersection was omitted. This was because the NGSIM database tracks the lane identification for each vehicle at each time interval (i.e. every tenth of a second); however, when a vehicle is in an intersection, the NGSIM database displays “0” as the lane identification, and therefore no risk-taking parameters could be derived. After this round of data screening, there

were 47 lane changing occurrences in dataset P1, and 51 lane changing occurrences in Dataset P2.

The formulae used for calculating the four risk-taking parameters have been presented in Equations (4.1) to (4.4). The NGSIM data consisted of vehicle positions at 0.1-second intervals. For each lane change, the instant *t*, when the subject vehicle (the front center of a vehicle, as seen in Figure 5.1) crossed the lane marker, was identified. The four lane changing parameters were calculated at *t*-0.4, *t*-0.3, *t*-0.2, *t*-0.1, and *t* seconds and the average values from *t*-0.4 to *t* seconds were used as the representative values of the "accepted" parameters. This method of averaging data to 0.5-second resolution was done for three reasons: (i) to reduce error caused by instantaneous values in NGSIM data; (ii) to be more consistent with human perception time; and (iii) to be consistent with other researchers that used NGSIM data. Instances where there were any missing surrounding vehicles (i.e. when G_{PB}, G_{PA}, G_{FA}, or D equals to ∞), the lane changing occurrence was omitted. The final dataset contained 29 lane changing events for dataset P1, and 32 lane changing events for dataset P2.

4.4: Freeway Data

This section describes the NGSIM data used for Chapters 6, 8, and 9. The data includes vehicle trajectories collected on a segment of Interstate 80 (I-80) Freeway in Emeryville (in the San Francisco Bay area), California collected on April 13, 2005 (Cambridge Systematics Inc., 2005a). The available data was collected between 4:00-4:15 p.m., 5:00-5:15 p.m., and 5:15-5:30 p.m. In this study, the data from 4:00-4:15 p.m. was used because it has the highest number of lane changes among the three 15-minute periods. The data collected represented travel on the northbound direction of the I-80 Freeway segment. The site was approximately 1,650-feet in length, with an on-ramp at Powell Street. The off-ramp at Ashby Avenue is just downstream of the study area. Lane numbering is incremented from 1 in the left-most lane to 6 in the auxiliary lane. The data collected from this I-80 Freeway site is named Dataset A.

The other NGSIM data used was collected on a southbound direction of U.S. Highway 101 (Hollywood Freeway) in Los Angeles, California (Cambridge Systematics Inc., 2005b). The site was approximately 2,100-feet in length, with five mainlines and an auxiliary lane. Similar to the I-80 Freeway site, the lane numbering is incremented from 1 in the left-most lane to 6 in the auxiliary lane. The data collected from U.S. Highway 101 is named Dataset B. The available data was collected between 7:50-8:05 a.m., 8:05-8:20 a.m., and 8:20-8:35 a.m. In this study, the data from 7:50-8:05 a.m. was used because it has the highest number of lane changes among the three 15-minute periods.

A summary of the NGSIM data sets that were used to answer these Research Questions (2-4), as well as the corresponding reference, is presented in Table 4.2.

TABLE 4.2. SUMMARY OF FREEWAY DATA SETS CONSTRUCTED FROM NGSIM DATABASE.

Research Question	Chapter	Data Used		Reference	Type of Lane Change
2	6	Dataset A	Interstate 80 (I-80) Freeway (**Emeryville, California**) April 13, 2005 4:00 – 4:15 p.m.	Cambridge Systematics Inc. (2005a)	MLC and DLC
		Dataset B	U.S. Highway 101 (**Los Angeles, California**) June 15, 2005 7:50 – 8:05 a.m.	Cambridge Systematics Inc. (2005b)	MLC and DLC
3	8	Dataset A	Interstate 80 (I-80) Freeway (**Emeryville, California**) April 13, 2005 4:00 – 4:15 p.m.	Cambridge Systematics Inc. (2005a)	MLC
		Dataset B	U.S. Highway 101 (**Los Angeles, California**) June 15, 2005 7:50 – 8:05 a.m.	Cambridge Systematics Inc. (2005b)	MLC
4	9	Dataset A	Interstate 80 (I-80) Freeway (**Emeryville, California**) April 13, 2005 4:00 – 4:15 p.m.	Cambridge Systematics Inc. (2005a)	MLC
		Dataset B	U.S. Highway 101 (**Los Angeles, California**) June 15, 2005 7:50 – 8:05 a.m.	Cambridge Systematics Inc. (2005b)	MLC

4.4.1: Methodology For Research Question 2

In order to answer Research Question 2, the vehicle trajectory data was processed as follows. The data processing steps were different from the steps performed by Balal et al. (2014, 2016):

- Only passenger cars were selected as subject vehicles.
- Subject vehicles that moved from lane 5 to lane 6, or from lane 6 to lane 5 were assumed to make MLCs, as the vehicles were likely attempting to exit the freeway or avoid exiting the freeway at the immediate downstream off-ramp.
- Vehicles that changed lanes between lanes 2, 3, and 4 were assumed to make DLCs, as there was no evidence to suggest that the drivers' motivation was to exit the freeway at the immediate downstream off-ramp.
- Vehicles that changed lanes to or from lane 1 were not considered because it was difficult to ascertain the motivation of these vehicles, as lane 1 is a high occupancy vehicle lane.
- For each identified subject vehicle, the time t when the lane changing event occurred was taken as the time when the front center of the subject vehicle crossed the lane markers.
- For each lane change, the values of the four risk-taking parameters were calculated at t-0.4, t-0.3, t-0.2, t-0.1, and t seconds and the average values from t-0.4 to t seconds were used to describe the subject driver's risk-taking behavior.
- If there were any missing surrounding vehicles (i.e. when G_{PB}, G_{PA}, G_{FA}, or D equals to ∞), the subject vehicle was not included in the analysis.

There are two data sets, Dataset A and Dataset B. The number of vehicles after data processing, for each data set, is tabulated in Table 4.3. Both Dataset A and Dataset B have approximately the same number of vehicles (for all vehicle types) in the 15-minute period. The traffic volumes were equivalent to 1,368 and 1,446 vehicles per hour per lane (vphpl), respectively. The corresponding space mean speeds were 28.74 and 41.30 km/h. The traffic in

Dataset A is more congested than Dataset B. Dataset A has 301 lane changes while Dataset B has only 199 lane changes. The higher lane changing movements in Dataset A probably caused the traffic to move at a slower speed compared to Dataset B. Furthermore, Dataset A has a higher proportion of vehicles making an MLC than Dataset B.

TABLE 4.3. SUMMARY OF DATASETS A AND B USED FOR RESEARCH QUESTIONS 2. 3, AND 4.

Dataset	A	B
Source	I-80 Freeway April 13, 2005 4:00 – 4:15 p.m.	U.S. Highway 101 June 15, 2005 7:50 – 8:05 a.m.
Total no. of vehicles (veh/15-minute)	2,052[#]	2,169[&]
Equivalent volume (vphpl)	1,368[#]	1,446[&]
Space mean speed (km/h)	28.74[#]	41.30[&]
No. of lane changes (cars as subject vehicles)	301	199
No. of MLCs	166	71
No. of DLCs	135	128

[#] from Cambridge (2005a)
[&] from Cambridge (2005b)

4.4.2: METHODOLOGY FOR RESEARCH QUESTION 3

In order to answer Research Question 3, the vehicle trajectory data was processed as follows:

- Only passenger cars were selected as subject vehicles. Trucks and motorcycles, which were expected to have different lane changing behavior, and have small sample sizes; therefore, they were not considered.
- Only the subject vehicles that originally traveled in lanes 5 and 6 were considered. They were assumed to make MLCs, as they were likely attempting to exit the

freeway (from lane 6) or avoid exiting the freeway (from lane 5). Vehicles in lanes 2, 3, and 4 were not considered, as to eliminate the possibility of drivers executing a DLC maneuver. Vehicles in lane 1 were not considered, as to eliminate the interference caused by any high occupancy vehicle lane. Although this procedure did not necessarily filter out all of the DLCs in lanes 5 and 6 within the data collection segment, this was the best guess that could be made from the NGSIM data.

- For each identified subject vehicle, the time t when the lane changing event occurred was taken as the time when the front center of the subject vehicle crossed the lane markers. This time reference t was used because it was impossible to determine from the NGSIM data when exactly a driver psychologically made his/her decision to change lanes.
- The NGSIM data consisted of vehicle positions at 0.1-second intervals. For each lane change, the instant t, when the subject vehicle (the front center of a vehicle, as seen in Figure 4.1) crossed the lane marker was identified. The four-lane change parameters were calculated at t-0.4, t-0.3, t-0.2, t-0.1, and t seconds, and the average values from t-0.4 to t seconds were used at the representative values of the "accepted" parameters. This method of averaging data to 0.5-second resolution was done for three reasons (i) to reduce error caused by instantaneous values in NGSIM data; (ii) to be more consistent with human perception time; and (iii) to be consistent with other researches that used NGSIM data. Instances where there was any missing surrounding vehicle (i.e. when G_{PB}, G_{PA}, G_{FA}, or D equals to ∞), the lane changing occurrence was omitted.

The number of vehicles after each round of data screening is presented in Table 4.4. The flow (in vph) in lanes 5 and 6 on I-80 was much higher than the flow in lanes 5 and 6 on U.S. 101, which is the reason there are approximately twice as many lane changing occurrences, as seen in Table 4.4. For some of the subject vehicles, there was no preceding or following vehicle,

which caused one or more of the parameters to be infinity. Therefore, any subject vehicle with a missing risk-taking parameter was omitted before analysis.

TABLE 4.4. DATA FILTRATION PROCESS FOR RESEARCH QUESTION 3.

Dataset	**A**	**B**
Source	Interstate 80 (I-80) April 13, 2005 4:00 – 4:15 p.m.	U.S. Highway 101 June 15, 2005 7:50 – 8:05 a.m.
	No. of Vehicles	**No. of Vehicles**
Original Data	2,052	2,169
Passenger Car Filter	1,942	2,086
Lane Change in Lanes 5 and 6 Filter	278	140
Final No. of Subject Vehicles	166	71

4.4.3: METHODOLOGY FOR RESEARCH QUESTION 4

In order to answer this research question, the vehicle trajectory data was processed as follows:

- Only passenger cars were selected as subject vehicles.
- Subject vehicles that changed lanes from lane 5 to lane 6, or from lane 6 to lane 5 were assumed to have made MLCs.
- Vehicles that changed lanes from or to lane 1 (high occupancy vehicle lane) were not considered because it was difficult to ascertain the motivation of these vehicles.
- For each identified subject vehicle, the time instant t was taken as the time when the front center of the subject vehicle crossed the lane markers.
- For each MLC, the coordinates of the vehicles of interest (*S*, *PB*, *PA*, and *FA*) were extracted at t-0.4, t-0.3, t-0.2, t-0.1, and t seconds from the NGSIM database.

The values of the four parameters were then calculated at each of these 0.1 second intervals. Then, the average values from *t*-0.4 to *t* seconds were used as inputs to the models at time *t*. For the purpose of calculating the model's decision accuracy, this vector (for every subject vehicle at time *t*) was labeled *OM*=1, where *OM* is the acronym for Observed Maneuver, and 1 represented "yes, change lanes". The values obtained were assembled to form a vector $\{t, G_{PB}, G_{PA}, G_{FA}, D, OM\}$.

- For every subject vehicle, at all other instances prior to *t*, the values of the four parameters were calculated and averaged in the same way but for *t*-0.5, *t*-1.0, *t*-1.5, etc. seconds. These vectors were labeled *OM*=0, where the 0 value meant "no, do not change lanes".

Once the data had been processed, three separate experiments were conducted. Each experiment will be described in the subsequent sections.

4.4.3.1: EXPERIMENT 1

Experiment 1 has three tests. Each test will be described in the subsequent sub-sections. Essentially, models will be developed using MLC data from Dataset A. Then, the models will be tested using Dataset B. The models will be evaluated based on their performance with Dataset B, as it will be proven in Chapter 8 that the MLC driving behaviors are different between the two sites.

In Experiment 2, the models are developed using Dataset B, and then tested with Dataset B (i.e. the opposite of Experiment 1). The purpose of having two experiments, each with opposite training and testing data, is to gain a better understanding when evaluating the models' performances.

Experiment 1-FIS-DN

This experiment is the Do Nothing (DN) option, simply by applying the FIS, which has been developed for DLCs, to the MLC test data.

A DLC FIS model was developed by Balal et al. (2016), using MATLAB (MATLAB, 2012). MATLAB has different Applications, or "Apps" within the program, one of which is the Fuzzy Logic Designer, which was used by Balal et al. (2016).

The Fuzzy Logic Designer is a graphical user interface (GUI), which allows the user to first select the number of inputs. These are essentially the risk-taking parameters (i.e. G_{PB}, G_{PA}, G_{FA}, and D). Then, the output is considered. The output for this model is a binary value {0,1}, which correspond with "no, do not change lanes" or "yes, change lanes," respectively. In between the input risk-taking parameters and the output, are the fuzzy logic IF-THEN rules, as previously described in Section 2.4.

The output of "yes, change lanes" would then be converted to a crisp value within the range of [0,1]. This is the defuzzification stage, and is based on the output membership functions provided by the user. Then, once the model has provided an output for all instances, a minimum threshold may be developed. Any value above the threshold would be considered as 1 (yes, change lanes). Likewise, any value below the threshold would be considered as 0 (no, do no change lanes). The threshold is specified by the user. These predicted output values may be compared to the actual values of 0 (no, do not change lanes) and 1 (yes, change lanes).

This process was the same process used by Balal et al. (2016) to model DLCs. MATLAB's Fuzzy Logic Designer file may be saved as a .fis file. For this experiment, the DLC FIS model developed will applied to Dataset B.

This experiment is titled Experiment 1DN, as this is a do-nothing experiment. The purpose of this do-nothing experiment is to set a benchmark of how well the existing DLC FIS model performs when presented with MLC data.

Experiment 1-FIS-A

Experiment 1-FIS-A (A for adaptation) is to determine the optimal defuzzification threshold (τ value) for the DLC FIS to achieve the best possible performance. This is essentially the best that an existing DLC FIS model can perform when presented with MLC data. The MLC data used for this experiment will be MLC data from Dataset B.

Experiment 1-ANFIS

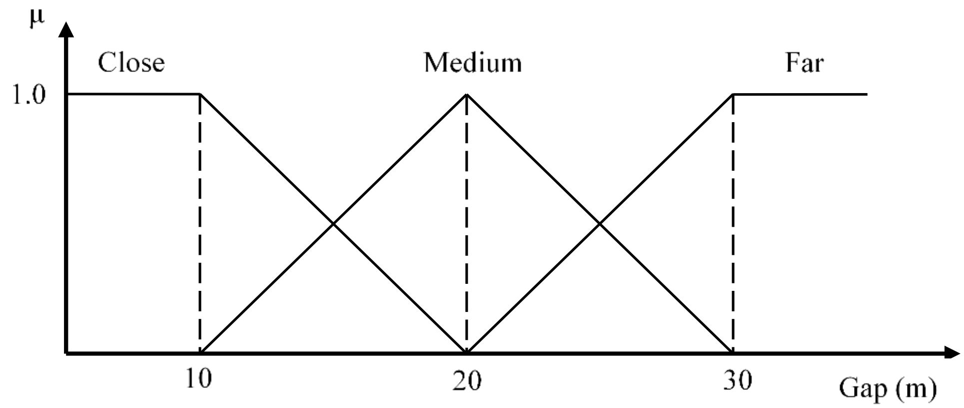
For this experiment, four different ANFIS models will be developed using Dataset A to train (or optimize) the models. The reason different ANFIS models will be developed is due to the starting positions. An ANFIS is an FIS that has been optimized using MLF optimization techniques. FISs may have many different combinations of membership function shapes, number of membership functions (which subsequently changes the number of IF-THEN rules), and composition methods. Therefore, four different ANFISs will be chosen. The four different types of ANFISs are:

1. A grid-partitioned membership function starting position with three *triangular* membership functions, and the max-min composition type;
2. A grid-partitioned membership function starting position with three *trapezoidal* membership functions, and the max-min composition type;
3. An ANFIS where the membership functions start similar to that of Balal et al. (2016) in their DLC FIS model, using both triangular and trapezoidal membership functions, and the *max-min* composition type; and
4. An ANFIS where the membership functions start similar to that of Balal et al. (2016) in their DLC FIS model, using both triangular and trapezoidal membership functions, and the *max-product* composition type.

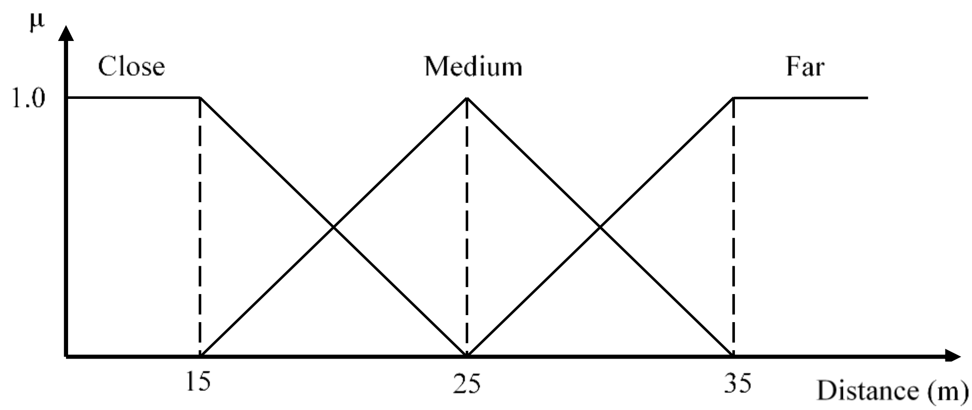
When developing an ANFIS from scratch, the membership functions must have a starting point. From this starting point, they will be adjusted and optimized based on the inputted training data as previously described in Section 2.4. The grid-partitioned membership functions essentially evenly space the membership functions between the minimum and maximum value of each input parameter. For example, if there are three triangular membership functions and the minimum and maximum value in the training data is 0 and 100, respectively, then the three triangular membership functions will be evenly spaced, thus partitioning the data into thirds. After each iteration, the membership functions are optimized based on the hybrid method as previously described in Section 2.4.

The reason three membership functions are chosen is based on the computational limitations of MATLAB. The addition of more membership functions exponentially increases the number of rules, which causes much more computational time for each epoch. Therefore, three membership functions is the maximum.

Instead of the evenly spaced grid-partitioning membership function starting positions, an alternative starting position of the membership functions from Balal et al., (2016) was selected as a better starting point for ANFIS models 3 and 4. This is because the DLC FIS by Balal et al. (2016) performed quite well using DLC data and no optimization. Figure 4.2a illustrates the membership functions recommended by Balal et al. (2016) for the input parameters G_{PB}, G_{PA}, and G_{FA}. Figure 4.2b illustrates the membership functions recommended by Balal et al. (2016) for the input parameter D. This starting position may converge to a different local minimum than the grid partition starting position (for ANFIS models 1 and 2), and is therefore considered once using the max-min composition method as well as the max-product composition method for ANFIS models 3 and 4, respectively.



(a) Gaps



(b) Distance

FIGURE 4.2. DLC MEMBERSHIP FUNCTIONS RECOMMENDED BY BALAL ET AL. (2016).

Each of these four ANFISs will be developed at least three times due to the random assigning of link weights in the ANFIS architecture. As mentioned in Section 2.4, the link weights are also randomly assigned based on the random seed generated by the computer. Therefore, in order to ensure each ANFIS is not reaching a local minimum, each ANFIS will be developed four times and the RMSE and number of epochs will be recorded.

In general, the architecture of each ANFIS will follow the general ANFIS architecture by Jang et al. (1997) (see Figure 2.3), and is presented in Figure 4.3.

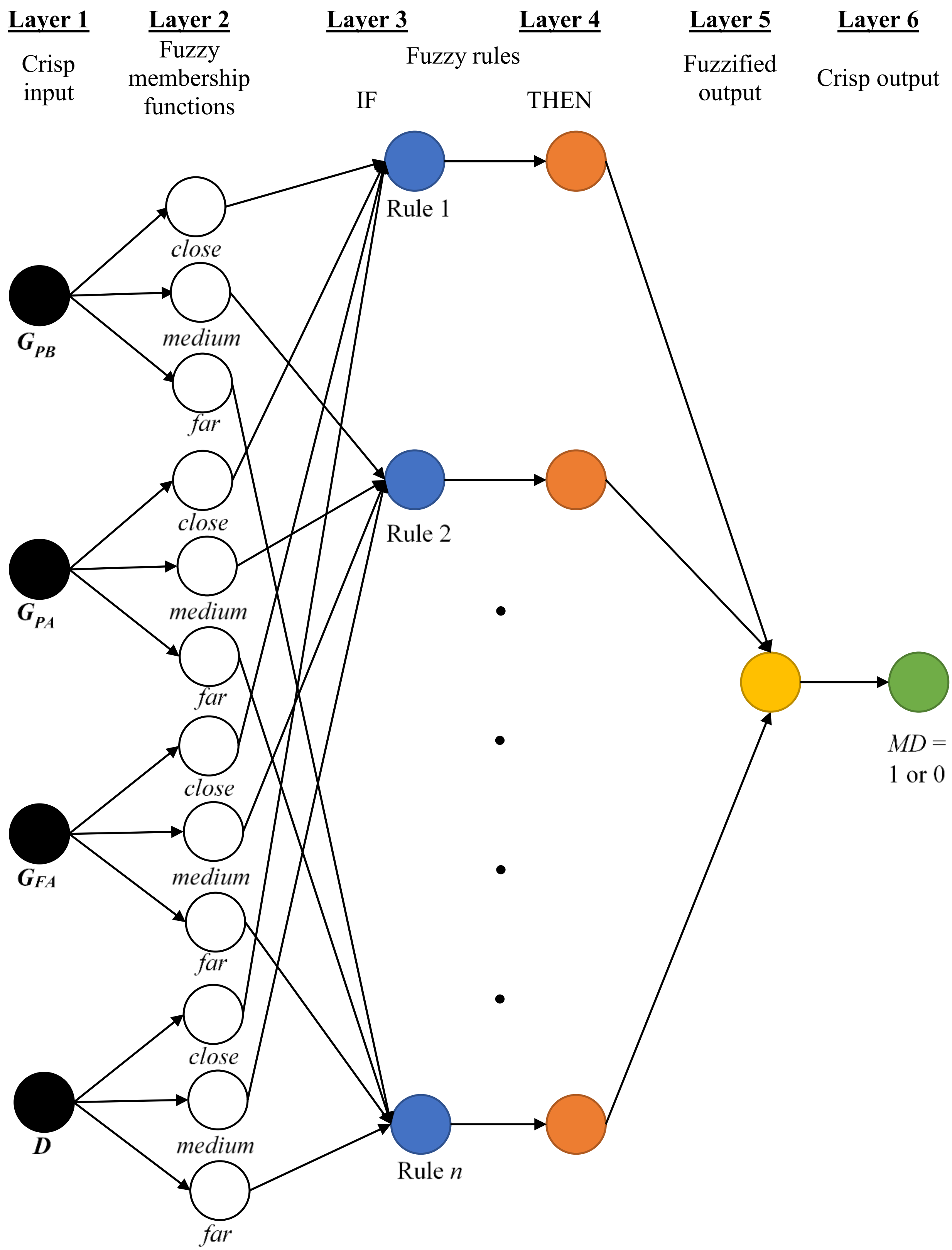


FIGURE 4.3. ARCHITECTURE OF MLC ANFIS MODELS.

In Figure 4.3, the top four input parameters (as will be discovered by the MLC survey in Chapter 7) will be used as the input neurons. Each input parameter consists of three membership functions, namely {*close*, *medium*, *far*}. With four input parameters, each having three membership functions, this yields 81 possible composition rules. This is presented as Layers 3 and 4 in Figure 4.3. The reason three membership functions were selected for each input parameter is due to the number of rules generated. By simply adding one more membership function for each input parameter, this would create 256 IF-THEN rules. At this point, the computational requirements become unreasonable. In Layer 5, all 81 rules are compiled via the max-min or max-product method, based on each rule's firing strength. This creates one crisp output in Layer 6. At this point, the model's decision (*MD*) may then be compared to the actual lane changing decision by the driver from the data. Various thresholds may be used in order to determine the optimal output. This will be discussed further in Chapter 9.

4.4.3.2: EXPERIMENT 2

Similar to Experiment 1, Experiment 2 also has three parts. Each part will be described in the subsequent sections. Essentially, Experiment 2 is the same as Experiment 1; however, instead of developing the models using Dataset A and then testing with Dataset B, the models will be developed using Dataset B and then tested with Dataset A. The models will be evaluated based on their performance with Dataset A. Again, the purpose of having two experiments, each with opposite training and testing data, is to gain a better understanding when evaluating the models' performances.

Experiment 2-FIS-DN

For Experiment 2-FIS-DN, the exact same procedure from Experiment 1-FIS-DN will be conducted. The only difference is that the DLC FIS model developed by Balal et al. (2016) will be applied to Dataset A as opposed to Dataset B.

Experiment 2-FIS-A

Similar to Experiment 1-FIS-A (A for adaptation), Experiment 2-FIS-A determines the optimal defuzzification threshold (τ value) for the DLC FIS to achieve the best possible performance. This is essentially the best that an existing DLC FIS model can perform when presented with MLC data. The MLC data used for this experiment will be MLC data from Dataset A.

Experiment 2-ANFIS

Experiment 2-ANFIS will follow the exact same procedure as Experiment 1-ANFIS. The only difference is the ANFIS models will be developed and trained using the Dataset B, and then tested with Dataset A.

4.4.3.3: EXPERIMENT 3

In the third experiment, the best performing model from both Experiments 1 and 2 will be selected. Then, the robustness of the best performing model will be evaluated as part of Experiment 3. For this experiment, one input parameter, based on the MLC survey results in Chapter 7, will be completely removed from the best performing model. The model will then be applied to test data again in order to test its robustness.

Chapter 5: Comparisons of Discretionary Lane Changing Behavior on an Arterial at Different Times of the Day[3]

5.1: Chapter Introduction

This chapter answers Research Question 1: *Do drivers have different risk-taking behavior when executing a discretionary lane changing maneuver on an arterial street at different times of the day?* A survey from 443 drivers in El Paso, Texas has found that the top four risk-taking parameters used in making DLC decisions by at least 81% of the respondents are gaps, primarily G_{PB}, G_{PA}, G_{FA}, and D (Balal et al., 2016). Statistical properties of these parameters were analyzed from vehicle trajectories in Datasets P1 and P2.

5.2: Statistical Analyses

5.2.1 Descriptive Statistics

The first step in the analysis of the lane changing risk-taking parameters was to examine the descriptive statistics. For each data set (Dataset P1 and Dataset P2), the descriptive statistics of the four risk-taking parameters are listed in Table 5.1. Both data sets were collected at the same location during the same day. Dataset P1 was collected during the afternoon peak hour, and Dataset P2 was taken around lunchtime (i.e. off-peak). Therefore, it makes sense that the average risk-taking parameter was smaller in Dataset P1 as compared to Dataset P2, as there is more density and thus smaller gaps.

Note that, in Table 5.1, the sample standard deviation values for each risk-taking parameter are greater than the sample means in Dataset P1. Intuitively, this would yield some negative values for each risk-taking parameter; however, the reason for this is a high variance accompanied with a high positive skew. An example illustration of this is presented later in the distribution fitting results in Figure 5.2. In Dataset P2, the sample standard deviation is not greater than the sample mean, and the skewness value, while still positive, is much lower.

[3] An earlier version of this Chapter was published as Vechione, M. Balal, E., and Cheu, R. (2018). "Comparisons of Discretionary Lane Changing Behavior: Implications for Autonomous Vehicles", *Institute of Transportation Engineers Journal*, Vol. 88, No. 6, pp. 37-43.

TABLE 5.1. DESCRIPTIVE STATISTICS OF LANE CHANGING PARAMETERS FOR DATASETS P1 AND P2.

Dataset	**P1**			
Parameters	G_{PB}	G_{PA}	G_{FA}	D
Sample Size	29	29	29	29
Unit	ft. (m)	ft. (m)	ft. (m)	ft. (m)
Min Value	14.34 (4.37)	26.15 (7.97)	29.79 (9.08)	78.51 (23.93)
Max Value	1,593.11 (485.58)	1,685.50 (513.74)	2,894.13 (882.13)	3,832.38 (1,168.11)
Mean	251.71 (76.72)	351.38 (107.10)	676.87 (206.31)	1,028.25 (313.41)
Std. Deviation	332.25 (101.27)	449.02 (136.86)	762.57 (232.43)	898.33 (273.81)
Skewness	2.93	2.03	1.62	1.49
Dataset	**P2**			
Parameters	G_{PB}	G_{PA}	G_{FA}	D
Sample Size	32	32	32	32
Unit	ft. (m)	ft. (m)	ft. (m)	ft. (m)
Min Value	38.32 (11.68)	54.79 (16.70)	90.29 (27.52)	270.24 (82.37)
Max Value	2,241.37 (683.17)	2,153.12 (656.27)	2,782.48 (848.10)	4,586.19 (1,397.87)
Mean	687.30 (209.49)	804.63 (245.25)	1,127.89 (343.78)	1,932.51 (589.03)
Std. Deviation	670.37 (204.33)	636.39 (193.97)	753.54 (229.68)	1,096.36 (334.17)
Skewness	1.05	0.72	0.39	0.41

5.2.2: Hypothesis Tests of the Difference Between Two Means

Hypothesis tests were conducted to determine if the average value for each parameter was statistically similar between the two data sets (i.e. late afternoon vs. mid-day). For each hypothesis test, the null hypothesis was that the population averages (μ_1 and μ_2) for each parameter were the same; and the alternate hypothesis was that the population averages for each parameter differ. The test statistic followed the t-distribution with small sample sizes; and it was assumed that the variances were unknown and not equal (Montgomery and Runger, 2011). Each hypothesis test was two-sided with an alpha value of 0.05 (i.e. $\alpha/2 = 0.025$). Table 5.2 presents the results of hypothesis tests.

Based on the results presented in Table 5.2, there is statistical evidence to suggest that the population averages for each parameter at different times of the day differ at 0.05 level of significance. This implies that drivers have different risk-taking thresholds based on time-of-day (which has different traffic congestion levels).

TABLE 5.2. HYPOTHESIS TESTS FOR RESEARCH QUESTION 1.

Dataset	P1	P2
G_{PB}	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	
Sample Mean, $\bar{X}$ (ft., m)	251.71 (76.72)	687.30 (209.49)
Sample Std. Dev., *s* (ft., m)	332.25 (101.27)	670.37 (204.33)
No. of Observations, *n*	29	32
t-Value	-3.26	
Conclusion	**Reject H_0**	
G_{PA}	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	
Sample Mean, $\bar{X}$ (ft., m)	351.38 (107.10)	804.63 (245.25)
Sample Std. Dev., *s* (ft., m)	449.02 (136.86)	636.39 (193.97)
No. of Observations, *n*	29	32
t-Value	-3.24	
Conclusion	**Reject H_0**	
G_{FA}	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	
Sample Mean, $\bar{X}$ (ft., m)	676.87 (206.31)	1,127.89 (343.78)
Sample Std. Dev., *s* (ft., m)	762.57 (232.43)	753.54 (229.68)
No. of Observations, *n*	29	32
t-Value	-3.24	
Conclusion	**Reject H_0**	
D	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	
Sample Mean, $\bar{X}$ (ft., m)	1,028.25 (313.41)	1,932.51 (589.03)
Sample Std. Dev., *s* (ft., m)	898.33 (273.81)	1,096.36 (334.17)
No. of Observations, *n*	29	32
t-Value	-3.54	
Conclusion	**Reject H_0**	

5.2.3 Hypothesis Tests of the Difference Between Observed Cumulative Distributions

For the same risk-taking parameters, the probability distributions were then tested on their difference. For this approach, the χ^2 goodness-of-fit test and the Kolmogorov-Smirnov (K-S) test were considered.

The χ^2 goodness-of-fit test groups the data points into *k* bins, and then computes the test statistics

$$\chi^2 = \sum_{i=1}^{k} \frac{(O_i - E_i)^2}{E_i} \tag{5.1}$$

In (5.1), O_i and E_i are the observed and expected (theoretical) frequencies of the two distributions (Ang and Tang, 1975). There were two problems when applying the DLC parameters in each data set to conduct this test. First, (5.1) implies that both the distributions have the same total frequency of occurrence, but these two data sets have unequal sample sizes. Second, between late afternoon and mid-day, it was not clear which time period should be assigned as O_i and E_i.

The K-S test was designed to test the difference of cumulative probability of *x*, denoted by $F(x)$, against the theoretical cumulative probability of *x*, denoted by $P(x)$. The maximum difference *d* is then compared against a critical value. *d* is defined as

$$d = \max_x |F(x) - P(x)| \tag{5.2}$$

In (5.2), $|F(x) - P(x)|$ is evaluated at every observed value of *x* (Ang and Tang, 1975). This is known as one sample K-S test (Zaiontz, n.d.). This application was to compare two observed samples (of say, *x* and *y*) which means that $|F(x) - F(y)|$ must be computed at every observed *x* and *y* value. That is

$$d = \max_{x,y} |F(x) - F(y)| \tag{5.3}$$

In this late afternoon and mid-day DLC data, *x* and *y* values did not coincide, which makes the computation of *d* difficult. A compromise was to organize the observed *x* and *y* values into bins and then evaluate the difference in cumulative probabilities at every bin. If the bin size is kept small, the computed *d* will be a good estimate of the actual *d*. In the K-S test results presented in Table 5.3, a bin size of 10.0 m was arbitrary selected and used in the computation of *d*, as the risk-taking values range from very small to up to 1,000 m.

Another issue addressed was the critical value of the test statistic. In the two sample K-S test (Zaiontz, n.d.), with n_1 and n_2 observations respectively, the two distributions are deemed different (i.e., observed samples are from two different populations) at α level of significance if $d > d_{n_1,n_2,\alpha}$

$$d_{n_1,n_2,\alpha} = k_\alpha \sqrt{\frac{n_1+n_2}{n_1 n_2}} \tag{5.4}$$

in which k_α is the statistic of the Kolmogorov distribution for parameter *K* with a tail-end probability of $P(K > k_\alpha) = \alpha$. k_α may be obtained from the standard K-S test table (Zaiontz, n.d.).

Table 5.3 presents the outcomes of the K-S tests, with α=0.10 and 0.05, respectively. For all four of the risk-taking parameters, the null hypothesis of

H_0: *the observed distributions of the risk-taking parameter for afternoon and mid-day DLCs are drawn from the same population*

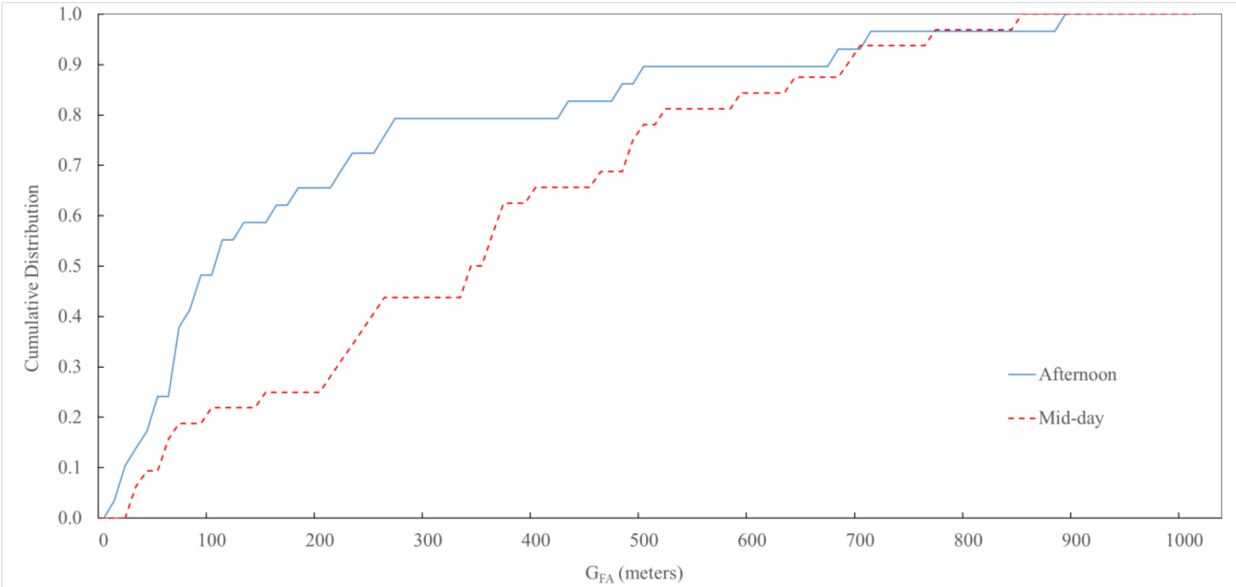
was rejected at α=0.10 and 0.05. This further implies that, in fact, drivers do behave differently based on the time of day when executing a DLC maneuver on an arterial street.

TABLE 5.3. KOLMOGOROV-SMIRNOV TESTS FOR RESEARCH QUESTION 1.

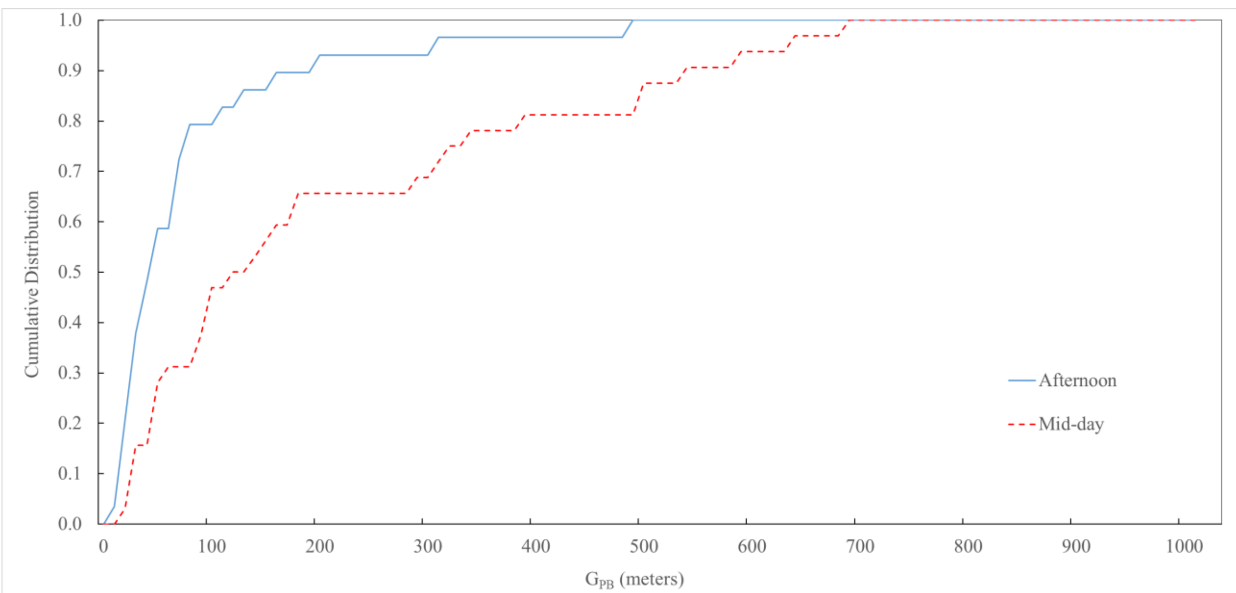
Afternoon vs. Mid-day				
Parameters	G_{PB}	G_{PA}	G_{FA}	D
d	0.481	0.477	0.405	0.428
Conclusion (α=0.10)[#]	**Reject H_0**	**Reject H_0**	**Reject H_0**	**Reject H_0**
Conclusion (α=0.05)[&]	**Reject H_0**	**Reject H_0**	**Reject H_0**	**Reject H_0**

[#] Critical value = 0.314
[&] Critical value = 0.348

The K-S tests are best visualized by plotting the cumulative probability distributions for afternoon and mid-day on the same graph. Figure 5.1 presents the best and worst cases for the K-S tests. Figure 5.1(a) shows the cumulative probability distributions of afternoon and mid-day for G_{FA}, which gave d=0.405. Figure 5.1(b) shows the cumulative probability distributions of afternoon and mid-day for G_{PB}, which gave d=0.481.



(a) G_{FA}



(b) G_{PB}

FIGURE 5.1. EXAMPLES OF KOLMOGOROV-SMIRNOV TESTS FOR OBSERVED CUMULATIVE DISTRIBUTIONS FOR RESEARCH QUESTION 1.

5.2.4 Probability Distribution Fittings

The probability distribution for each parameter was then fitted and analyzed using @RISK (Palisade, 2013). In Table 5.4, the top three fitted distributions for each parameter, among the 26 distributions tested, were chosen based on the Akaike Information Criterion (AIC) for goodness-of-fit. It is preferred to have one probability distribution to fit the gaps and distances (Balal et al., 2014). A numeric scoring system was used to select one probability distribution. The distributions that provide the best, second-best, and third-best fits were assigned scores of 3, 2, and 1, respectively. The distribution with the highest total score was recommended.

TABLE 5.4. PROBABILITY DISTRIBUTION FITTINGS FOR RESEARCH QUESTION 1.

Parameters	G_{PB}	G_{PA}	G_{FA}	D
Unit	m	m	m	m
Dataset P1				
Best Fit	Log-logistic	Pareto 2	Pareto 2	Exponential
2nd Best Fit	Pearson	**Log-normal**	Exponential	Pareto 2
3rd Best Fit	**Log-normal**	Log-normal 2	Erlang	Pert
Recommended	Log-normal			
Log-normal Location Parameter, λ	3.836	4.190	4.920	5.464
Log-normal Scale Parameter, ξ	1.004	0.984	0.905	0.753
Dataset P2				
Best Fit	Exponential	Triangle	Triangle	Triangle
2nd Best Fit	Erlang	Exponential	Pert	Rayleigh
3rd Best Fit	Pareto 2	Pareto 2	Uniform	Pert
Recommended	Log-normal			
Log-normal Location Parameter, λ	5.010	5.259	5.655	6.239
Log-normal Scale Parameter, ξ	0.818	0.697	0.607	0.528

At first glance in Table 5.4, there are no log-normal fittings in Dataset P2; however, since the log-normal distribution scored in the fourth and fifth best fits, and since it is a more commonly known distribution, it is recommended as the best distribution for both Datasets P1 and P2. The log-normal distribution has also been recommended for the DLC risk-taking

parameters by Balal et al. (2014). The log-normal distribution has a probability density function of

$$f(x|\lambda,\xi) = \frac{1}{\sqrt{2\pi}\lambda\xi} e^{-\frac{1}{2}\left(\frac{\ln x-\lambda}{\xi}\right)^2} \quad , x > 0 \qquad (5.5)$$

where $\lambda > 0$ is the location parameter while $\xi > 0$ is the scale parameter.

An example of the @RISK log-normal distribution fitting of G_{PA} for Dataset P1 is illustrated in Figure 5.2.

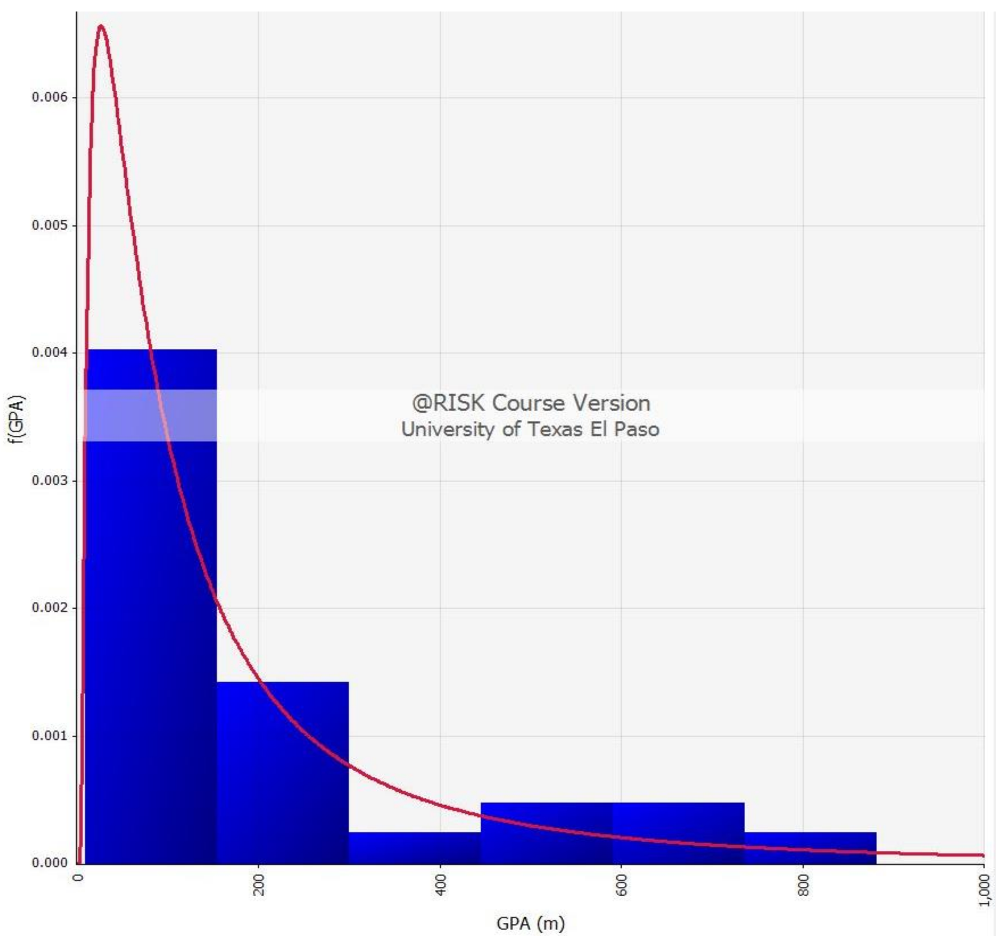


FIGURE 5.2. LOG-NORMAL DISTRIBUTION FITTING OF G_{PA} FOR DATASET P1.

5.2.5: Hypothesis Tests of the Difference Between Fitted Cumulative Distributions

The last set of statistical tests applied was the K-S test to test the difference between the log-normal probability distributions fitted to Dataset P1 and Dataset P2, respectively. For each test, the *d* value obtained for each pair of log-normal cumulative probabilities is listed in Table 5.5.

The outcomes of the tests are similar to the previous set of K-S tests performed for the observed distributions. For all four risk-taking parameters, the null hypothesis of

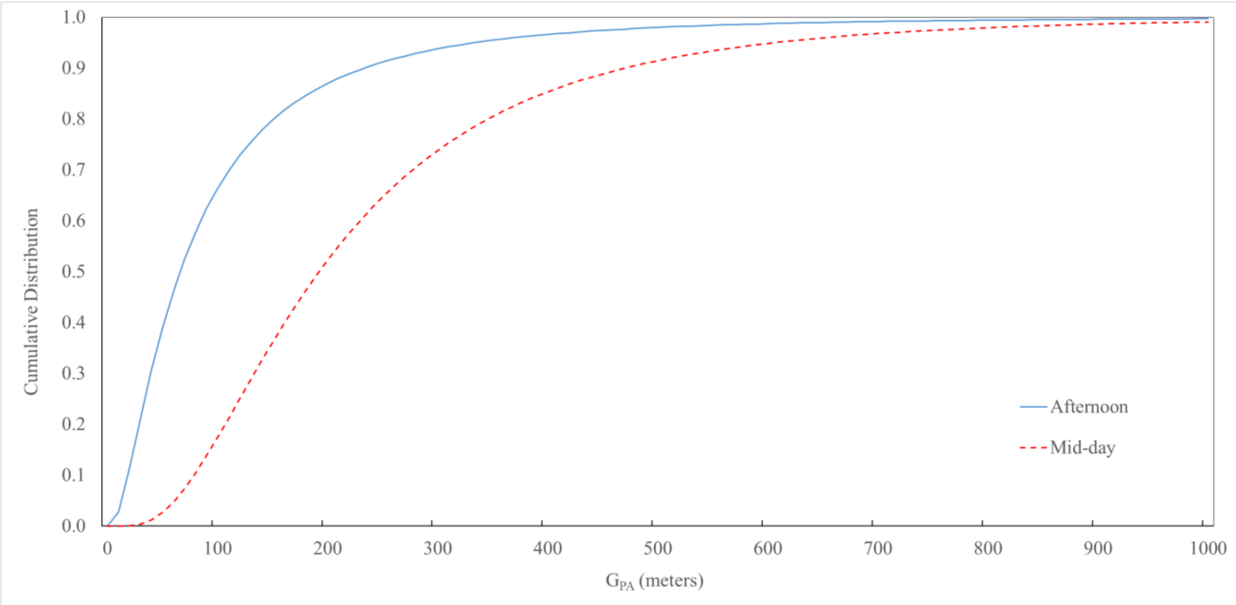
H_0: *the distributions of the risk-taking parameter for afternoon and mid-day DLCs are fitted to the same population*

was rejected at α=0.10 and at α=0.05.

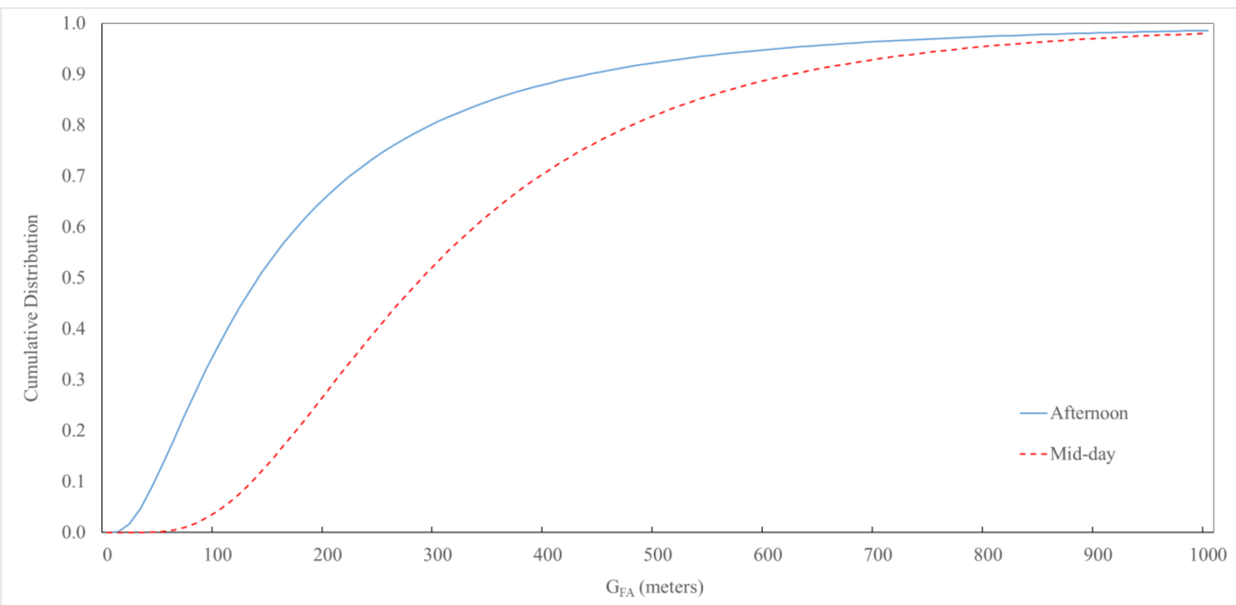
Figure 5.3(a) plots the log-normal cumulative distributions of G_{PA} for readers to visualize the difference. Figure 5.3(b) plots the log-normal cumulative distributions of G_{FA} in Dataset B to illustrate the smallest *d* value (0.398).

Table 5.5. Kolmogorov-Smirnov tests for fitted cumulative distributions for Research Question 1.

Afternoon vs. Mid-day					
Parameters		G_{PB}	G_{PA}	G_{FA}	D
d		0.485	0.489	0.398	0.471
α**=0.10**	**Critical Value**	0.055	0.055	0.055	0.055
	Conclusion	**Reject H_0**	**Reject H_0**	**Reject H_0**	**Reject H_0**
α**=0.05**	**Critical Value**	0.061	0.061	0.061	0.061
	Conclusion	**Reject H_0**	**Reject H_0**	**Reject H_0**	**Reject H_0**



(a) G_{PA}



(b) G_{FA}

FIGURE 5.3. EXAMPLES OF KOLMOGOROV-SMIRNOV TESTS FOR FITTED CUMULATIVE PROBABILITY DISTRIBUTIONS FOR RESEARCH QUESTION 1.

5.3: Discussions

The findings of this research have two important applications in the lane changing decision model. In step (3) of the four-step process by Moridpour et al. (2010), the driver (or sensors of the automated vehicle) estimate G_{PB}, G_{PA}, G_{FA}, or D, and compare each parameter with their respective thresholds.

Microscopic traffic simulation is a commonly used approach used by transportation engineers to perform traffic impact studies. A simulation approach has also been used by researchers to investigate the impacts of gradual introduction of autonomous vehicles or connected vehicles in mixed traffic stream (Krueger et al., 2016; Park and Smith, 2012; Talebpour and Mahmassani, 2016). In traffic simulation models, the stochastic behavior of drivers of conventional vehicles are represented by using probability distributions to generate the parameter values. The recommended log-normal distributions may be used in simulation software to represent the varied thresholds used by drivers with a varying degree of aggressiveness.

It is expected that, in automated vehicles, such lane changing thresholds be fixed at more conservative values, and thus ensuring the safety in lane change maneuvers. However, using a more conservative threshold (e.g., large gap), which although improves safety, may compromise capacity - the two benefits always promoted by proponents of autonomous vehicles. The results of hypothesis tests have suggested that, the thresholds of an automated vehicle may be adjusted automatically depending on the time-of-day (by the clock time), or based on the traffic density (by receiving data from surrounding connected vehicles).

5.4: Chapter Summary

The NGSIM data on Peachtree St. was processed to analyze the four gap and distance parameters. In all of the analyses conducted, the results indicate that there is statistical evidence to suggest that the population averages for each parameters differ based on driving conditions

(i.e. time-of-day). In addition, the log-normal distribution is recommended for all four parameters for both data sets, as it is more commonly known.

This research has performed the above hypothesis tests and K-S tests using real data; however, as in all research, there are limitations. Similar analysis should be conducted using data on arterial streets in other regions of the United States, if available in the future, to determine if there is any local effect on the parameter values.

Chapter 6: Comparisons of Mandatory and Discretionary Lane Changing Behavior on Freeways[4]

6.1: Chapter Introduction

In Chapter 5, two NGSIM data sets (namely Datasets P1 and P2) were used to statistically compare DLCs at the same arterial street location at different times of the day. This chapter answers Research Question 2: *Do drivers have different risk-taking behavior between mandatory and discretionary lane changes on freeways?*

The approach to answering this Research Question is to perform statistical comparisons of the lane changing parameters between MLCs and DLCs. This research used NGSIM data collected at two sites: I-80 Freeway at Emeryville (Dataset A) and U.S. Highway 101 in Los Angeles (Dataset B), both in California. This chapter assumed that the drivers used the same decision parameters in DLCs for MLCs.

6.2: Statistical Analyses

6.2.1: Descriptive Statistics

The first step in the analysis of the lane changing risk-taking parameters was to examine the descriptive statistics. For each data set (Dataset A and Dataset B), the descriptive statistics of the four risk-taking parameters, further separated into MLCs and DLCs, are listed in Table 6.1. Since DLCs are executed in a more relaxed driving condition, one would naturally expect that the minimum, maximum, and average values of the risk-taking parameters are greater than those for MLCs; however, as can be observed in Table 6.1(a), this is not always the case. For example, the minimum value of G_{FA} for DLCs is 0.49 m, which is smaller than the G_{FA} for MLCs at 1.40 m. As expected, the sample mean of DLCs is always greater than the sample mean of MLCs, for all of the risk-taking parameters in Table 6.1(a). In Dataset B (Table 6.1(b)), the sample mean of G_{PB} for DLCs, at 19.11 m, is remarkably smaller than the sample mean of 50.74 m for MLCs.

[4] An earlier version of this Chapter was published as Vechione, M., Balal, E., and Cheu, R. (2018). "Comparisons of Mandatory and Discretionary Lane Changing Behavior on Freeways", *International Journal of Transportation Science and Technology*, Vol. 7, No. 2, pp. 124-136.

This is counter-intuitive, and implies that drivers were, on average, more aggressive and accepted much smaller gaps when executing a DLC compared to an MLC.

Note that, in some cases in Table 6.1, the sample standard deviation values for each risk-taking parameter are greater than the sample means. Intuitively, this would yield some negative values for each risk-taking parameter; however, the reason for this is a high positive skew. An example illustration of this is presented later in the distribution fitting results in Figure 6.2.

TABLE 6.1. DESCRIPTIVE STATISTICS OF LANE CHANGING PARAMETERS FOR DATASETS A AND B.

Dataset	**A**							
Parameters	G_{PB}		G_{PA}		G_{FA}		D	
	MLC	**DLC**	**MLC**	**DLC**	**MLC**	**DLC**	**MLC**	**DLC**
Sample Size	166	135	166	135	166	135	166	135
Unit	m		m		m		m	
Min Value	0.61	4.33	0.31	0.07	1.40	0.49	10.25	6.06
Max Value	124.26	76.97	47.75	105.37	80.03	93.07	115.33	162.15
Mean	15.08	15.18	10.32	11.46	15.35	17.58	30.12	33.42
Std. Deviation	13.97	8.63	8.66	13.43	12.10	14.66	16.65	20.85
Skewness	4.07	3.13	1.97	3.44	2.11	1.94	1.91	2.65
Dataset	**B**							
Parameters	G_{PB}		G_{PA}		G_{FA}		D	
	MLC	**DLC**	**MLC**	**DLC**	**MLC**	**DLC**	**MLC**	**DLC**
Sample size	71	128	71	128	71	128	71	128
Unit	m		m		m		m	
Min	5.63	3.79	3.46	0.82	1.93	0.45	11.51	15.24
Max	185.81	74.08	160.89	216.07	92.06	103.51	172.54	234.74
Mean	50.74	19.11	22.44	20.83	22.88	20.95	49.72	46.06
Std. deviation	40.70	12.72	24.01	24.82	18.69	16.10	30.80	27.49
Skewness	1.11	2.06	3.35	4.65	1.59	2.37	1.64	3.34

6.2.2: HYPOTHESIS TESTS OF THE DIFFERENCE BETWEEN TWO MEANS

Having examined the descriptive statistics, the next step in the analysis involved hypothesis testing on the difference between two means. The test has the null hypothesis of $H_0 : \mu_{MLC} = \mu_{DLC}$ and alternate hypothesis of $H_1 : \mu_{MLC} \neq \mu_{DLC}$, where μ_{MLC} is the population mean of a risk-taking parameter for MLCs and μ_{DLC} is the population mean of the same risk-taking parameter for DLCs. The *t*-statistics for unequal sample sizes and unknown variances were computed (Montgomery and Runger, 2011). The default two-tail decision criterion was $t_{\alpha/2, n_{MLC}+n_{DLC}-2}$, with $\alpha/2$=0.025, in which n_{MLC} is the sample size of MLCs and n_{DLC} is the sample size of DLCs. The test was performed eight times, four for the four risk-taking parameters in Dataset A, and another four times for the four risk-taking parameters in Dataset B. The test results are tabulated in Table 6.2.

The results listed in Table 6.2(a) indicate that the population means of the same risk-taking parameter for MLCs and DLCs are not significantly different at $\alpha/2$=0.025. However, in Table 6.2(b), the test result of G_{PB} indicates that, for this risk-taking parameter, the population means of the MLCs and DLCs are significantly different, with *p*=0.000. As discussed in Section 6.2.1, in Dataset B, the sample mean of 50.74 m for MLCs is much larger than the sample mean of 19.11 m for DLCs. It turned out that, as found in the survey in Chapter 7, drivers ranked G_{PB} as the least frequently used among the four parameters when making MLC decisions. This will be discussed in more detailed in Chapter 7. For the other three risk-taking parameters (G_{PA}, G_{FA}, and D), the test results do not find significant difference between the means of MLCs and DLCs.

TABLE 6.2. HYPOTHESIS TESTS FOR RESEARCH QUESTION 2.

Dataset	**A**							
Parameters	G_{PB}		G_{PA}		G_{FA}		D	
	MLC	**DLC**	**MLC**	**DLC**	**MLC**	**DLC**	**MLC**	**DLC**
Sample Size	166	135	166	135	166	135	166	135
Unit	m		m		m		m	
Mean	15.08	15.18	10.32	11.46	15.35	17.58	30.12	33.42
Std. Deviation	13.97	8.63	8.66	13.43	12.10	14.66	16.65	20.85
t-statistic	-0.07		-0.85		-1.42		-1.49	
p-value	0.944		0.398		0.157		0.137	
Conclusion ($\alpha/2$=0.025)	Fail to reject H_0		Fail to reject H_0		Fail to reject H_0		Fail to reject H_0	
Dataset	**B**							
Parameters	G_{PB}		G_{PA}		G_{FA}		D	
	MLC	**DLC**	**MLC**	**DLC**	**MLC**	**DLC**	**MLC**	**DLC**
Sample size	71	128	71	128	71	128	71	128
Unit	m		m		m		m	
Mean	50.74	19.11	22.44	20.83	22.88	20.95	49.72	46.06
Std. deviation	40.70	12.72	24.01	24.82	18.69	16.10	30.80	27.49
t-statistic	6.38		0.45		0.73		0.83	
p-value	0.000		0.654		0.466		0.406	
Conclusion ($\alpha/2$=0.025)	**Reject H_0**		Fail to reject H_0		Fail to reject H_0		Fail to reject H_0	

6.2.3 Hypothesis Tests of the Difference Between Observed Cumulative Distributions

For the same risk-taking parameters in the same data set, the probability distributions of MLC and DLC data were then tested on their difference. For this approach, the χ^2 goodness-of-fit test and the Kolmogorov-Smirnov (K-S) test were considered. Similar to Chapter 5, the K-S test was used. Table 6.3 presents the outcomes of the K-S tests, with α=0.10 and 0.05, respectively. For G_{PA}, G_{FA} and D, the null hypothesis of

H_0: *the observed distributions of the risk-taking parameter for MLCs and DLCs are drawn from the same population*

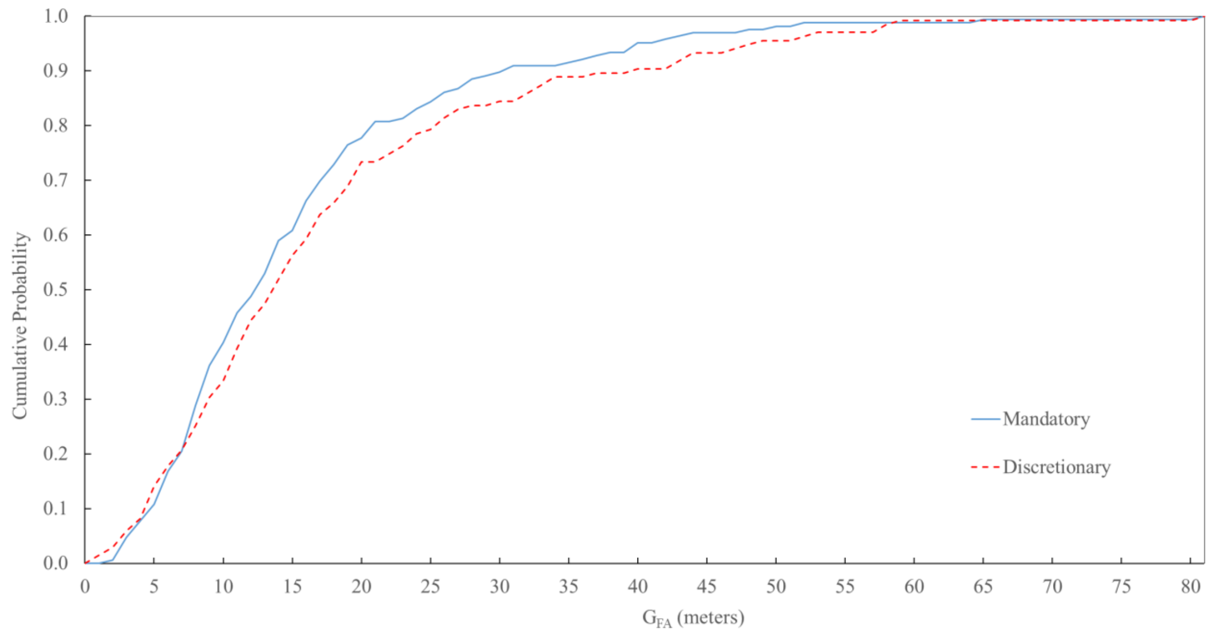
was not rejected at α=0.10 and 0.05. The conclusion for G_{PB} was different. For this risk-taking parameter, H_0 was rejected at both α=0.10 and 0.05, which implied that, statistically, G_{PB} for MLCs and DLCs were from different populations with different distributions. This suggests that drivers who make MLCs may not use G_{PB} as a risk-taking parameter. Again, this finding coincides with the survey results in Chapter 7.

TABLE 6.3. KOLMOGOROV-SMIRNOV TESTS FOR RESEARCH QUESTION 2.

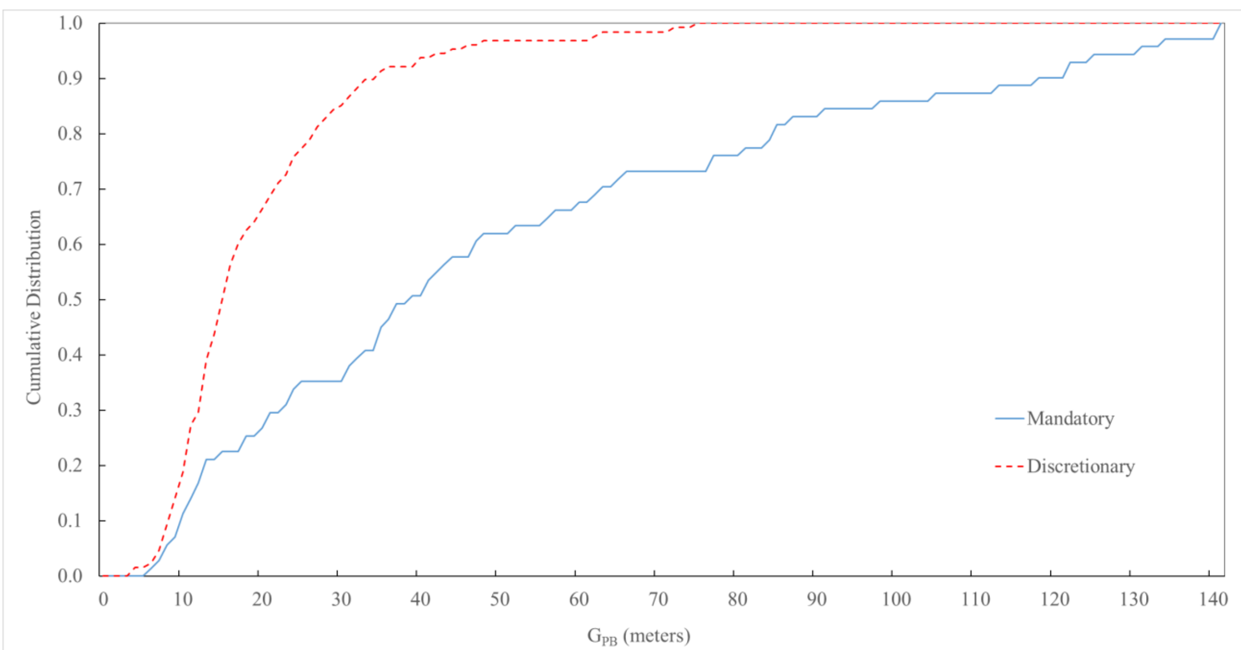
Dataset A				
Parameters	G_{PB}	G_{PA}	G_{FA}	D
d	0.164	0.126	0.076	0.085
Conclusion (α=0.10)[#]	**Reject H_0**	Fail to reject H_0	Fail to reject H_0	Fail to reject H_0
Conclusion (α=0.05)[&]	**Reject H_0**	Fail to reject H_0	Fail to reject H_0	Fail to reject H_0
Dataset B				
Parameters	G_{PB}	G_{PA}	G_{FA}	D
d	0.499	0.101	0.108	0.146
Conclusion (α=0.10)[%]	**Reject H_0**	Fail to reject H_0	Fail to reject H_0	Fail to reject H_0
Conclusion (α=0.05)[@]	**Reject H_0**	Fail to reject H_0	Fail to reject H_0	Fail to reject H_0

[#] Critical value = 0.142
[&] Critical value = 0.157
[%] Critical value = 0.181
[@] Critical value = 0.201

The K-S tests are best visualized by plotting the cumulative probability distributions of MLCs and DLCs on the same graph. Figure 6.1 presents the best and worst cases for the K-S tests. Figure 6.1(a) shows the cumulative probability distributions of MLCs and DLCs for G_{FA} in Dataset A, which gave d=0.076. Figure 6.1(b) shows the cumulative probability distributions of MLCs and DLCs for G_{PB} in Dataset B, which gave d=0.499. Figure 6.1(b) is evidence that the observed distributions of G_{PB} are significantly different between MLCs and DLCs. Therefore, it was not surprising that H_0 was rejected at both α=0.10 and 0.05.



(c) G_{FA} in Dataset A



(d) G_{PB} in Dataset B

FIGURE 6.1. EXAMPLES OF KOLMOGOROV-SMIRNOV TESTS FOR OBSERVED CUMULATIVE DISTRIBUTIONS FOR RESEARCH QUESTION 2.

6.2.4: Probability Distribution Fittings

The observed data was then fitted with probability distributions. The following probability distributions, all with a positive skew, are among those that were fitted: beta, exponential, gamma, inverse Gaussian, log-logistic, log-normal, Pearson 5, and Weibull. The distribution fitting was performed using @RISK (Palisade, 2013), with Akaike Information Criterion (AIC) as the criterion for the goodness-of-fit. Note again, new probability distributions were fitted to the DLC data because the DLC data that was processed for this research had different sample from Balal et al. (2014).

The best three fitted distributions are listed in Table 6.4 (for MLCs) and Table 6.5 (for DLCs). The inverse Gaussian, log-normal, and Pearson 5 distributions most frequently appeared as the best-fitted distributions. The log-normal distribution was recommended for all of the risk-taking parameters, as it is the most commonly known distribution among the three.

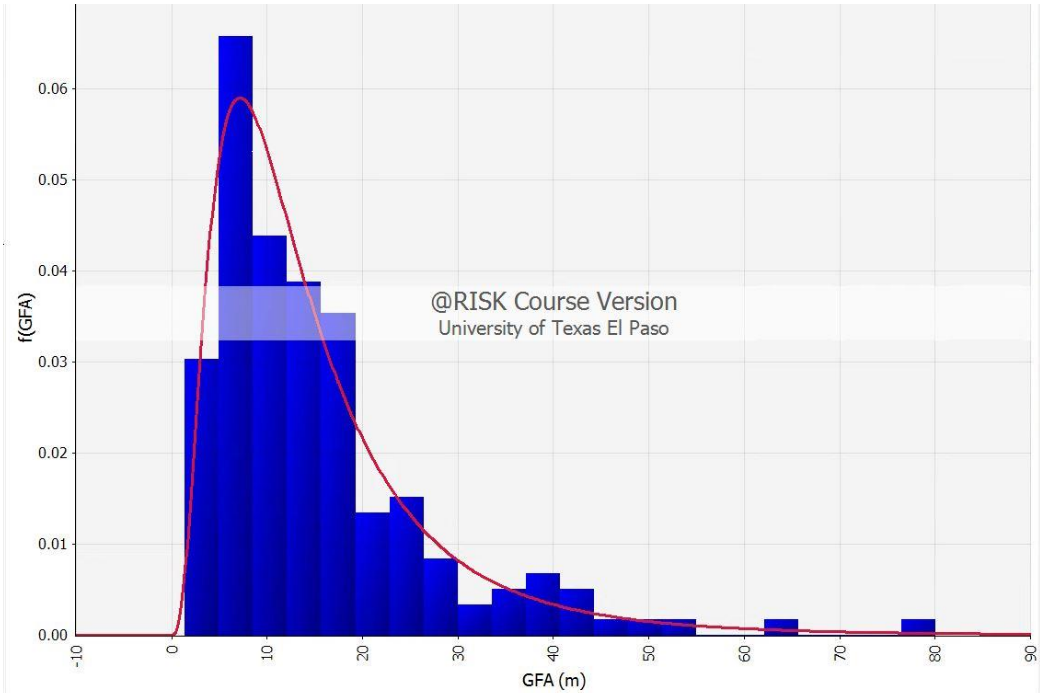
The fitted log-normal location and scale parameters are shown in Table 6.4 and Table 6.5. An example of the log-normal distribution fitted for G_{FA} in Dataset A (MLC) is illustrated in Figure 6.2(a). Another example of the log-normal distribution fitted for G_{PA} in Dataset B (DLC) is illustrated in Figure 6.2(b). Both Figure 6.2(a) and 6.2(b) illustrate the goodness-of-fit of the log-normal distribution. Note again, these are two different risk-taking parameters in two different lanes (i.e. original and target lane), at two different sites (Datasets A and B), and for two different lane changing types (MLC and DLC).

TABLE 6.4. PROBABILITY DISTRIBUTIONS FITTINGS FOR MANDATORY LANE CHANGES FOR RESEARCH QUESTION 2.

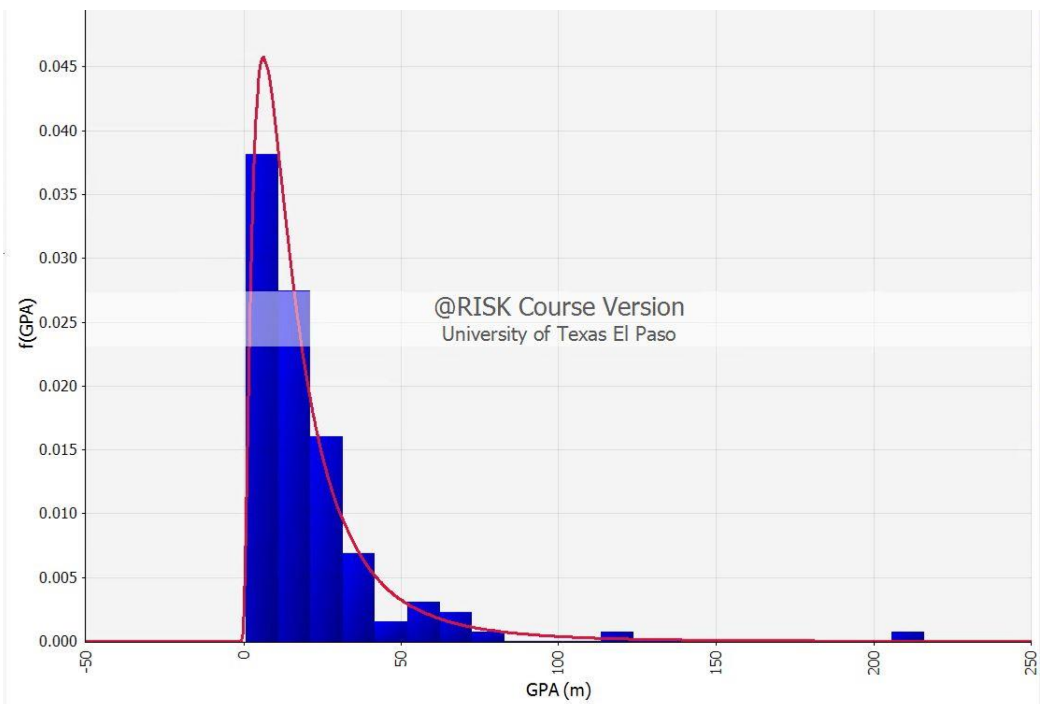
Dataset A				
Parameters	G_{PB}	G_{PA}	G_{FA}	D
Unit	m	m	m	m
Best Fit	Log-logistic	Pearson 5	**Log-normal**	Gamma
2nd Best Fit	Pearson 5	**Log-normal**	Inverse Gaussian	Inverse Gaussian
3rd Best Fit	**Log-normal**	Inverse Gaussian	Pearson 5	**Log-normal**
Recommended	Log-normal			
Log-normal Location Parameter, λ	2.404	2.068	2.489	3.272
Log-normal Scale Parameter, ξ	0.787	0.730	0.695	0.516
Dataset B				
Parameters	G_{PB}	G_{PA}	G_{FA}	D
Unit	m	m	m	m
Best Fit	Exponential	Inverse Gaussian	Inverse Gaussian	Inverse Gaussian
2nd Best Fit	Inverse Gaussian	**Log-normal**	**Log-normal**	Gamma
3rd Best Fit	**Log-normal**	Pearson 5	Pearson 5	**Log-normal**
Recommended	Log-normal			
Log-normal Location Parameter, λ	3.678	2.729	2.874	3.744
Log-normal Scale Parameter, ξ	0.705	0.873	0.715	0.570

TABLE 6.5. PROBABILITY DISTRIBUTION FITTINGS FOR DISCRETIONARY LANE CHANGES FOR RESEARCH QUESTION 2.

Dataset A				
Parameters	***G_{PB}***	***G_{PA}***	***G_{FA}***	***D***
Unit	m	m	m	m
Best Fit	Pearson 5	Exponential	Inverse Gaussian	Log-logistic
2nd Best Fit	Log-logistic	**Log-normal**	**Log-normal**	Pearson 5
3rd Best Fit	**Log-normal**	Inverse Gaussian	Pearson 5	**Log-normal**
Recommended	Log-normal			
Log-normal Location Parameter, λ	2.580	2.006	2.603	3.345
Log-normal Scale Parameter, ξ	0.529	0.930	0.726	0.573
Dataset B				
Parameters	***G_{PB}***	***G_{PA}***	***G_{FA}***	***D***
Unit	m	m	m	m
Best Fit	Pearson 5	**Log-normal**	Log-logistic	Log-logistic
2nd Best Fit	**Log-normal**	Log-logistic	Pearson 5	Pearson 5
3rd Best Fit	Log-logistic	Pearson 5	**Log-normal**	**Log-normal**
Recommended	Log-normal			
Log-normal Location Parameter, λ	2.767	2.594	2.810	3.678
Log-normal Scale Parameter, ξ	0.606	0.940	0.681	0.552



(a) G_{FA} from Dataset A (MLC)



(b) G_{PA} from Dataset B (DLC)

FIGURE 6.2. EXAMPLES OF FITTED LOG-NORMAL DISTRIBUTIONS FOR RESEARCH QUESTION 2.

6.2.5: Hypothesis Tests of the Difference Between Fitted Cumulative Distributions

The last set of statistical tests applied was the K-S test to test the difference between the log-normal probability distributions fitted to the MLC and DLC data, respectively. For each test, the d value obtained for each pair of log-normal cumulative probabilities is listed in Table 6.6. For this test, the scale and shape parameters used for the log-normal distributions were as shown in Tables 6.4 and 6.5. $|P(x) - P(y)|$ was evaluated n times, from 0 m to max$\{x, y\}$ at 1.0 m intervals. The max$\{x, y\}$ was taken from the observed ranges of MLC and DLC values found in Table 6.1. The critical value was taken from the standard K-S test table.

The outcomes of the tests are similar to the previous set of K-S tests performed for the observed distributions, except for G_{PB}. For G_{PB} in Dataset A, the null hypothesis of

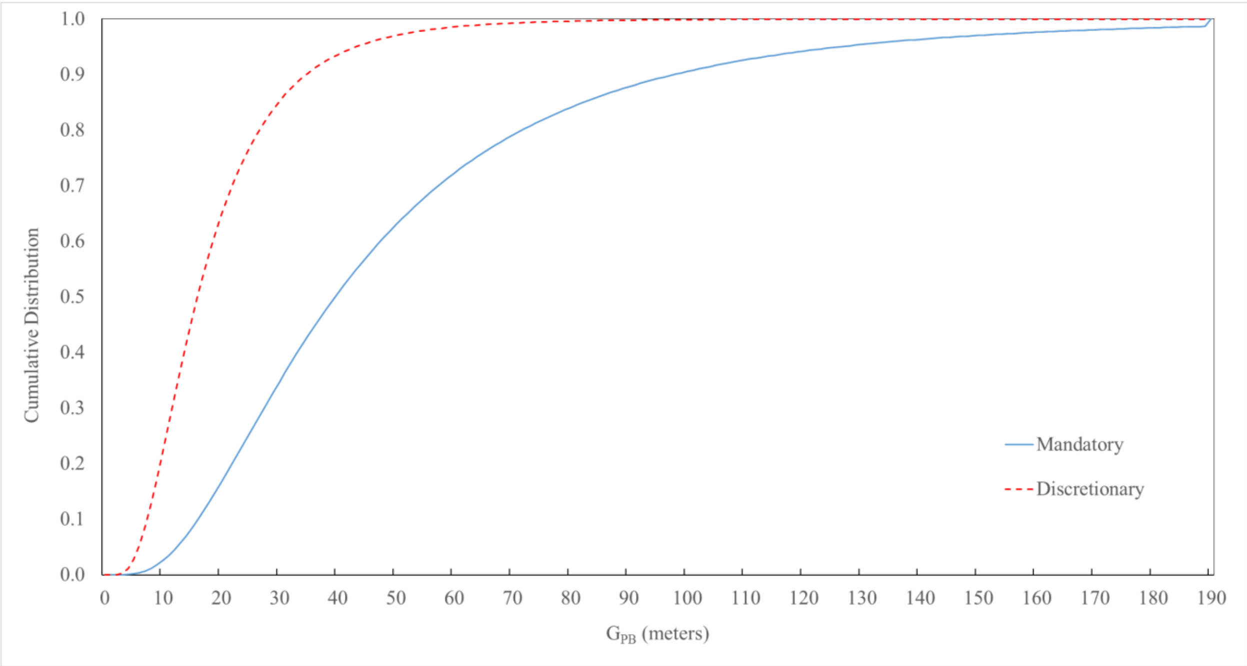
H_0: *the distributions of the risk-taking parameter for MLCs and DLCs are fitted to the same population*

was rejected at α=0.10, but not at α=0.05. That is, the p-value lies somewhere between 0.05 and 0.10. The outcome of this K-S test for G_{PB} in Dataset A may be considered as marginal. For G_{PB} in Dataset B, the K-S test rejected the H_0 at both α=0.10 and 0.05. Thus, it may be concluded that the fitted log-normal distributions for G_{PB} between MLCs and DLCs are statistically different. However, for G_{PA}, G_{FA}, and D, the differences are not statistically significant.

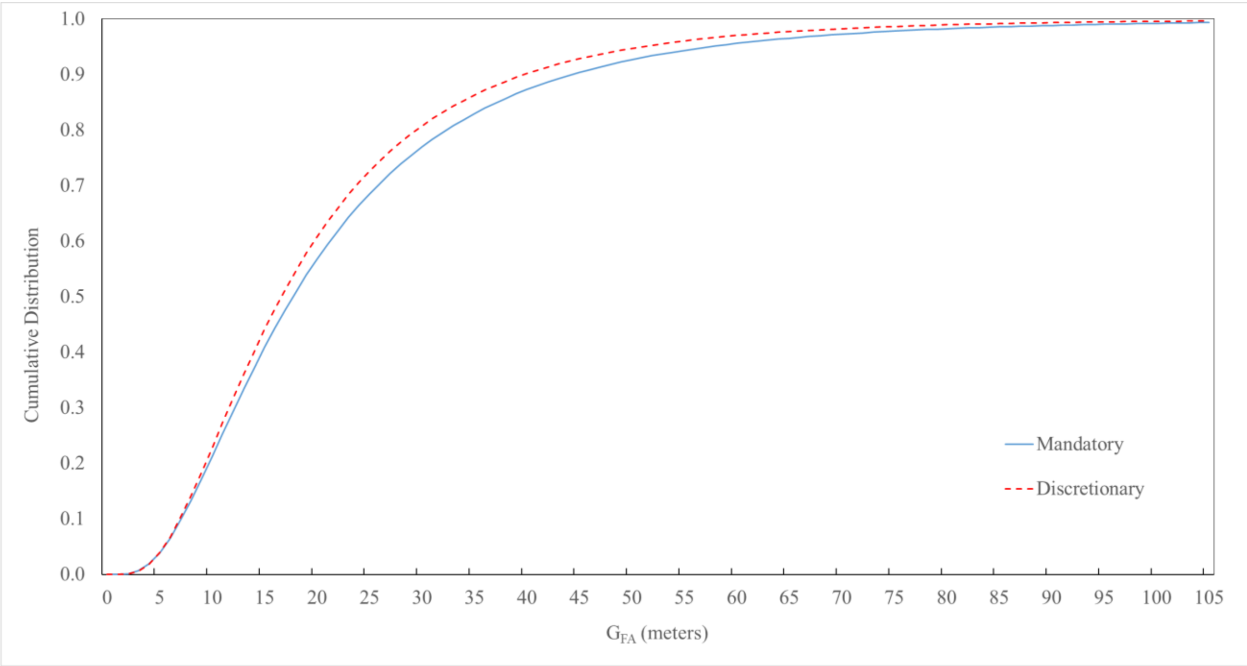
Figure 6.3(a) plots the log-normal cumulative distributions of G_{PB} in Dataset B for readers to visualize the difference. Figure 6.3(b) plots the log-normal cumulative distributions of G_{FA} in Dataset B to illustrate how close these two distributions are in order for the K-S test to not reject H_0.

TABLE 6.6. KOLMOGOROV-SMIRNOV TESTS FOR FITTED CUMULATIVE DISTRIBUTIONS FOR RESEARCH QUESTION 2.

Dataset A					
Parameters		G_{PB}	G_{PA}	G_{FA}	D
d		0.168	0.077	0.066	0.066
α=0.10	**Critical Value**	0.155	0.165	0.178	0.135
	Conclusion	**Reject H_0**	Fail to reject H_0	Fail to reject H_0	Fail to reject H_0
α=0.05	**Critical Value**	0.172	0.183	0.197	0.150
	Conclusion	Fail to reject H_0	Fail to reject H_0	Fail to reject H_0	Fail to reject H_0
Dataset B					
Parameters		G_{PB}	G_{PA}	G_{FA}	D
d		0.515	0.066	0.041	0.049
α=0.10	**Critical Value**	0.126	0.117	0.169	0.113
	Conclusion	**Reject H_0**	Fail to reject H_0	Fail to reject H_0	Fail to reject H_0
α=0.05	**Critical Value**	0.139	0.129	0.187	0.125
	Conclusion	**Reject H_0**	Fail to reject H_0	Fail to reject H_0	Fail to reject H_0



(c) G_{PB} in Dataset B



(d) G_{FA} in Dataset B

FIGURE 6.3. EXAMPLES OF KOLMOGOROV-SMIRNOV TESTS FOR FITTED CUMULATIVE PROBABILITY DISTRIBUTIONS FOR RESEARCH QUESTION 2.

6.2.6: Summary of Test Results

Based on the statistical tests conducted, there appears to be no significant difference in the three risk-taking parameters in the target lane, i.e., G_{PA}, G_{FA}, and D, between MLCs and DLCs. However, for G_{PB}, there are significance differences:

- The difference in the population means between MLCs and DLCs in Dataset B (U.S. Highway 101 in Los Angeles, CA) are significantly different at $\alpha/2$=0.025.
- The observed probability distributions of MLCs and DLCs in Dataset A (I-80 Freeway in Emeryville, CA) are significantly different at α=0.05.
- The observed probability distributions of MLCs and DLCs in Dataset B are significantly different at α=0.05.
- The fitted log-normal distributions of MLCs and DLCs in Dataset A are significantly different at α=0.05.
- The fitted log-normal distributions of MLCs and DLCs in Dataset B are significantly different at α=0.05.

This implies that the distribution of G_{PB} for drivers making MLCs and DLCs were drawn from different populations. From the fitted distributions (in Section 6.2.4), it appeared that the probability distributions of G_{PB} during MLCs and DLCs followed the log-normal distribution, but with different parameter values (see Table 6.4 and 6.5).

6.3 Discussions

6.3.1: Major Findings and Recommendations

This Research Question has performed statistical tests that made pairwise comparisons between MLCs and DLCs for four risk-taking parameters (G_{PB}, G_{PA}, G_{FA}, and D). The data used was from I-80 Freeway (Dataset A) and U.S. Highway 101 (Dataset B), which are parts of the NGSIM database. The major findings are:

- The tests of the difference between two means have shown no significant difference between the mean of MLCs and DLCs, in all the tests except for G_{PB} in Dataset B;
- All the K-S tests conducted showed no significant difference between the observed distributions of MLCs and DLCs for all of the risk-taking parameters except for G_{PB} in Datasets A and B;
- The risk-taking parameters may be described by log-normal distributions; and
- Another set of K-S tests revealed no significant difference between the fitted log-normal distributions of the risk-taking parameters between MLCs and DLCs, except for G_{PB} in Datasets A and B.

Based on the results, it may be inferred that that G_{PA}, G_{FA}, and D may be the common risk-taking parameters used by drivers when making MLC and DLC decisions, and the risk-taking behavior (as described by the means and probability distributions of these three parameters, which were presented in Sections 6.2.2-6.2.5) is not significantly different.

The results of statistical tests conducted for G_{PB} showed significant differences between the means and distributions of this risk-taking parameters used by drivers in MLCs and DLCs. The survey by Balal et al. (2016) has found that G_{PB} was one of the most frequently used parameters in DLCs. This survey finding is logical because one of the main reasons that motivates subject vehicles to make DLCs is to gain speed, greater following distance or sight distance of the road ahead. These are usually caused by a slow moving *PB*. However, in MLCs, the motivations are to move into the correct lane to enter or exit the highways. Therefore, in MLCs, G_{PB} may not be a main consideration for some drivers. In light of the above possible reason, a new driver survey should be conducted to determine the most frequently used risk-taking parameters for MLCs.

This study appears to confirm the suggestions made in previous studies (Pan et al., 2016; Zheng, 2014) that MLCs and DLCs should be modeled separately. In the future, MLCs and DLCs could be modeled separately based on the findings of this study. A higher-level decision

model may be created which first distinguishes between MLCs and DLCs (based on the drivers route choices in the vehicle navigation systems), and then, based on the type of lane change, activates a lower level decision model (such as the binary decision model to change lanes or not and the respective risk-taking parameters described in Balal et al. (2016)).

6.3.2: LIMITATIONS

The answer to this Research Question consisted of statistical analyses of MLC and DLC behavior, using real data from the NGSIM database (Datasets A and B). As in all research, there are some limitations. The conclusions are arrived with the following major limitations:

- The subject vehicles are passenger cars;
- The lane changes took place in moderate to congested traffic flow; and
- Both data collection sites, although in cities more than 300 miles (500 km) apart, are located in California.

6.4: Chapter Summary

This research is perhaps the first attempt that uses NGSIM data to compare drivers' behavior between MLCs and DLCs. Should researchers and modelers develop separate models for MLCs and DLCs for freeway driving? These statistical test results indicate yes. These test results further suggest that both models may use three common risk-taking parameters of G_{PA}, G_{FA}, and D. The differences between the MLC and DLC models lie on the additional risk-taking parameters used and the decision logics. The concept of developing separate models for MLCs and DLCs will enable connected and automated vehicles to move more like manually driven vehicles. The distinct MLC and DLC models also enable microscopic traffic simulation tools to model vehicle movements closer to driving conditions in the field. Both will lead to, macroscopically, more precise replication of the existing highway capacity, and microscopically, improved representation of a driver's risk-taking behavior when making a lane change.

Chapter 7: Survey on Mandatory Lane Changing Parameters

7.1: Purpose

A survey was conducted to determine the most important risk-taking parameters that drivers consider when executing an MLC, so that the input parameters for the model may be better understood. The minimum age for licensed drivers in Texas is 16. It was determined that students, faculty, and staff from The University of Texas at El Paso (UTEP) are all experienced drivers with at least two to three years of driving experience, and as such, would be acceptable survey subjects.

7.2: Survey Instrument

A survey instrument was created, which incorporated questions about the ten possible risk-taking parameters when executing an MLC maneuver (i.e. gaps, times-to-collision, and speed), which were also used by Balal et al. (2014, 2016). Once the survey was developed, it was submitted to UTEP's Institutional Review Board (IRB) for approval. The final versions of the consent forms and survey instruments are in the Appendix. The final version of the survey instrument consisted of 15 questions organized into two parts:

Part 1: Ten questions on safety checks (i.e. the ten possible risk-taking parameters) when making an MLC decision

Part 2: Five questions on participants' demographics and driving experience

For each question in Part 1 (i.e. each possible risk-taking parameter), the respondent was asked to select if the risk-taking parameter was used all the time, most of the time, sometimes, seldom, or never when making his/her MLC decision. The language used in the survey was presented in non-technical language (i.e. layman's terms).

7.3: Survey Implementation

After coordinating with various faculty members within the university to survey students in their classes, it was determined that surveying may be conducted between March and May

2018. No tangible incentives were to be given to the survey respondents; however, extra credit was offered to some students at the discretion of the professors.

Hard copies of the consent form and survey instrument were brought to each classroom at a time agreed upon by the appropriate professor. General background of MLCs was presented, and the hard copies of the consent form and survey instrument were distributed. At the end of each survey day, the responses were manually entered to Qualtrics for post-survey analysis.

7.4: Survey Results

A total of 286 responses were collected. The answers to the questions in Part 1 are tabulated in Table 7.1.

TABLE 7.1. RESULTS OF DRIVERS' SURVEY

Risk-taking Parameters (*n* = 286)	**Reported Frequency of Use (% Distribution)**						
	All of the time	**Most of the time**	**Sometimes**	**Seldom**	**Never**	**Total**	**All or most of the time**
	(a)	**(b)**	**(c)**	**(d)**	**(e)**	**(a) + (b) + (c) + (d) + (e)**	**(a) + (b)**
G_{PA}	55%	29%	11%	3%	2%	100%	**84%**
G_{FA}	69%	25%	6%	0%	0%	100%	**94%**
G_{PB}	42%	33%	19%	6%	0%	100%	**75%**
G_{FB}	26%	26%	23%	17%	8%	100%	52%
D	63%	25%	8%	3%	1%	100%	**88%**
V	36%	29%	20%	9%	6%	100%	65%
T_{PB}	18%	29%	27%	14%	13%	100%	47%
T_{FB}	17%	22%	25%	18%	18%	100%	39%
T_{PA}	25%	36%	18%	10%	11%	100%	61%
T_{FA}	27%	28%	24%	11%	11%	100%	55%

After collecting 100 responses, the results of the survey were recorded. Then, for each 50 surveys collected thereafter, the changes in percentages from Table 7.1 were recorded. After every subsequent 50 surveys conducted after the first 100, the result percentages in Table 7.1 did not change significantly. Table 7.2 presents the maximum percent change for each risk-taking parameter for every 50 subsequent surveys collected. The results from Table 7.2 show that, for most of the risk-taking parameters, the maximum percent change decreases after every 50 subsequent surveys conducted. It was determined that a sample size of 286 was enough.

TABLE 7.2. MAXIMUM PERCENT CHANGE FOR EACH RISK-TAKING PARAMETER.

	150 – 100 Responses	**200 – 150 Responses**	**250 – 200 Responses**	**286-250 Responses**
G_{PA}	2.8%	3.2%	1.6%	0.6%
G_{FA}	5.7%	2.3%	1.2%	1.4%
G_{PB}	2.6%	2.7%	0.7%	0.5%
G_{FB}	2.4%	3.7%	1.0%	2.4%
D	2.2%	0.9%	1.5%	1.6%
V	1.6%	1.1%	2.0%	1.1%
T_{PB}	3.3%	2.8%	1.9%	1.9%
T_{FB}	1.7%	2.8%	2.1%	1.2%
T_{PA}	2.3%	2.1%	2.6%	1.5%
T_{FA}	3.3%	4.4%	2.3%	1.9%

Table 7.1 depicts the percentage distribution for each possible risk-taking parameter when executing an MLC. The rightmost column lists the percentage of respondents who answered that they considered that particular input parameter all of the time or most of the time. Out of the ten parameters, G_{FA} is used all or most of the time by 94% of respondents, followed by D at 88%, G_{PA} at 84%, and G_{PB} at 75%.

The MLC survey results in Table 7.1 were very similar to the DLC survey conducted by Balal et al. (2016). The top four input parameters, that were used all or most of the time when executing a lane change, were the same. A comparison of the top four input parameters, based on their percentages is tabulated in Table 7.3.

TABLE 7.3. COMPARISON OF THE TOP FOUR RISK-TAKING PARAMETERS FOR DLCS AND MLCS.

DLC Survey (Balal et al., 2016)		**MLC Survey (from Table 7.1)**	
Top Four Risk-Taking Parameters	**Used All or Most of the Time**	**Top Four Risk-Taking Parameters**	**Used All or Most of the Time**
G_{FA}	94%	G_{FA}	94%
D	90%	D	88%
G_{PA}	88%	G_{PA}	84%
G_{PB}	81%	G_{PB}	75%

The results from Table 7.3 indicate that the top four risk-taking parameters for MLCs (from Table 7.1) were the same as those from Balal et al. (2016). The percentages for each risk-taking parameter, used all or most of the time, were very similar for all four risk-taking parameters.

The differences in the percentages between DLCs and MLCs for the most frequently used parameter, G_{FA}, is 0%. Likewise, the differences in the percentages for D and G_{PA} are 2% and 4%, respectively. The parameter with the greatest differences in percentages is G_{PB} at 6%. This may explain why there were differences found for G_{PB} in the statistical tests performed in Chapter 6. The reason that there is a lower percentage of survey respondents who reported G_{PB} as an important parameter, when compared with DLCs, is likely caused by the motivating factors.

When executing a DLC, drivers are typically trying to gain speed, and the preceding vehicle is a key factor (i.e. G_{PB} is important); however, the motivating factors are different when executing an MLC, and this is likely why there is a lower percentage of survey respondents who reported G_{PB} as an important parameter when making MLCs.

7.5: Fault Tolerance Analysis of G_{PB}

Because of the apparent lack of use of G_{PB} in MLC decisions, it will be interesting to test if there are changes in the drivers' decisions if drivers do not use G_{PB} as one of the inputs. A previous fault tolerance analysis for lane changing has been conducted as part of a separate paper (Balal et al., 2019)[5]. The test results have shown that the models perform the best with no faulty or missing data. The performance measures worsened when there were more input vectors that had faulty or missing data.

The work of Balal et al. (2019) considered random faulty or missing data for any of the input vectors and for any of the input parameters. The fault tolerance test for this dissertation will be to remove the G_{PB} input from all the vectors. Then, with the missing G_{PB} data, evaluate the performance of each model with respect to each model's performance without the missing G_{PB} data.

7.6: Survey Summary

Since the top four input parameters when making an MLC are the same as those for a DLC, a universal lane changing model may be developed, which includes the same four input parameters (i.e. G_{PB}, G_{PA}, G_{FA}, and D). On the other hand, if a minimum threshold of 80% is used for the most important risk-taking parameters, then G_{PB} may not be used in an MLC lane changing model. This is consistent with the results in Chapter 6.

[5] This manuscript was submitted to an ASCE Journal as Balal, E., Vechione, M., and Cheu, R. (2019). "Fault Tolerance Evaluation of a Fuzzy Inference System-Based Lane Changing Model".

Chapter 8: Comparisons of Mandatory Lane Changing Behavior at Different Freeway Sites

8.1: Chapter Introduction

This chapter answers Research Question 3: *Do drivers have different risk-taking behavior when executing a mandatory lane changing maneuver at different freeway sites?* Similar to the objectives and methodology in Chapter 5, this Chapter aims to compare the same risk-taking parameters (i.e. G_{PB}, G_{PA}, G_{FA}, and D) but for MLCs on two different freeway segments.

8.2: Statistical Analyses

8.2.1: Descriptive Statistics

Table 8.1 lists the descriptive statistics of the four parameters analyzed for both Dataset A and Dataset B. For the same parameter, the minimum, maximum, mean, and standard deviation values for Dataset A are smaller than the corresponding values in Dataset B.

Note that, in some cases in Table 8.1, the sample standard deviation values for each risk-taking parameter are greater than the sample means. Intuitively, this would yield some negative values for each risk-taking parameter; however, the reason for this is a high positive skew. An example illustration of this is presented later in the distribution fitting results in Figure 8.2.

TABLE 8.1. DESCRIPTIVE STATISTICS OF MANDATORY LANE CHANGING PARAMETERS FOR DATASETS A AND B.

Dataset	**A**			
Parameters	G_{PB}	G_{PA}	G_{FA}	D
Unit	ft. (m)	ft. (m)	ft. (m)	ft. (m)
Sample Size	166	166	166	166
Min Value	2.02 (0.62)	1.01 (0.31)	4.60 (1.40)	33.65 (10.26)
Max Value	407.67 (124.26)	156.65 (47.75)	262.56 (80.03)	378.37 (115.33)
Mean	49.48 (15.08)	33.87 (10.32)	50.35 (15.35)	98.82 (30.12)
Std. Deviation	45.84 (13.97)	28.40 (8.66)	39.71 (12.11)	54.62 (16.65)
Skewness	4.07	1.97	2.11	1.91
Dataset	**B**			
Parameters	G_{PB}	G_{PA}	G_{FA}	D
Unit	ft. (m)	ft. (m)	ft. (m)	ft. (m)
Sample Size	71	71	71	71
Min Value	18.49 (5.63)	11.36 (3.46)	6.34 (1.93)	37.77 (11.51)
Max Value	609.60 (185.81)	527.86 (160.89)	302.04 (92.06)	566.08 (172.54)
Mean	166.46 (50.74)	73.62 (22.44)	75.05 (22.88)	163.14 (49.72)
Std. Deviation	133.53 (40.70)	78.77 (24.01)	61.31 (18.69)	101.04 (30.80)
Skewness	1.11	3.35	1.59	1.64

8.2.2: Hypothesis Tests of the Difference Between Two Means

Hypothesis tests were then conducted to determine if the average value for each parameter was statistically similar between the two datasets (i.e. based on location and time-of-day). For each hypothesis test, the null hypothesis was that the population averages (μ_A and μ_B) for each parameter were the same; and the alternate hypothesis was that the population averages for each parameter differ. The test statistic followed the t-distribution with small sample sizes; and it was assumed that the variances were unknown and not equal (Montgomery and Runger, 2011). Each hypothesis test was two-sided with an alpha value of 0.05 (i.e. $\alpha/2 = 0.025$). Table 8.2 presents the results of hypothesis tests.

Based on the results presented in Table 8.2, there is statistical evidence to suggest that the population averages for each parameter at different locations and times of the day differ at $\alpha/2$=0.025. This implies that drivers have different rules and/or risk-taking behaviors based on location and time-of-day (which could have different traffic congestion levels).

TABLE 8.2. HYPOTHESIS TESTS FOR RESEARCH QUESTION 3.

Dataset	A	B
G_{PB}	$H_0: \mu_A = \mu_B$	
Sample Mean, $\bar{X}$ (ft., m)	49.48 (15.08)	166.46 (50.74)
Sample Std. Dev., *s* (ft., m)	45.84 (13.97)	133.53 (40.7)
No. of Observations, *n*	166	71
t-Value	-7.20	
Conclusion	**Reject H_0**	
G_{PA}	$H_0: \mu_A = \mu_B$	
Sample Mean, $\bar{X}$ (ft., m)	33.87 (10.32)	73.62 (22.44)
Sample Std. Dev., *s* (ft., m)	28.40 (8.66)	78.77 (24.01)
No. of Observations, *n*	166	71
t-Value	-4.14	
Conclusion	**Reject H_0**	
G_{FA}	$H_0: \mu_A = \mu_B$	
Sample Mean, $\bar{X}$ (ft., m)	50.35 (15.35)	75.05 (22.88)
Sample Std. Dev., *s* (ft., m)	39.71 (12.11)	61.31 (18.69)
No. of Observations, *n*	166	71
t-Value	-3.13	
Conclusion	**Reject H_0**	
D	$H_0: \mu_A = \mu_B$	
Sample Mean, $\bar{X}$ (ft., m)	98.82 (30.12)	163.14 (49.72)
Sample Std. Dev., *s* (ft., m)	54.62 (16.65)	101.04 (30.80)
No. of Observations, *n*	166	71
t-Value	-5.06	
Conclusion	**Reject H_0**	

8.2.3 Hypothesis Tests of the Difference Between Observed Cumulative Distributions

For the same risk-taking parameters, the probability distributions were then tested on their difference. For this approach, the χ^2 goodness-of-fit test and the Kolmogorov-Smirnov (K-S) test were considered. Similar to Chapters 5 and 6, the K-S test was used. Table 8.3 presents the outcomes of the K-S tests, with α=0.10 and 0.05, respectively. For all four of the risk-taking parameters, the null hypothesis of

H_0: *the observed distributions of the MLC risk-taking parameter at different sites are drawn from the same population*

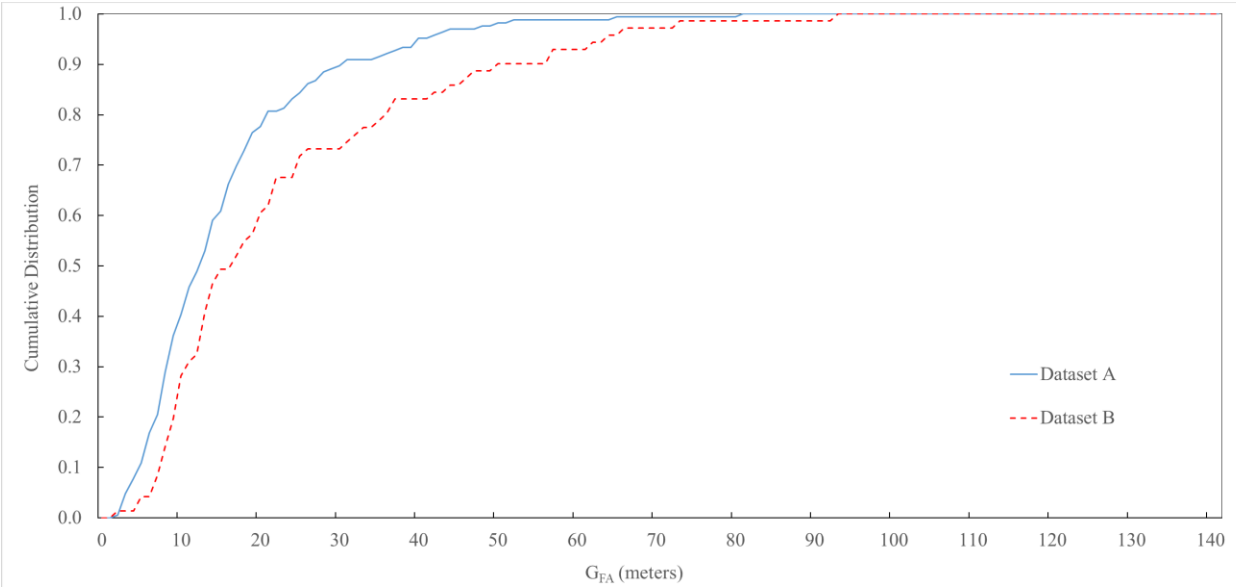
was rejected at α=0.10 and 0.05. This further implies that, in fact, drivers do behave differently based on the location when executing an MLC maneuver on a freeway.

TABLE 8.3. KOLMOGOROV-SMIRNOV TESTS FOR RESEARCH QUESTION 3.

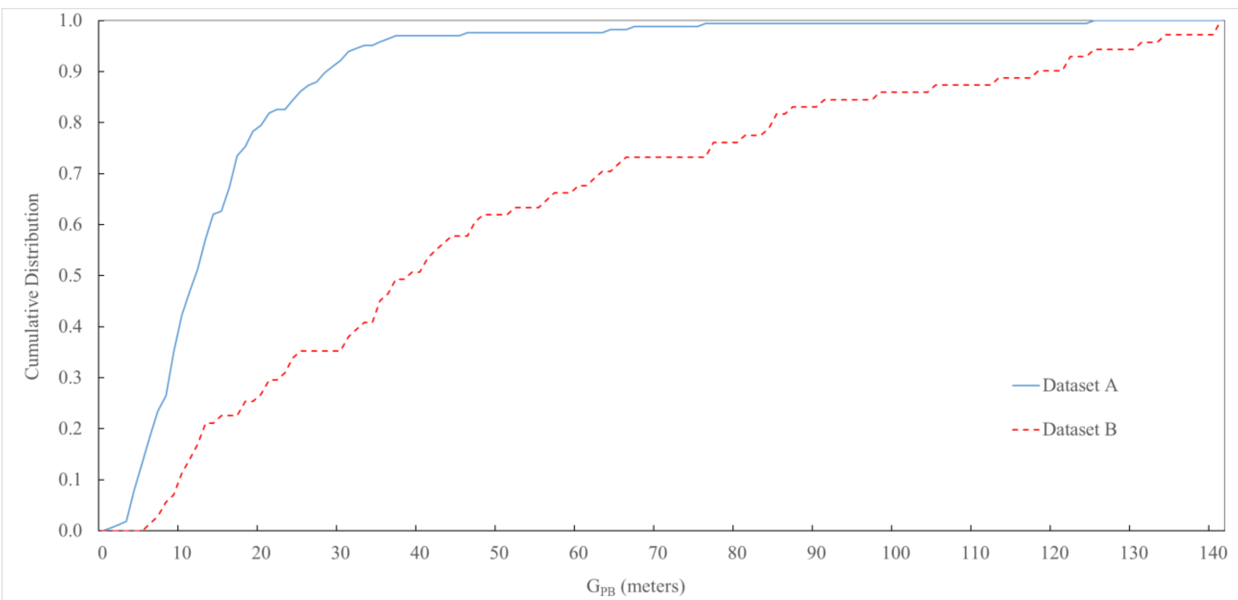
Dataset A vs. Dataset B				
Parameters	G_{PB}	G_{PA}	G_{FA}	D
d	0.570	0.375	0.202	0.387
Conclusion (α=0.10)#	**Reject H_0**	**Reject H_0**	**Reject H_0**	**Reject H_0**
Conclusion (α=0.05)&	**Reject H_0**	**Reject H_0**	**Reject H_0**	**Reject H_0**

\# Critical value = 0.174
& Critical value = 0.193

The K-S tests are best visualized by plotting the cumulative probability distributions for the different freeway sites on the same graph. Figure 8.1 presents the best and worst cases for the K-S tests. Figure 8.1 (a) shows the cumulative probability distributions Dataset A and Dataset B for G_{FA}, which gave d=0202. Figure 8.1(b) shows the cumulative probability distributions of afternoon and mid-day for G_{PB}, which gave d=0.570.



(a) G_{FA}



(b) G_{PB}

FIGURE 8.1. EXAMPLES OF KOLMOGOROV-SMIRNOV TESTS FOR OBSERVED CUMULATIVE DISTRIBUTIONS FOR RESEARCH QUESTION 3.

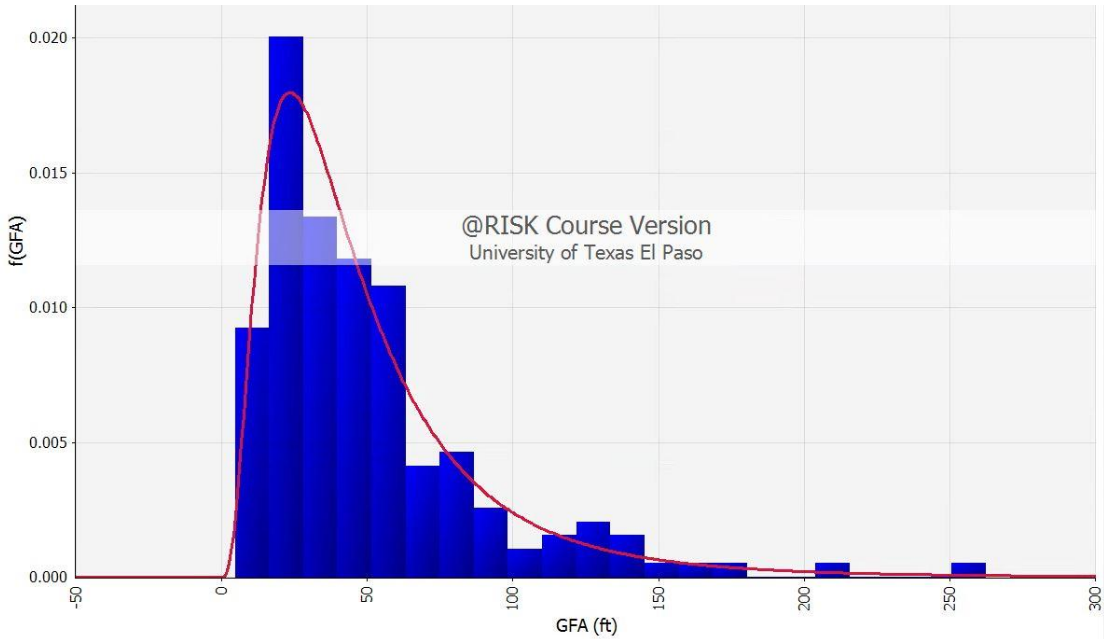
8.2.4: PROBABILITY DISTRIBUTION FITTING

The probability distribution for each risk-taking parameter was then analyzed using @RISK (Palisade, 2013). In Table 8.4, the top three fitted distributions for each parameter, among the 26 distributions tested, were chosen based on the Akaike Information Criterion (AIC) for goodness of fit. AIC is an indicator for the goodness-of-fit that considers the number of estimated distribution parameters. It is preferred to have one probability distribution to fit gaps and distance (Balal et al., 2014). A numeric scoring system was used to select one probability distribution. Distributions that provide the best, second-best, and third-best fits were assigned scores of 3, 2, and 1, respectively. The distribution with the highest total score was recommended – log-normal.

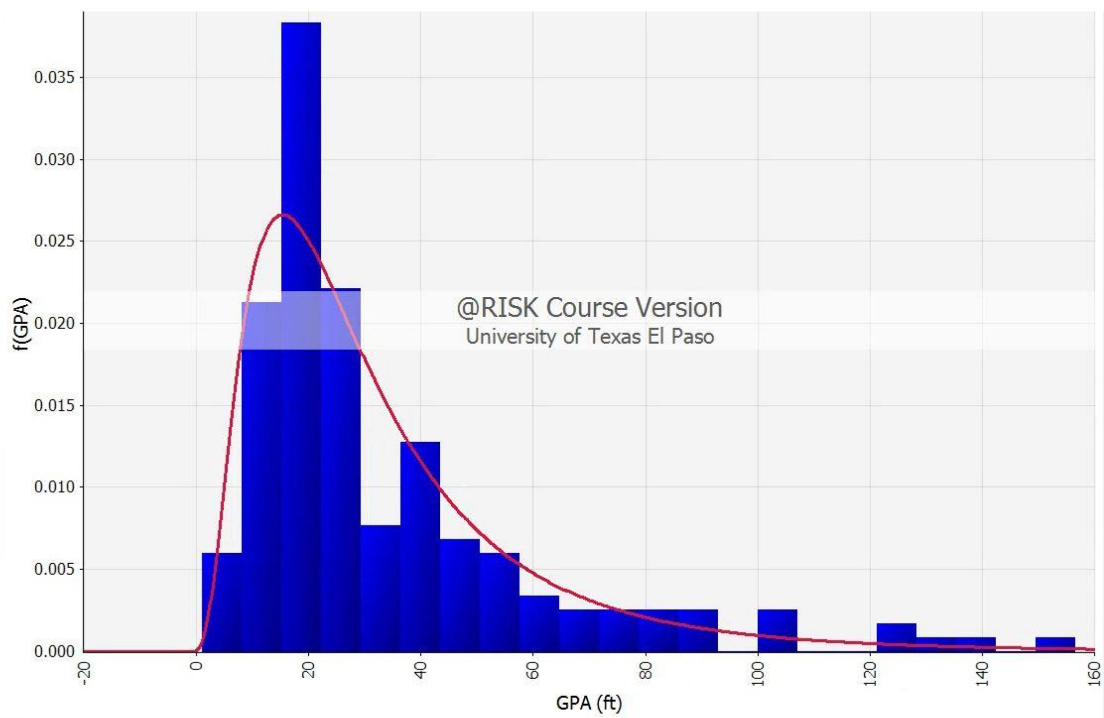
The log-normal distribution was recommended for both Datasets A and B, as it is a more commonly known distribution. An example of the @RISK log-normal distribution fitting of G_{FA} for Dataset A is illustrated in Figure 8.2(a). Another example of the @RISK log-normal distribution fitting of G_{PA} for Dataset B is illustrated in Figure 8.2(b).

TABLE 8.4. PROBABILITY DISTRIBUTION FITTINGS FOR RESEARCH QUESTION 3.

Parameters	G_{PB}	G_{PA}	G_{FA}	D
Unit	m	m	m	m
Dataset A				
Best Fit	Log-logistic	Pearson 5	**Log-normal**	Gamma
2nd Best Fit	Pearson 5	**Log-normal**	Log-normal 2	Inverse Gaussian
3rd Best Fit	**Log-normal**	Log-normal 2	Inverse Gaussian	**Log-normal**
Recommended	Log-normal			
Log-normal Location Parameter, λ	2.404	2.068	2.489	3.272
Log-normal Scale Parameter, ξ	0.787	0.730	0.695	0.516
Dataset B				
Best Fit	Program Evaluation and Review Technique (Pert)	Inverse Gaussian	Inverse Gaussian	Inverse Gaussian
2nd Best Fit	Exponential	**Log-normal**	**Log-normal**	Gamma
3rd Best Fit	Pareto 2	Log-normal 2	Log-normal 2	**Log-normal**
Recommended	Log-normal			
Log-normal Location Parameter, λ	3.678	2.729	2.874	3.744
Log-normal Scale Parameter, ξ	0.705	0.873	0.715	0.570



(a) G_{FA} from Dataset A.



(b) G_{PA} from Dataset B.

FIGURE 8.2. EXAMPLES OF FITTED LOG-NORMAL DISTRIBUTIONS FOR RESEARCH QUESTION 3.

8.2.5: Hypothesis Tests of the Difference Between Fitted Cumulative Distributions

The last set of statistical tests applied was the K-S test to test the difference between the log-normal probability distributions fitted to Datasets A and B, respectively. For each test, the *d* value obtained for each pair of log-normal cumulative probabilities is listed in Table 8.5. The outcomes of the tests are similar to the previous set of K-S tests performed for the observed distributions. For all four risk-taking parameters, the null hypothesis of

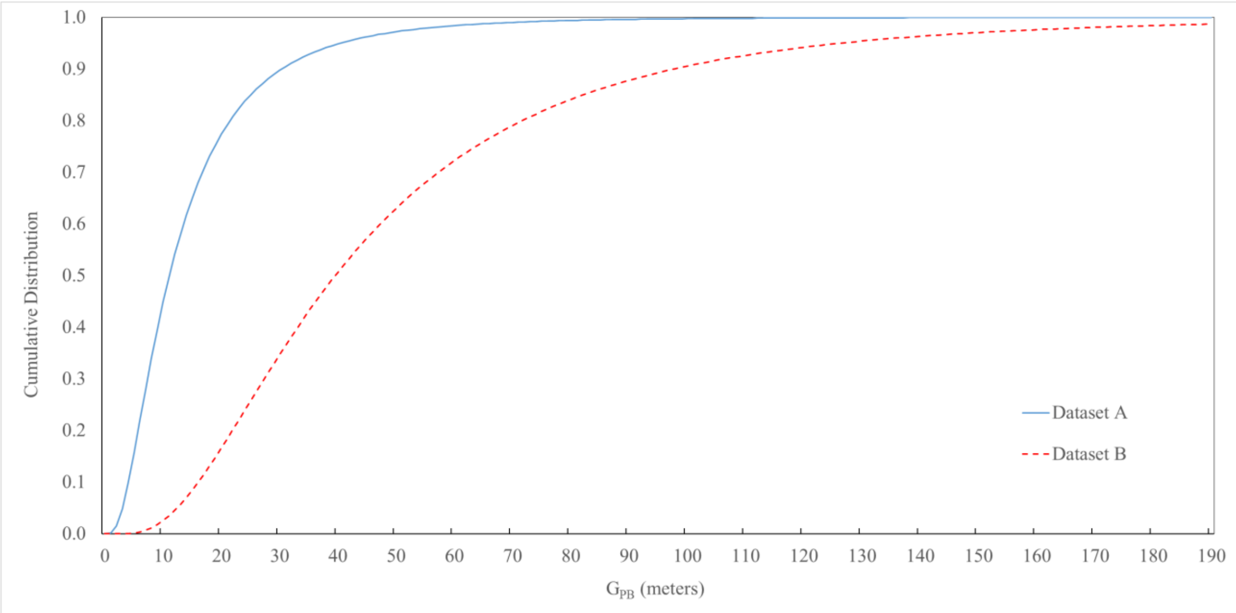
H_0: *the distributions of the risk-taking parameter for MLCs from each freeway site are fitted to the same population*

was rejected at α=0.10 and at α=0.05.

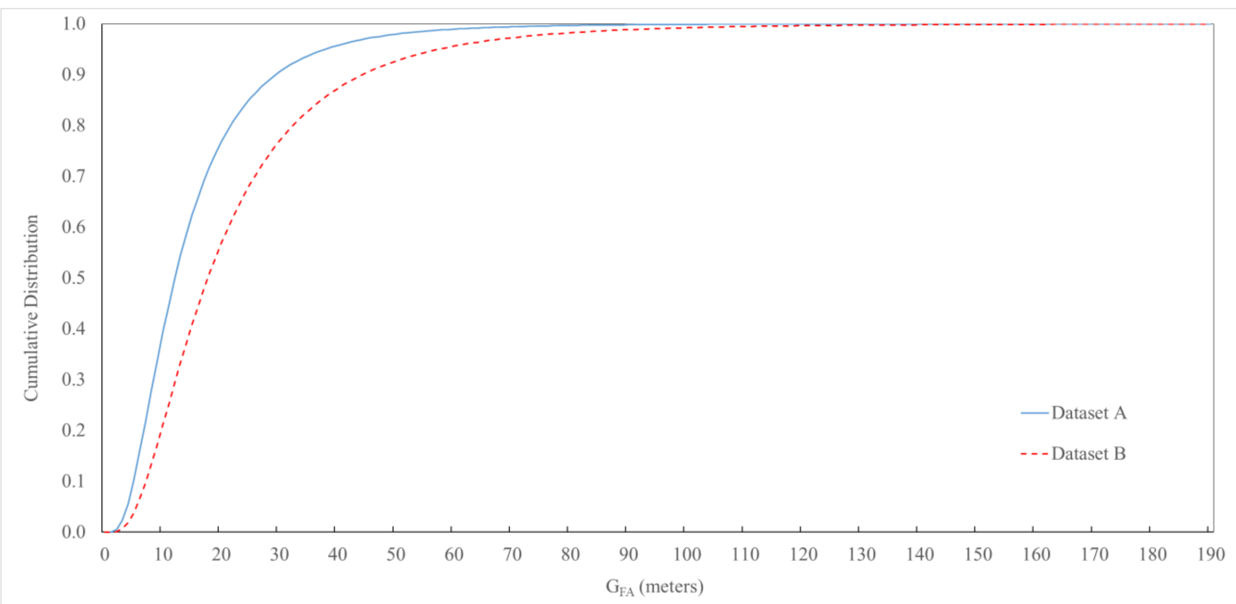
Figure 8.3(a) plots the log-normal cumulative distributions of G_{PB} for readers to visualize the difference. Figure 8.3(b) plots the log-normal cumulative distributions of G_{FA} in Dataset B to illustrate the smallest *d* value (0.215).

Table 8.5. Kolmogorov-Smirnov tests for fitted cumulative distributions for Research Question 3.

Afternoon vs. Mid-day					
Parameters		G_{PB}	G_{PA}	G_{FA}	D
d		0.608	0.327	0.215	0.338
α=0.10	**Critical Value**	0.146	0.146	0.146	0.146
	Conclusion	**Reject H_0**	**Reject H_0**	**Reject H_0**	**Reject H_0**
α=0.05	**Critical Value**	0.162	0.162	0.162	0.162
	Conclusion	**Reject H_0**	**Reject H_0**	**Reject H_0**	**Reject H_0**



(a) G_{PB}



(b) G_{FA}

FIGURE 8.3. EXAMPLES OF KOLMOGOROV-SMIRNOV TESTS FOR FITTED CUMULATIVE PROBABILITY DISTRIBUTIONS FOR RESEARCH QUESTION 3.

8.3: Discussions

The findings of this Research Question have two important applications in the lane changing decision model. In step (3) of the four-step process by Moridpour et al. (2010), the driver (or sensors of the automated vehicle) estimate G_{PB}, G_{PA}, G_{FA}, or D and compare each parameter with their respective thresholds.

Microscopic traffic simulation is a commonly used approach used by transportation engineers to perform traffic impact studies. Simulation approach has also been used by researchers to investigate the impacts of gradual introduction of automated vehicles or connected vehicles in mixed traffic stream (Krueger et al., 2016; Park and Smith, 2012; Talebpour and Mahmassani, 2016). In traffic simulation models, the stochastic behavior of drivers of conventional vehicles are represented by using probability distributions to generate the parameter values. The recommended log-normal distributions may be used in the simulation software to represent the varied thresholds used by drivers with varying degree of aggressiveness.

It is expected that, in automated vehicles, such lane changing thresholds be fixed at more conservative values, thus ensuring safety in lane changing maneuvers. However, using a more conservative threshold (e.g., large gap), which although improves safety, may compromise capacity - the two benefits always promoted by proponents of automated vehicles. The results of hypothesis tests have suggested that, the thresholds of an autonomous vehicle may be adjusted automatically depending on the location, time-of-day (by the clock time), or based on the traffic density (by receiving data from surrounding connected vehicles).

The fitted distributions describe the interactions between vehicles at the critical instances of lane changing events. Such distributions may be used to quantify the risk-taking behavior of the drivers of subject vehicles.

8.4: Chapter Summary

This chapter has studied four risk-taking parameters that describe vehicle interactions when the subject vehicle crosses the lane markers during a lane change, and analyzed the

probability distributions of these parameters, using the NGSIM data. It is found that, overall, all four parameters, which are related to gaps and distances, may be described by the log-normal distribution.

The distributions fitted to the NGSIM data on Interstate 80 (I-80) and U.S. Highway 101 were compared. Although the same distribution was fitted to the same lane changing parameter, the fitted distribution parameter values were different for the two sites. This indicates that drivers behaved differently at the two data collection sites.

Hypothesis test results indicate that there is statistical evidence to suggest that population averages for each parameter differ based on driving conditions (i.e. location, time-of-day, and traffic congestion levels).

This research has performed the analysis using real data. However, in all research, there are limitations. The major limitations of this study are:

- The subject vehicles are passenger cars. The probability distributions of the parameters for other types of vehicles are likely to be different; however, their sample sizes are much smaller, and therefore were not studied at the time of writing.
- The lane changes took place in moderate to congested traffic flow. It is yet to be determined if the correlations and probability distributions of the parameters in relatively free-flowing traffic are similar.
- The two data collection sites are located in California. The probability distributions are yet to be verified with data in other states.
- For each lane changing event, the parameter values were taken at the time instant *t* when the front center of the subject vehicle crossed the lane markers. The driver of the subject vehicle usually makes his/her decision to change lanes a fraction of a second to a few seconds prior to *t*. However, it is impossible to determine when he/she psychologically makes this decision and measure the decision parameters at this point in time.

- A successful lane changing event may be preceded by several unused (or unsafe) lane changing opportunities. This is synonymous to the gap acceptance scenario where there are more rejected gaps than accepted gaps. The distributions of the same parameters without an observed lane change are yet to be studied.

Similar analysis should be conducted for MLCs using NGSIM data on arterial streets, as well as trucks (i.e. non-passenger vehicles).

Chapter 9: Adaptation of a Freeway Discretionary Lane Changing Model to a Freeway Mandatory Lane Changing Model

9.1: Chapter Introduction

This chapter answers Research Question 4: *If the answer to any of the above Research Questions (i.e. Research Questions 1-3 in Chapters 5, 6, and 8, respectively) is "yes," can a lane changing decision model, which has been developed to meet a specific set of driving condition, be customized to meet another set of driving conditions?* Based on the results from Chapter 6, MLCs should be modeled separately from DLCs. Furthermore, since the top four risk-taking parameters from the MLC survey (in Chapter 7) coincide with the DLC survey results by Balal et al. (2016), an MLC model may be developed using the same four risk-taking parameters.

The specific approach taken to answer this question consists of five steps as previously described in Section 4.4.3:

(i) Simply apply the existing FIS model, which has been developed for DLCs by Balal et al. (2016), to MLC test data;

(ii) Adapt the DLC FIS by Balal et al. (2016) to MLCs by optimizing the defuzzification threshold, τ, with MLC test data in order to determine the FIS's best performance when presented with MLC data; and

(iii) Develop four different ANFISs using MLC training data and apply them to MLC test data.

Each of these abovementioned approaches will be conducted as part of one experiment (Experiment 1), using the NGSIM data from one freeway site. A second experiment (Experiment 2) will also be conducted where the data sets are reversed for a better understanding of the models' performances. Once both experiments have been conducted, then the last two steps may be performed as part of Experiment 3:

(iv) Select the model between steps (ii) and (iii) that performs the best with the MLC test data for both experiments; and

(v) If there are any differences in the input parameters from the MLC survey in Chapter 7, when compared to those found from the DLC survey conducted by Balal et al. (2016), remove the input parameter from the best model in step (iv) and apply it to the MLC test data again to compare the differences.

Each of the steps will be discussed in more detail in the subsequent sections.

9.2: Statistical Analyses

9.2.1: Descriptive Statistics

The first step in the analysis of the lane changing risk-taking parameters was to examine the descriptive statistics. In each data set (Dataset A for Interstate 80 and Dataset B for U.S. Highway 101, respectively), each subject vehicle that executes an MLC does so after a series of unaccepted gaps. This means that every vector carried a label of *OM*=0 or *OM*=1. The *OM* value, which stands for Observed Maneuver, indicated if a lane change actually occurred. Both of these scenarios have been presented in Figure 1.2. Table 9.1 presents the number of vectors, for both *OM*=1 and *OM*=0, for both data sets. The average number of vectors per subject vehicle refers to the average number of vectors (i.e. 0.5 second intervals) of *OM*=0 before *OM*=1 actually occurs.

TABLE 9.1. MLC DESCRIPTIVE STATISTICS FOR BOTH DATA SETS.

Dataset A	
No. of MLCs or subject vehicles =	166
Total no. of vectors =	5,111
Average no. of vectors per subject vehicle =	30.79
No. of vectors labeled *OM*=0 or “No, do not change lanes” =	4,945
No. of vectors labeled *OM*=1 or “Yes, change lanes” =	166
Dataset B	
No. of MLCs or subject vehicles =	71
Total no. of vectors =	590
Average no. of vectors per subject vehicle =	8.31
No. of vectors labeled *OM*=0 or “No, do not change lanes” =	519
No. of vectors labeled *OM*=1 or “Yes, change lanes” =	71

Once the raw data had been processed and examined, there were instances where there were negative parameter values. This was because one of the preceding vehicles in the target lane was behind the subject vehicle, measured longitudinally, for a period of time until eventually getting in front of the subject vehicle (still in the target lane). Likewise, there were instances where a following vehicle was in front of the subject vehicle in the target lane, measured longitudinally. Eventually, the subject vehicle would progress ahead of the following vehicle before the MLC occurred.

In practical terms, sensors would be deployed on a partially or fully automated vehicle. In these scenarios, the MLC controller and sensors would have to be aware that there could be a preceding vehicle or following vehicle in the target lane that’s adjacent to the subject vehicle. Therefore, all negative input parameters have been truncated to zero. The truncated descriptive statistics for each input parameter are presented in Table 9.2, which includes all vectors (i.e. for *OM*=0 and *OM*=1).

TABLE 9.2. DESCRIPTIVE STATISTICS OF MLC PARAMETERS.

Dataset A				
Parameters	G_{PB}	G_{PA}	G_{FA}	D
Sample Size	166	166	166	166
Unit	m	m	m	m
Min Value	0	0	0	1.94
Max Value	140.19	132.53	143.5	115.33
Mean	15.11	11.70	20.07	21.57
Std. Deviation	17.12	17.68	24.93	15.96
Skewness	3.99	2.23	2.07	1.40
Dataset B				
Parameters	G_{PB}	G_{PA}	G_{FA}	D
Sample Size	71	71	71	71
Unit	m	m	m	m
Min Value	0	0	0	2.79
Max Value	186.41	160.89	92.06	172.54
Mean	40.95	22.74	21.72	47.83
Std. Deviation	35.82	22.78	20.02	28.09
Skewness	1.26	2.30	1.36	1.10

9.2.1.1: PERFORMANCE MEASURES

When a vector is presented to any of the models, the model's output was denoted as *MD* (for Model's Decision), where *MD*=0 meant "no, do not change lanes" and *MD*=1 for "yes, change lanes". The model was said to make a correct decision when *MD*=0|*OM*=0. Likewise, the model was said to make a correct recommendation (for semi-automated vehicles) or decision (for fully automated vehicles) when *MD*=1|*OM*=1. On the other hand, the model was said to make a wrong decision when *MD*=1|*OM*=0 or *MD*=0|*OM*=1. Therefore, the model's decision making accuracy was measured by:

- $P(MD = 0|OM = 0)$ which is the percent of input vectors in a data set with *MD*=0|*OM*=0 (i.e. the correct decision accuracy); and
- $P(MD = 1|OM = 1)$ which is the percent of input vectors in a data set with *MD*=1|*OM*=1 (i.e. the correct recommendation accuracy).

9.2.1.2: DEFUZZIFICATION THRESHOLD

The next step, in order to compare the *MD* and *OM* values, involved the defuzzification threshold τ. The threshold value τ could fall within the range of [0,1]. Therefore, in order to determine each model's performance, various τ values may be used. Each model (i.e. the DLC FIS by Balal et al. (2016) and each ANFIS model) may be applied to the test data (i.e. Dataset B) nine times, where each application uses a unique τ. Each unique τ value varies from 0.1 to 0.9 in increments of 0.1. The idea was, by plotting the operating characteristic curves of $P(MD = 0|OM = 0)$ versus τ and $P(MD = 1|OM = 1)$ versus τ, the optimal τ value that maximizes the decision accuracies for MLCs could be found. This process was used to adapt the FIS, which had been developed for DLCs, to MLCs, as well as determine the best τ for each ANFIS model.

9.2.2: Experiment 1

Once the data had been processed, the performance measures had been established, and the defuzzification threshold optimization method had been established, both Experiment 1 and 2 may be conducted. The results for each experiment are described in the subsequent sections.

9.2.2.1: Experiment 1-FIS-DN

The DLC FIS by Balal et al. (2016) was initially selected as the benchmark to determine how well an FIS, trained for DLCs, performs in MLC situations. This was essentially the do-nothing condition. In the defuzzification stage of this FIS, if the composite output of the rule is less than or equal to a threshold value τ, the output was defuzzified to MD=0; otherwise MD=1, where MD stands for Model's Decision, 0 corresponds to "no, do not change lanes," and 1 corresponds to "yes, change lanes." This FIS was denoted as $FIS_{\tau=0.5}$ because Balal et al. (2016) recommended τ=0.5 for DLCs.

Table 9.3 illustrates the results of applying the $FIS_{\tau=0.5}$ to DLC data from U.S. Highway 101. The statistics are directly taken from Balal et al. (2016). In $FIS_{\tau=0.5}$, τ =0.5 was selected by Balal et al. (2016) in order to produce the highest accuracy for DLCs. Therefore, the 82.5% and 99.5% accuracies, for OM=1 and OM=0, respectively, are expected when presented with MLC data.

TABLE 9.3. DLC FIS MODEL APPLIED TO DLC DATA FROM U.S. HIGHWAY 101 (Balal et al., 2016).

		$FIS_{\tau=0.5}$ Recommendations for DLC test data from U.S. Highway 101			
		MD=1 Yes, change lanes	*MD*=0 No, do not change lanes	Total	Correct Recommendation or Decision Accuracy
Observed Maneuver	*OM*=1 Changed Lanes	141	30	171	82.5%
	OM=0 Did not change lanes	6,285	203,396	209,681	97.0%
	Total	6,426	203,426	209,852	N/A

Table 9.4 shows the results when this $FIS_{\tau=0.5}$, without modification, was applied to the test data set assembled in this dissertation (i.e. MLCs from Dataset B). This tested if the $FIS_{\tau=0.5}$, which was developed to make decisions for DLCs, can generate accuracies as high when making decisions for MLCs. The decision accuracies dropped by 41.7% and 32.5% for *OM*=1 and *OM*=0, respectively. The correct decision rate of 64.5% for *OM*=0 was too low to be acceptable. Even the 40.8% for *OM*=1 was unacceptable. The significant reductions in the decision accuracies indicated that, at a minimum, the $FIS_{\tau=0.5}$ should be customized for MLCs.

TABLE 9.4. DLC FIS MODEL APPLIED TO DATASET B.

		$FIS_{\tau=0.5}$ Recommendations for Dataset B			
		MD=1 Yes, change lanes	*MD*=0 No, do not change lanes	Total	Correct Recommendation or Decision
Observed Maneuver	*OM*=1 Changed Lanes	29	42	71	40.8%
	OM=0 Did not change lanes	184	335	519	64.5%
	Total	213	377	590	61.7%

9.2.2.2: EXPERIMENT 1-FIS-A

The FIS$_{\tau=0.5}$ was subsequently adapted to make decisions for MLCs. This was done by selecting the τ value that maximized the accuracies for MLCs in the test data set. The selected τ value was 0.9. Table 9.5 shows the outcomes when the FIS was applied with τ=0.9 to test the data set. By adapting the "best" τ value, the decision accuracy for *OM*=1 vectors decreased by 8.4% from 40.8% to 32.4%; but for *OM*=0 vectors, there was a marginal improvement from 64.5% to 71.1%. These rates are still not practical. The much lower decision accuracies in Tables 9.4 and 9.5, when compared with Table 9.3 indicated that a new methodology other than the FIS should be developed using test data, specifically for MLCs.

According to the reasons provided by Balal et al. (2016), only marginal improvements can be expected by manipulating the fuzzy membership functions and the IF-THEN rules of the FIS. Furthermore, the defuzzification stage had already been "optimized" by selecting the best τ value. The best opportunity for performance improvement was by changing the composition from the Mamdani method to the Sugeno method, and ANFIS was a potential alternative. An ANFIS not only implements the Sugeno composition method, but its training algorithm also optimizes the fuzzy membership functions and the inference rules, which will be discussed in the subsequent section.

TABLE 9.5. DLC FIS MODEL APPLIED WITH τ=0.9 TO DATASET B.

		FIS$_{\tau=0.9}$ Recommendations for Dataset B			
		MD=1 Yes, change lanes	*MD*=0 No, do not change lanes	Total	Correct Recommendation or Decision
Observed Maneuver	*OM*=1 Changed Lanes	23	48	71	32.4%
	OM=0 Did not change lanes	150	369	519	71.1%
	Total	173	417	590	66.4%

9.2.2.3: EXPERIMENT 1-ANFIS

In Experiment 1-ANFIS, four ANFIS models were developed and trained using Dataset A. The architecture of each ANFIS models, as previously described in Section 4.3.4, is reiterated below.

1. A grid-partitioned membership function starting position with three *triangular* membership functions, and the max-min composition type;
2. A grid-partitioned membership function starting position with three *trapezoidal* membership functions, and the max-min composition type;
3. An ANFIS where the membership functions start similarly to that of Balal et al. (2016) in their DLC FIS model, using both triangular and trapezoidal membership functions, and the *max-min* composition type; and
4. An ANFIS where the membership functions start similarly to that of Balal et al. (2016) in their DLC FIS model, using both triangular and trapezoidal membership functions, and the *max-product* composition type.

In general, for all four ANFIS models, the training procedure was as follows. The number of membership functions for each input parameter was set to three (i.e., fuzzy set of three for {*close*, *medium*, *far*}). One limitation when developing an ANFIS from scratch in MATLAB is that all membership functions must be of the same type. Therefore, for ANFIS model 1, the membership functions were set to triangular. Likewise, for ANFIS model 2, the membership functions were set to trapezoidal. For both ANFIS models 1 and 2, the membership functions were established with an initial starting position following a grid partition. In a grid partitioned ANFIS, the membership functions are evenly spaced apart initially, before optimization. For example, if there are three triangular membership functions and the minimum and maximum value in the training data is 0 and 100 m, respectively, then the three triangular membership functions will be evenly spaced, thus partitioning the data into thirds. After each epoch, the membership functions are optimized based on the hybrid method as previously described in Section 2.4.

With regards to ANFIS Models 3 and 4, the membership functions follow that of Balal et al. (2016). The membership functions recommended by Balal et al. (2016) were trapezoidal and triangular (see Figure 4.2). Therefore, when developing these ANFIS models, the membership functions were set to triangular as a default, and the models were ran for a small number of epochs (i.e. less than 10) in order to establish the model and rule base. Then, the membership functions were manually changed to follow that recommended by Balal et al. (2016). For each ANFIS model, the output membership functions were set to linear. This means that each ANFIS was a first order Sugeno-type.

Then, the membership functions and fuzzy rules were optimized for many epochs until the RMSE for the training data and testing data converged to a minimum. At that point, the number of epochs was recorded for each ANFIS model as well as the minimum training and test data RMSE. One issue with MLF and ANFIS models is that the starting values of the link weights are assigned randomly, typically done using the random number seed from the computer. So, multiple trials of each ANFIS should be developed to ensure no ANFIS model converged to a local minimum. Therefore, four trials of each model were developed. The results for each ANFIS model and each trial is presented in Table 9.6. Since the training data RMSE and testing data RMSE both converge to the same value after the same number of iterations for all four trials, it was determined that four trials was sufficient.

TABLE 9.6. ANFIS MODEL DEVELOPMENT FOR EXPERIMENT 1-ANFIS.

ANFIS Model 1			
Trial	**No. of Epochs**	**Minimum Training Data RMSE**	**Minimum Testing Data RMSE**
1	1,000	0.161663	16.722
2	1,000	0.161663	16.722
3	1,000	0.161657	16.722
4	1,000	0.161657	16.722
ANFIS Model 2			
ANFIS Model No.	**No. of Epochs**	**Minimum Training Data RMSE**	**Minimum Testing Data RMSE**
1	1,000	0.166769	27.6473
2	1,000	0.166769	27.6524
3	1,000	0.166769	27.6524
4	1,000	0.166769	27.6524
ANFIS Model 3			
ANFIS Model No.	**No. of Epochs**	**Minimum Training Data RMSE**	**Minimum Testing Data RMSE**
1	10	0.156351	1.69423
2	10	0.156351	1.69423
3	10	0.156351	1.69423
4	10	0.156351	1.69423
ANFIS Model 4			
ANFIS Model No.	**No. of Epochs**	**Minimum Training Data RMSE**	**Minimum Testing Data RMSE**
1	13	0.155243	1.72561
2	13	0.155243	1.72561
3	13	0.155243	1.72561
4	13	0.155243	1.72561

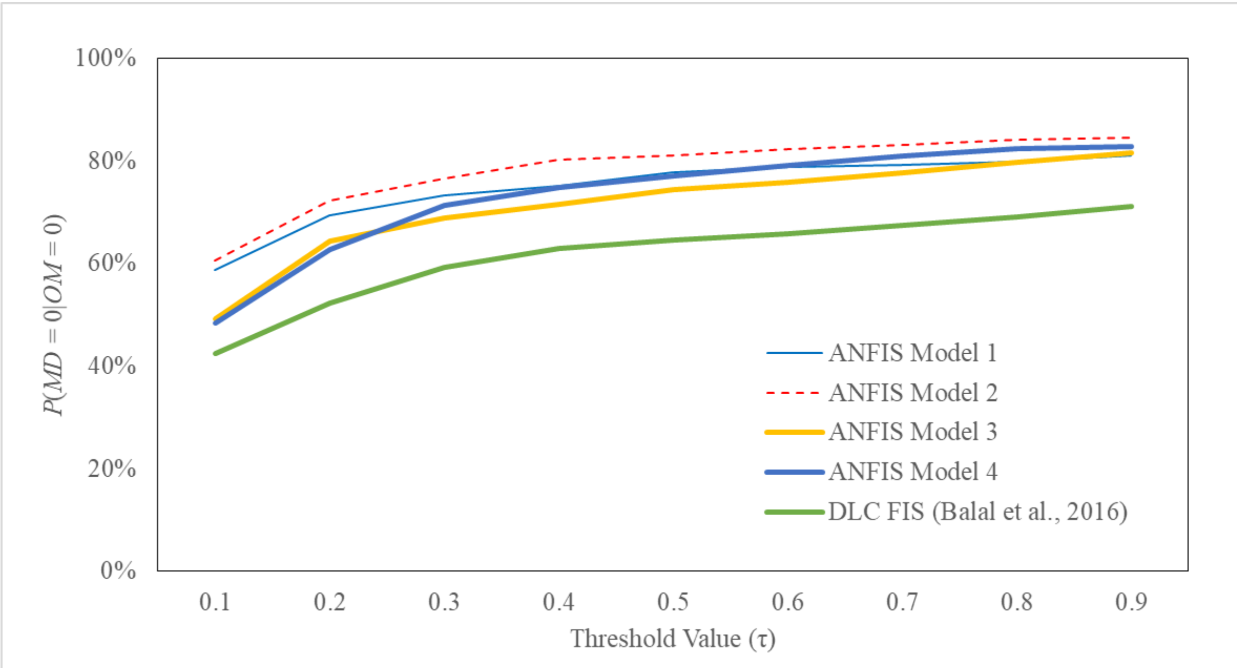
In all four trials, ANFIS models 1 and 2 took much longer to converge to minimum RMSE values (i.e. approximately 1,000 epochs) for the training and test data sets. Conversely, ANFIS models 3 and 4 took only a few epochs before overfitting of the training data occurred. More importantly, the testing data RMSE was much smaller than that of ANFIS models 1 and 2. This is likely because ANFIS models 3 and 4 had membership functions that start with that recommended by Balal et al. (2016), whereas ANFIS models 1 and 2 were simply set-up with evenly spaced (i.e. grid partitioned) membership functions, all of which were of the same type.

9.2.2.4: Comparative Evaluation

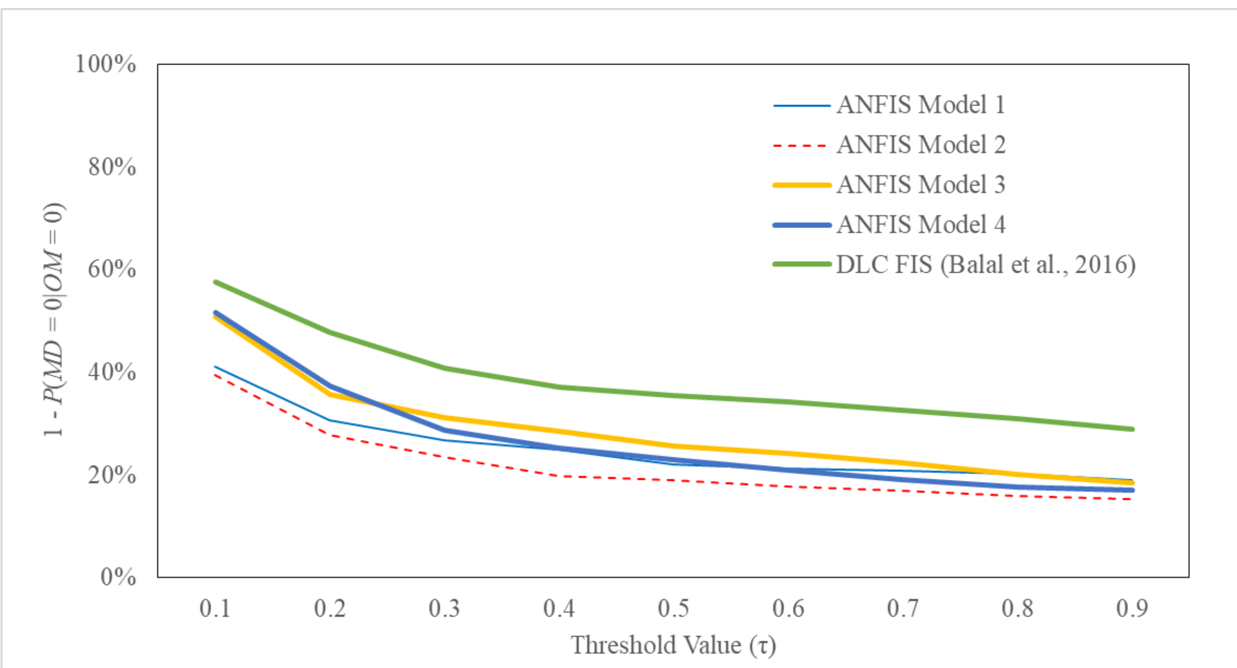
Once the four ANFIS models had been trained, test data (i.e. Dataset B) was presented to each of the ANFIS models as well as the DLC FIS by Balal et al. (2016). The next step involved measuring the performance of each model when presented with new, unseen test data.

In order to determine the optimal τ value, the results for each model were applied nine times to the test data, as previously described in Section 9.2.1. Figure 9.1a plots the correct decision accuracy ($P(MD = 0|OM = 0)$) of the DLC FIS by Balal et al. (2016) as well as the four ANFIS models with varying τ values. In general, as the τ values increase, each *MD* is more accurate. This is because, as the τ values increases, more and more *MD* values become 0 for "no, do not change lanes," and thus are more accurate.

Figure 9.1b plots the inverse of Figure 9.1a, which may be seen as the incorrect decision accuracy. An incorrect decision may lead to an incident (e.g. a crash or accident). Therefore, the goal is to select the model that has the highest decision accuracy in Figure 9.1a or the model that has the lowest incorrect decision accuracy in Figure 9.1b.



(a) Correct decision accuracy



(b) Incorrect decision accuracy

FIGURE 9.1. CORRECT AND INCORRECT DECISION ACCURACIES FOR EXPERIMENT 1.

On the contrary, as the τ value increases, the correct recommendation accuracy ($P(MD = 1|OM = 1)$) decreases. Figure 9.2 plots the correct recommendation accuracy of the DLC FIS by Balal et al. (2016) as well as the four ANFIS models with varying τ values. In general, as the τ value increases, *MD* becomes less accurate. This is because, as the τ values increases, more and more *MD* values become 0 for "no, do not change lanes," when the *OM* was actually 1 for "yes, change lanes."

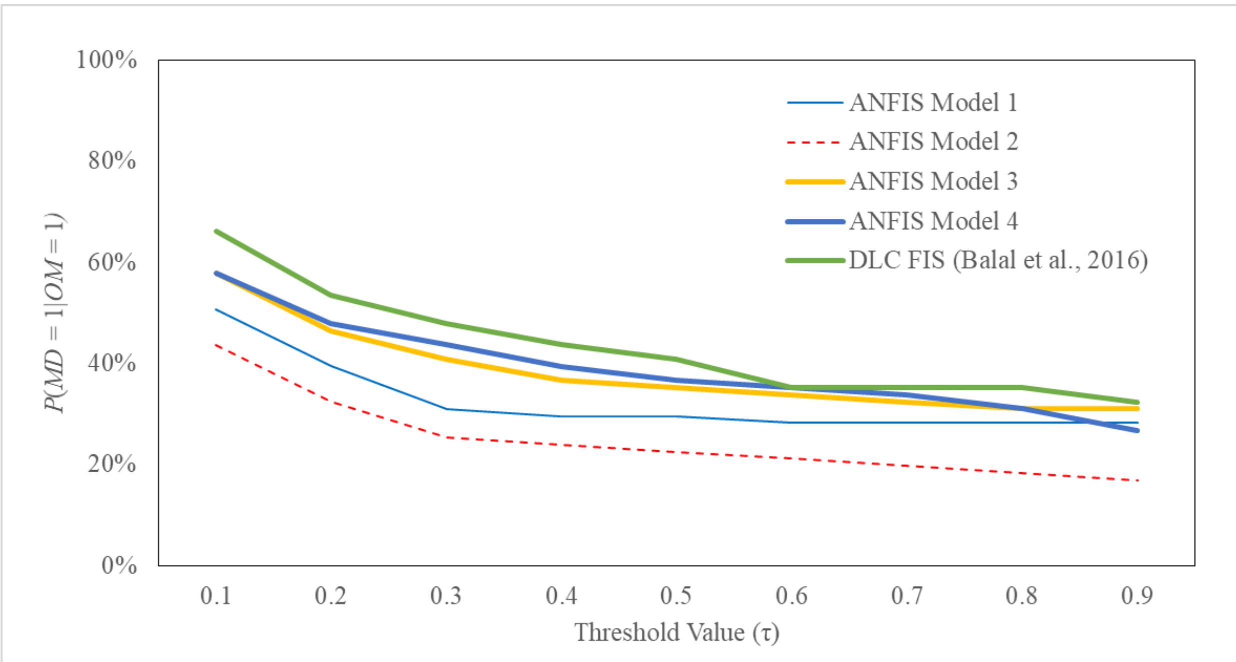


FIGURE 9.2. CORRECT RECOMMENDATION ACCURACY FOR EXPERIMENT 1.

The best performing model should be selected as the model with the smallest incorrect decision accuracy (from Figure 9.1b), as it is the safer model. If a model does not have a high recommendation accuracy, this means that the driver (or automated vehicle) may not execute the MLC and have to, for example, take the next downstream exit and reroute. However, if a model does not have a high correct decision accuracy (from Figure 9.1b), then this could lead to an incident (e.g. an accident or possibly a fatality).

In essence, the goal when selecting the best model should be the model with the lowest incorrect decision accuracy (from Figure 9.1b), but that still has a relatively high recommendation accuracy (from Figure 9.2). Furthermore, much more weight should be given to the model with the lowest incorrect decision accuracy from Figure 9.1b, due to the cost of an incorrect decision with respect to an incorrect recommendation.

9.2.3: EXPERIMENT 2

The process for Experiment 2 is the same as that of Experiment 1 in its entirety, with the exception of the data sets being reversed for training and testing. The reason for a second experiment is for a better understanding of the ANFIS models and further conclusiveness behind the selection of the best model.

9.2.3.1: EXPERIMENT 2-FIS-DN

Experiment 2DN is the do-nothing condition, where the existing DLC FIS model by Balal et al. (2016) was simply applied to the test data (in this case Dataset A). The process was exactly the same as Experiment 1-FIS-DN, which includes applying the $FIS_{\tau=0.5}$ by Balal et al. (2016) directly to Dataset A. Similar to Experiment 1-FIS-DN, high decision and recommendation accuracies are expected when presented with MLC data.

Table 9.7 shows the results when this $FIS_{\tau=0.5}$, without modification, was applied to the test data set assembled in this dissertation (i.e. MLCs from Dataset A). This tested if the $FIS_{\tau=0.5}$, which was developed to make decisions for DLCs, can generate accuracies as high when making decisions for MLCs.

TABLE 9.7. DLC FIS MODEL APPLIED TO DATASET A.

		FIS$_{\tau=0.5}$ Recommendations for Dataset A			
		MD=1 Yes, change lanes	*MD*=0 No, do not change lanes	Total	Correct Recommendation or Decision
Observed Maneuver	*OM*=1 Changed Lanes	14	152	166	8.4%
	OM=0 Did not change lanes	0	4,945	4,945	100%
	Total	14	5,097	590	97.0%

At first glance, the DLC FIS performs quite well when presented with the MLC data from Dataset A. This is likely because the DLC FIS was developed using DLC data from Interstate 80 (i.e. DLCs at the same site). The decision accuracies for *OM*=1 and *OM*=0 were 8.4% and 100%, respectively. Although the decision accuracy for *OM*=0 was 100%, the recommendation accuracy for *OM*=1 was very low at only 8.4%. This means that the FIS model only makes a correct MLC recommendation less than 10% of the time, which is far too low to be acceptable. Similar to Experiment 1-FIS-DN, this again indicates that the FIS$_{\tau=0.5}$ should be customized for MLCs.

9.2.3.2: EXPERIMENT 2-FIS-A

Similar to Experiment 1-FIS-A, the FIS$_{\tau=0.5}$ was subsequently adapted to make decisions for MLCs. This was done by selecting the τ value that maximized the accuracies for MLCs in the test data set. The selected τ value was 0.3. Table 9.8 shows the outcomes when the FIS was applied with τ=0.3 to test the data set. By adapting the "best" τ value, the decision accuracy for *OM*=1 vectors marginally improved from 8.4% to 26.5%; and for *OM*=0 vectors, there was essentially no decrease in performance from 100% to 99.5%. These rates are safe, yet still not practical. The much lower decision accuracies in Tables 9.7 and 9.8, when compared with Table 9.3 further indicated that a new methodology other than the FIS should be developed using test data, specifically for MLCs, which further supplements the results obtained from Experiment 1.

TABLE 9.8. DLC FIS MODEL APPLIED WITH τ=0.3 TO DATASET A.

		$FIS_{\tau=0.3}$ Recommendations for Dataset A			
		MD=1 Yes, change lanes	*MD*=0 No, do not change lanes	Total	Correct Recommendation or Decision
Observed Maneuver	*OM*=1 Changed Lanes	44	122	166	26.5%
	OM=0 Did not change lanes	27	4,918	4,945	99.5%
	Total	71	5,040	590	97.1%

9.2.3.3: EXPERIMENT 2-ANFIS

In Experiment 2-ANFIS, four ANFIS models were developed and trained using Dataset B. The general training procedure for each ANFIS was the exact same as that from Experiment 1-ANFIS, with the exception that each ANFIS was trained using Dataset B. Four separate trials were conducted when training each ANFIS, thus reducing the opportunity that no ANFIS reached a local minimum of the RMSE, similar to Experiment 1-ANFIS. The results for each ANFIS model and each trial is presented in Table 9.9. Since the training data RMSE and testing data RMSE both converge to the same value after the same number of iterations for all four trials, it was determined that four trials was sufficient.

TABLE 9.9. ANFIS MODEL DEVELOPMENT FOR EXPERIMENT 2-ANFIS.

ANFIS Model 1			
Trial	**No. of Epochs**	**Minimum Training Data RMSE**	**Minimum Testing Data RMSE**
1	250	0.230189	44.9285
2	250	0.230189	44.9285
3	250	0.230189	44.9285
4	250	0.230189	44.9285
ANFIS Model 2			
Trial	**No. of Epochs**	**Minimum Training Data RMSE**	**Minimum Testing Data RMSE**
1	150	0.258068	3.50783
2	150	0.258068	3.50783
3	150	0.258068	3.50783
4	150	0.258068	3.50783
ANFIS Model 3			
Trial	**No. of Epochs**	**Minimum Training Data RMSE**	**Minimum Testing Data RMSE**
1	10	0.208654	88.5562
2	10	0.208654	88.5562
3	10	0.208654	88.5562
4	10	0.208654	88.5562
ANFIS Model 4			
Trial	**No. of Epochs**	**Minimum Training Data RMSE**	**Minimum Testing Data RMSE**
1	150	0.208614	100.933
2	150	0.208614	100.933
3	150	0.208614	100.933
4	150	0.208614	100.933

In all four trials, ANFIS models 1, 2, and 4 took approximately the same number of epochs to converge to minimum training and testing data RMSE values (i.e. between 150-250 epochs). On the other hand, ANFIS model 3 almost immediately converged before overfitting of the training data occurred. More importantly, the testing data RMSE was much smaller for ANFIS model 2 when compared to the other three models. ANFIS model 2 was a simple trapezoidal membership function, grid partitioned ANFIS with the max-min composition.

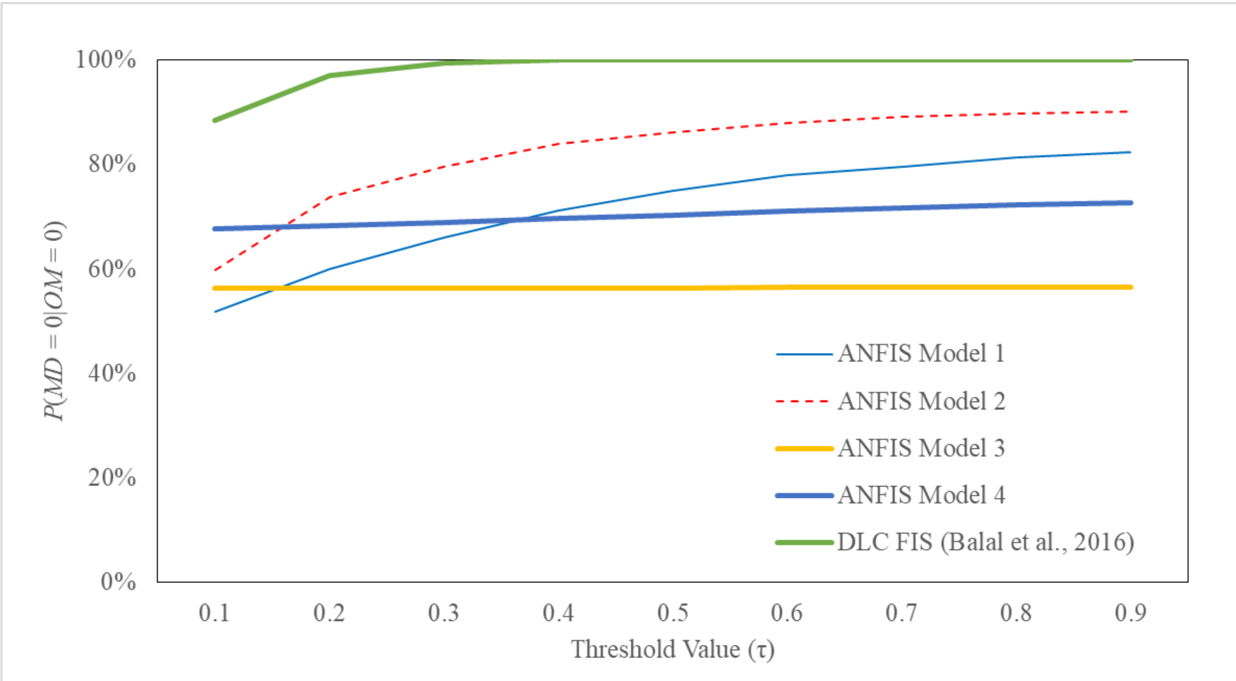
9.2.3.4: Comparative Evaluation

Once the four ANFIS models had been trained, test data (i.e. Dataset A) was presented to each of the ANFIS models as well as the DLC FIS by Balal et al. (2016). The next step involved measuring the performance of each model when presented with new, unseen test data.

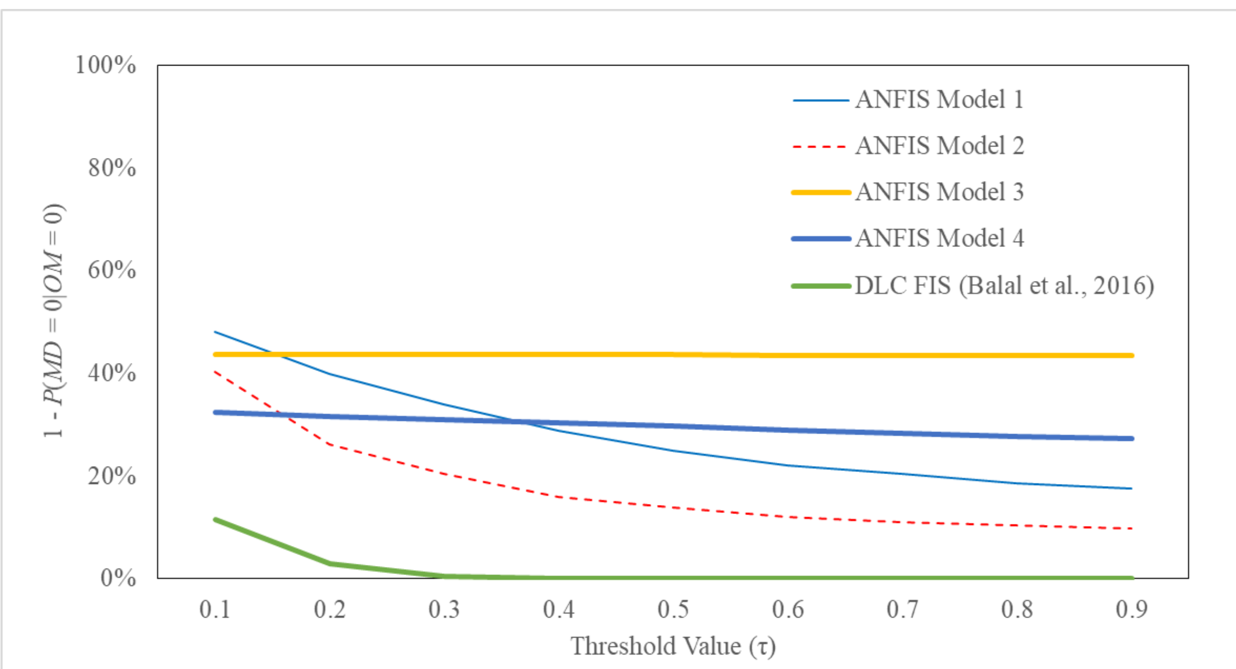
The same procedure as Experiment 1-ANFIS was followed in selecting the optimal τ value. The results for each model were applied nine times to the test data.

Figure 9.3a plots the correct decision accuracy ($P(MD = 0|OM = 0)$) of the DLC FIS by Balal et al. (2016) as well as the four ANFIS models with varying τ values. Similar to Experiment 1-ANFIS, as the τ values increase, each *MD* is more accurate. This is because, as the τ values increases, more and more *MD* values become 0 for "no, do not change lanes," and thus are more accurate.

Figure 9.3b plots the inverse of Figure 9.3a, which may be seen as the incorrect decision accuracy. With decision accuracies, an incorrect decision may lead to an incident (e.g. a crash or accident). Therefore, the goal is to select the model that has the highest decision accuracy in Figure 9.3a or the model that has the lowest incorrect decision accuracy in Figure 9.3b.



(a) Correct decision accuracy



(b) Incorrect decision accuracy

FIGURE 9.3. CORRECT AND INCORRECT DECISION ACCURACIES FOR EXPERIMENT 2.

On the contrary, as the τ value increases, the correct recommendation accuracy ($P(MD = 1|OM = 1)$) decreases. Figure 9.4 plots the correct recommendation accuracy of the DLC FIS by Balal et al. (2016) as well as the four ANFIS models with varying τ values. In general, as the τ values increase, each *MD* is less accurate. This is because, as the τ values increases, more and more *MD* values become 0 for "no, do not change lanes," when the *OM* was actually 1 for "yes, change lanes."

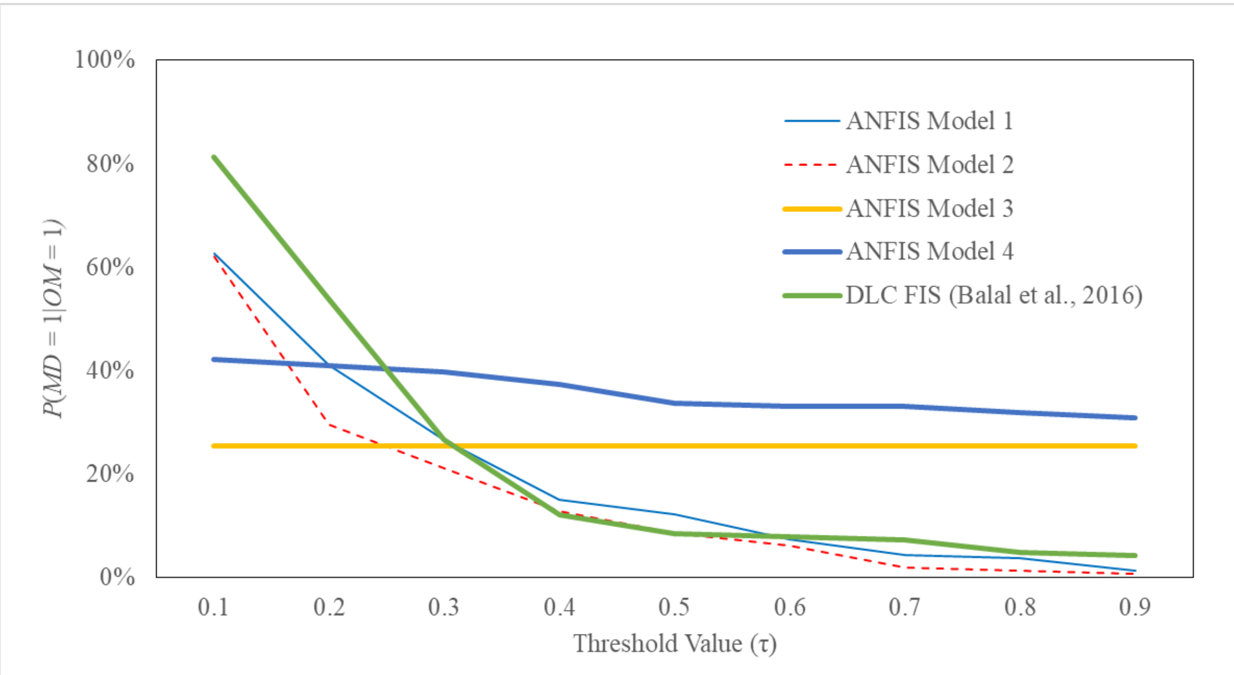


FIGURE 9.4. CORRECT RECOMMENDATION ACCURACY FOR EXPERIMENT 2.

Similar to Experiment 1, the best performing model should be selected as the model with the smallest incorrect decision accuracy (from Figure 9.3b), as it is the safer model. If a model does have a high recommendation accuracy, this means that the driver (or automated vehicle) may not execute the MLC and have to, for example, take the next downstream exit and reroute. However, if a model does not have a low incorrect decision accuracy (from Figure 9.3b), then this could lead to an incident (e.g. an accident or possibly a fatality).

In essence, the goal when selecting the best model should be the model with the lowest incorrect decision accuracy (from Figure 9.3b), but that still has a relatively high recommendation accuracy (from Figure 9.4). Furthermore, much more weight should be given to the model with the lowest incorrect decision accuracy from Figure 9.3b, due to the cost of an incorrect decision with respect to an incorrect recommendation.

9.2.4: EXPERIMENT 3

Based on the results from Experiment 1 and when giving much more weight to models with lower incorrect decision accuracies (see Figure 9.1b), ANFIS models 4 and 2 perform the best and safest. It should be noted that the DLC FIS by Balal et al. (2016) performed the worst of the five models considered.

Based on the results from Experiment 2 and when giving much more weight to models with lower incorrect decision accuracies (see Figure 9.3b), the DLC FIS by Balal et al. (2016) and ANFIS model 2 perform the best and safest. The reason that the DLC FIS by Balal et al. (2016) performs so well is likely due to the fact that the DLC FIS was developed using DLC data from the same site as Dataset B (i.e. from Interstate 80).

From both experiments, it is recommended that ANFIS model 2 be used for MLCs. Although ANFIS model 2 had the highest test data RMSE of 27.6473 in Experiment 1-ANFIS (see Table 9.6) and the lowest correct recommendation accuracy in Experiment 1-ANFIS(see Figure 9.2), it is recommended based on the following reasons:

- In Experiment 1-ANFIS, ANFIS model 2 had the lowest incorrect decision accuracy, thus making it the safest of the five models tested (see Figure 9.1b);
- In Experiment 2-ANFIS, ANFIS model 2 had the lowest RMSE of testing data at 3.50783 (see Table 9.9); and
- In Experiment 2-ANFIS, ANFIS model 2 had the second lowest incorrect decision accuracy (see Figure 9.3b).

Since ANFIS model 2 performed well with in both Experiment 1-ANFIS and Experiment 2-ANFIS, it is recommended as the best model; however, there are two versions of the ANFIS model 2: one developed in Experiment 1-ANFIS and the other in Experiment 2-ANFIS. Between the two models, the ANFIS model 2 from Experiment 1-ANFIS is recommended as the best overall MLC model. This is because in both experiments, ANFIS model 2 was the safest or second safest model (see Figures 9.1b and 9.3b); however, in Experiment 1-ANFIS, ANFIS model 2 provides a higher recommendation accuracy than in Experiment 2-ANFIS (see Figures 9.2 and 9.4). Furthermore, the number of vectors in Dataset A when training ANFIS model 2 in Experiment 1-ANFIS is far greater than the number of vectors in Dataset B when training ANFIS model 2 in Experiment 2-ANFIS (see Table 9.1).

The optimal τ value for ANFIS model 2 from Experiment 1-ANFIS is 0.9. This value was chosen, as it provides the minimal number of incorrect decisions. The greater the τ value, in general, the more conservative and thus safer the model will perform. On the contrary, a high τ value usually translates to a lower recommendation accuracy. This is the tradeoff between a correct decision and a correct recommendation; however, an incorrect decision is much more costly than an incorrect recommendation. Therefore, ANFIS model 2 from Experiment 1-ANFIS is recommended with a τ value of 0.9 as a safety measure. Table 9.10 presents the results when applying test data from Dataset B to ANFIS model 2 from Experiment 1-ANFIS, which was trained using Dataset A.

TABLE 9.10. ANFIS MODEL 2 (τ=0.9) APPLIED TO DATASET B.

		ANFIS Model 2 $_{\tau=0.9}$ Recommendations for Dataset B			
		MD=1 Yes, change lanes	*MD*=0 No, do not change lanes	Total	Correct Recommendation or Decision
Observed Maneuver	*OM*=1 Changed Lanes	12	59	71	16.9%
	OM=0 Did not change lanes	80	439	519	84.6%
	Total	92	498	590	76.4%

Despite the relatively low recommendation accuracy of 16.9% and an imperfect decision accuracy of 84.6% in Table 9.10, the recommended ANFIS model still performs much better and is much safer than the existing DLC FIS by Balal et al. (2016), before and after optimizing the τ value, as seen in Tables 9.4 and 9.5, respectively.

9.2.4.1: FAULT TOLERANCE TEST

The next step is to then present ANFIS model 2 from Experiment 1-ANFIS (τ=0.9) with faulty data. This is essentially done by removing all data for G_{PB}, as it was discovered in the MLC survey from Chapter 7 that G_{PB} is the least frequently used parameter out of the four common parameters shared between MLCs and DLCs.

For each vector, the faulty data may be replaced by an arbitrarily high value or zero. This is because MATLAB does not allow for a missing value the numeric array during the FIS evaluation process (MATLAB, 2012). Furthermore, for the arbitrarily high value, it must be within the range of [0, max(G_{PB})], where max(G_{PB}) is the maximum G_{PB} value that was used when training the ANFIS. When the max(G_{PB}) value was used, the results were not as desired. This is because: (i) the *MD* values were more aggressive, since one of the input parameters is quite large; and (ii) since this is a first order Sugeno-type ANFIS and the output is a linear function of the input, the outputs were quite large. In some cases, the ANFIS output did not fall within the range of [0,1]. For these reasons, a value of zero was used as the missing G_{PB} input

value for Experiment 3. Furthermore, a zero value essentially tells the model that the G_{PB} input parameter is very small, thus causing the model to make more conservative (i.e. safer) decisions to execute less MLCs. The results for ANFIS model 2 with τ=0.9 presented with missing G_{PB} data are presented in Table 9.11.

TABLE 9.11. ANFIS MODEL 2 (τ=0.9) APPLIED TO DATASET B WITH MISSING G_{PB} DATA.

		ANFIS Model 2 $_{\tau=0.9}$ Recommendations for Dataset B (No G_{PB} Data)			
		MD=1 Yes, change lanes	*MD*=0 No, do not change lanes	Total	Correct Recommendation or Decision
Observed Maneuver	*OM*=1 Changed Lanes	4	67	71	5.6%
	OM=0 Did not change lanes	52	467	519	90.0%
	Total	56	534	590	79.8%

In Table 9.11, the ANFIS model 2 from Experiment 1-ANFIS (τ=0.9) was presented with faulty G_{PB} data, as values of zero. Even with essentially no G_{PB} data, the model actually performed in a safer matter. The correct decision accuracy actually improved from 84.6% in Table 9.10 to 90.0% in Table 9.11. On the contrary, the recommendation accuracy dropped only marginally from 16.9% in Table 9.10 to 5.6% in Table 9.11. This may be seen as very insignificant given the cost of an incorrect decision is much greater than that of an incorrect recommendation. Therefore, based on the results from Experiment 3, the ANFIS model 2 from Experiment 1-ANFIS (τ=0.9) is a robust model that actually performs safer given faulty G_{PB} data.

9.3: Discussions

9.3.1: Major Findings and Recommendations

This Research Question has evaluated the performance of an existing DLC FIS by Balal et al. (2016) as well as four newly developed ANFIS models using a training and test data set. Two experiments were conducted where the training and test data sets were reversed. The data used was from I-80 Freeway (Dataset A) and U.S. Highway 101 (Dataset B), which are parts of the NGSIM database. It was recommended that ANFIS model 2 from Experiment 1-ANFIS (τ=0.9) be used in lieu of the existing DLC FIS by Balal et al. (2016) to make MLC decisions.

Based on the results, it may be inferred that the existing DLC FIS by Balal et al. (2016) is not adequate when presented with MLC data. This suggests that, at a minimum, a separate model should be developed and customized for MLCs. Such models were developed in Experiments 1-ANFIS and 2-ANFIS.

The recommended MLC model should also be robust enough to perform well when presented with faulty or missing data. In Experiment 3, faulty input data for G_{PB} was presented to the ANFIS model 2 from Experiment 1-ANFIS (τ=0.9) and the model performed in an even safer matter with a lower incorrect decision accuracy.

9.3.2: Limitations

The answer to this Research Question consisted of developing and evaluating multiple ANFIS models for MLCs on freeways as well as an existing DLC FIS by Balal et al. (2016). As in all research, there are some limitations. The conclusions are arrived with the following limitations:

- The subject vehicles are passenger cars;
- The lane changes took place in moderate to congested traffic flow; and
- Both data collection sites, although in cities more than 300 miles (500 km) apart, are located in California.

9.4: Chapter Summary

This research is perhaps the first attempt that uses real world trajectory data from the NGSIM database to develop multiple models comprised of an FIS and MLF, which is termed an ANFIS. This research has proven that the existing DLC FIS by Balal et al. (2016) did not perform well when presented with MLC data. This results from this Research Question have gone deeper to understand the effects of faulty or missing input data, where the input parameter was determined based on a survey in Chapter 7.

A more accurate MLC model, with fewer input parameters should enable connected and automated vehicles to move more like manually driven vehicles. The recommended MLC model may be programmed into microscopic traffic simulation tools to model vehicle movements closer to driving conditions in the field. Both benefits will lead to, macroscopically, more precise replication of the existing highway capacity; and microscopically, improved representation of a driver's risk-taking behavior when making a lane change.

CHAPTER 10: CONCLUSIONS

10.1: Summary of Answered Research Questions

There are four Research Questions that this dissertation has successfully answered:

1) Do drivers have different risk-taking behavior when executing a discretionary lane changing maneuver on an arterial street at different times of the day?
2) Do drivers have different risk-taking behavior between mandatory and discretionary lane changes on freeways?
3) Do drivers have different risk-taking behavior when executing a mandatory lane changing maneuver at different freeway sites?
4) If the answer to any of the above Research Questions is "yes", can a lane changing decision model, which has been developed to meet a specific set of driving conditions, be customized to meet another set of driving conditions?

Do drivers have different risk-taking behavior when executing a DLC on an arterial street at different times of the day? It was discovered in Chapter 5 that there is enough statistical evidence to conclude that drivers have different risk-taking behavior when executing a DLC maneuver on an arterial street at different times of the day.

Do drivers have different risk-taking behavior between mandatory and discretionary lane changes on freeways? The results in Chapter 6 indicate that there is not enough evidence to suggest that there are major differences between MLCs and DLCs on freeways for all parameters except G_{PB}.

Do drivers have different risk-taking behavior when executing an MLC at different freeway sites? It was discovered that, again, there is enough statistical evidence to conclude that drivers have different risk-taking behavior when executing an MLC at different freeway sites.

If the answer to any of the above Research Questions is "yes", can a lane changing decision model, which has been developed to meet a specific set of driving conditions, be customized to meet another set of driving conditions? The results in Chapter 9 have proven that

an existing DLC model (by Balal et al. (2016)) did not perform as well when presented with MLC data. It was customized by using similar membership functions, and then trained and optimized of the membership functions and fuzzy rules occurred to make an ANFIS. Several ANFISs were developed, and the best model outperformed the existing DLC FIS by Balal et al. (2016).

10.2: Significance & Contributions

10.2.1: Intellectual Merit

Although lane changing has received little attention relative to car-following, its importance in automated vehicle control cannot be ignored. Therefore, lane changing has begun to receive more attention, especially in recent years. As such, researchers must consider the differences in drivers' lane changing behavior. This dissertation is possibly the first to not only provide a comparison of drivers' behavior during MLCs and DLCs, but also comparing drivers' MLC and DLC behavior with themselves at different locations during the same time of day, and at the same location at different times during the day. Since drivers have different risk-taking behavior, future research must consider these differences (i.e. location and time-of-day).

This dissertation has also helped bridge the gap between MLC and DLC research. An MLC survey has been conducted, by which future MLC researchers may consider the most important risk-taking parameters when developing new models.

Additionally, the majority of lane changing research has been focusing on freeways. The results in Chapter 5 were perhaps the first to use actual trajectory data to analyze DLCs on an arterial street. Future research in lane changing should focus more on drivers' risk-taking behavior on arterials. Based on the results from Chapter 5, a DLC and/or MLC model may be developed for arterial streets. Also, this research was perhaps the first to attempt to adapt a DLC model to make MLC decisions. Similar models have been developed and optimized using MLC training data. These models outperformed one DLC model found from the literature.

10.2.2: BROADER IMPACTS

At a broader scale, the new lane changing model may be incorporated into existing traffic simulation tools (software) to improve the modeling accuracy. The higher prediction accuracies for lane changes in the simulation models will yield better, more accurate results for the simulation tool as a whole.

In the near future, as connected and automated vehicle research and implementation progresses, there needs to be a better understanding of how drivers behave when changing lanes. Most vehicles sold today are only partially autonomous, meaning that the vehicle may assist the driver with speed and steering. For now, and in the foreseeable future, divers may still have to change lanes themselves, with the guidance from sensors (i.e. whether it is safe or unsafe to change lanes). The initial results from this dissertation have shown that drivers behave differently based on time-of-day, type of lane change, and location. This demonstrates the need for automated vehicles to have a dynamic lane changing model that can adapt to different driving conditions. Such new MLC models have been presented and demonstrated in this dissertation, including the removal of one risk-taking input parameter and thus illustrating the models' robustness.

10.3: Documents and Publications

From this dissertation, specific chapters have been and will be considered for publication.

Chapter 5 compares the lane changing behavior of drivers on arterial streets at different times during the day. An earlier version of this chapter, which is titled *"Comparisons of Discretionary Lane Changing Behavior: Implications for Autonomous Vehicles"* has been published in the Institute of Transportation Engineers Journal, Vol. 88, No. 6, pp. 37-43.

Chapter 6 of this dissertation compares the lane changing behavior between drivers conducting an MLC and DLC on freeways using statistical tests. An earlier version of this chapter, which is titled *"Comparisons of Mandatory and Discretionary Lane Changing Behavior*

on Freeways", has been published in the International Journal of Transportation Science and Technology, Vol. 7, No. 2, pp. 124-136.

Chapter 9 of this dissertation answers the most important question: *If the answer to any of the first three Research Questions is "yes", can a lane changing decision model, which has been developed to meet a specific set of driving conditions, be customized to meet another set of driving conditions?* This question is based on the results from Chapters 5-8 of this dissertation. At the time of completion of this dissertation, the results from Chapter 9 are being prepared to be submitted to Transportation Research: Part C for the development and testing of the ANFIS models. The results for the fault tolerance testing of G_{PB} (i.e. Experiment 3) are being prepared to be submitted to an artificial intelligence journal.

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APPENDIX

Transportation Survey on Lane Changing

UTEP is conducting research on how drivers change lanes on highways and freeways. We want to understand how drivers make decisions on when to change lanes. Your answers will help us to understand lane changing motivation and behavior.

This survey has 2 parts and a total of 15 questions.

Suppose you are entering a two-lane freeway, as shown in Figure 1. In Figure 1, you are the subject vehicle (vehicle S). You **must** change lanes to continue on the freeway. You are surrounded by up to 4 vehicles (vehicles **A, B, C,** and **D**).

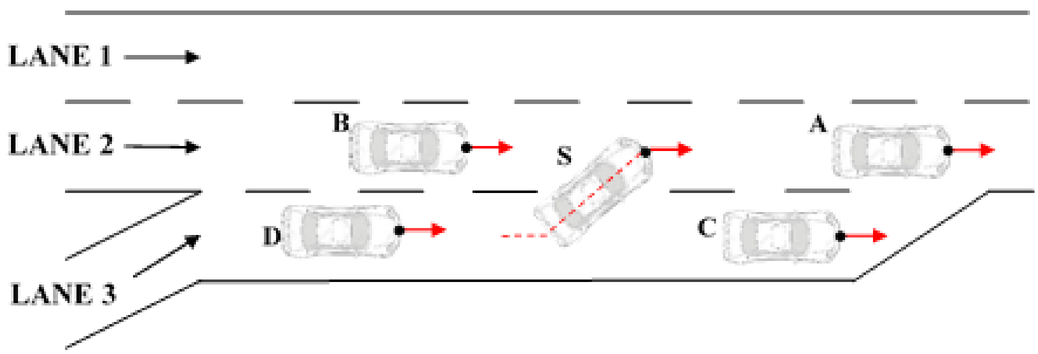

Figure 1. Changing lanes to enter a freeway.

Another scenario is that you are currently on a two-lane freeway, as shown in Figure 2. In Figure 2, you are the subject vehicle (vehicle S). You **must** change lanes to exit the freeway; otherwise, you will miss your exit. You are surrounded by up to 4 vehicles (vehicles **A, B, C,** and **D**).

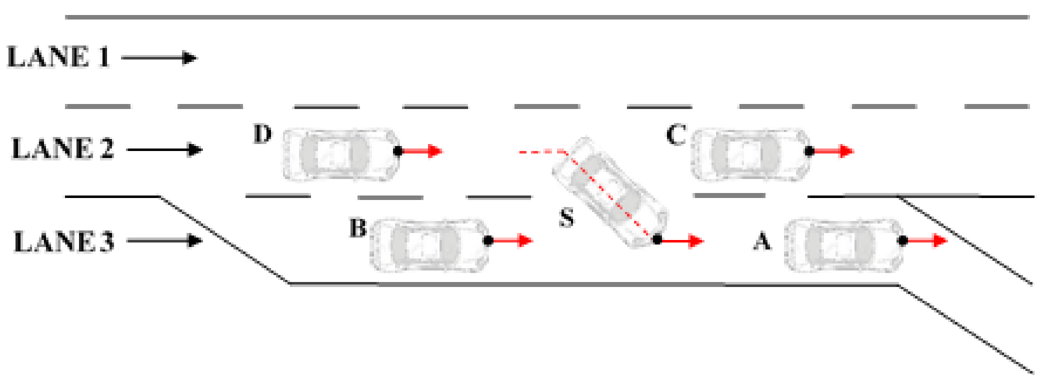

Figure 2. Changing lanes to exit a freeway.

Part 1 – Safety Checks (Please circle 1 answer per question)

1 - When you want to move from lane **3** to lane **2** (in Figure 1) or from lane **2** to lane **3** (in Figure 2), how often do you check the *distance* between your vehicle (S) and vehicle **A**?

- **a-** All the time
- **b-** Most of the time
- **c-** Sometimes
- **d-** Seldom
- **e-** Never

2 - When you want to move from lane **3** to lane **2** (in Figure 1) or from lane **2** to lane **3** (in Figure 2), how often do you check the *distance* between your vehicle (S) and vehicle **B**?

- **a-** All the time
- **b-** Most of the time
- **c-** Sometimes
- **d-** Seldom
- **e-** Never

3 - When you want to move from lane **3** to lane **2** (in Figure 1) or from lane **2** to lane **3** (in Figure 2), how often do you check the *distance* between your vehicle (S) and vehicle **C**?

- **a-** All the time
- **b-** Most of the time
- **c-** Sometimes
- **d-** Seldom
- **e-** Never

4 - When you want to move from lane **3** to lane **2** (in Figure 1) or from lane **2** to lane **3** (in Figure 2), how often do you check the *distance* between your vehicle (S) and vehicle **D**?

- **a-** All the time
- **b-** Most of the time
- **c-** Sometimes
- **d-** Seldom
- **e-** Never

5 - When you want to move from lane **3** to lane **2** (in Figure 1) or from lane **2** to lane **3** (in Figure 2), how often do you check the *distance* between vehicle **A** and vehicle **B**?

- **a-** All the time
- **b-** Most of the time
- **c-** Sometimes
- **d-** Seldom
- **e-** Never

6 - When you want to move from lane **3** to lane **2** (in Figure 1) or from lane **2** to lane **3** (in Figure 2), how often do you check the *speed* of your vehicle (S)?

- **a-** All the time
- **b-** Most of the time
- **c-** Sometimes
- **d-** Seldom
- **e-** Never

It is written in the Texas Driver's Handbook that

> **"A good driver always keeps a safe distance from the car in front of him/her. A good rule is to stay at least 2 to 4 seconds behind the vehicle ahead of you."**

Other states also have a similar guideline.

7 - How often do you check this *time* (**2** to **4** seconds) between your vehicle (S) and vehicle **C** before changing lanes?

- **a-** All the time
- **b-** Most of the time
- **c-** Sometimes
- **d-** Seldom
- **e-** Never

8 - How often do you check this *time* (**2** to **4** seconds) between your vehicle (S) and vehicle **D** before changing lanes?

- **a-** All the time
- **b-** Most of the time
- **c-** Sometimes
- **d-** Seldom
- **e-** Never

9 - How often do you check this *time* (**2** to **4** seconds) between your vehicle (S) and vehicle **A** after changing lanes?

- **a-** All the time
- **b-** Most of the time
- **c-** Sometimes
- **d-** Seldom
- **e-** Never

10 - How often do you check this *time* (**2** to **4** seconds) between your vehicle (**S**) and vehicle **B** after changing lanes?

a- All the time
b- Most of the time
c- Sometimes
d- Seldom
e- Never

Part 2 – About yourself

11 - Please tell us your age: ______ years

12 - Please circle your gender: Male / Female

13 - Year when you first received your driver's license (e.g. 2012): ________

14 - What type of vehicle do you drive most often? (Please circle only 1 answer)

a- Sedan
b- SUV
c- Van
d- Pickup Truck
e- Other (please specify):____________________

15 - How often do you drive on a highway or freeway? (Please circle only 1 answer)

a- Everyday
b- Almost every day (4-6 times a week)
c- Sometimes (1-3 times a week)
d- Seldom (less than once a week)
e- Never

End of survey. Thank you!

VITA

Matthew Vechione was born and raised in El Paso, Texas. He received his Bachelor of Science in Civil Engineering degree (with cum laude honors) from the University of Texas at Tyler (UT Tyler) in 2014, where he was also a student athlete on the men's tennis team for four years. He is an Engineer-in-Training (EIT) and worked for two years after graduation at Moreno Cardenas Inc. in El Paso as a project engineer.

He began seeking his doctoral degree in civil engineering in 2016 at The University of Texas at El Paso (UTEP), where he worked for one year as a teaching assistant. Since then, he has traveled to Guadalajara, Mexico for a study abroad course on Smart Cities; has been working as a research assistant under the direction of Dr. Ruey (Kelvin) Cheu in the Border Intermodal Gateway (BIG) Transportation Lab; and served as President of the Institute of Transportation Engineers (ITE) student chapter at UTEP for two years. He has given poster and panel presentations at state and international conferences, and has received multiple fellowships and awards from both UTEP and external sources. He has two papers regarding his research on lane changing, both of which were published in June 2018.

During the spring 2019 semester, Matthew has been a lecturer at his alma mater, UT Tyler, in the Department of Civil and Environmental Engineering teaching two courses while finalizing his dissertation. After graduating with his doctoral degree in May 2019, Matthew will continue his academic career at UT Tyler as an Assistant Professor in the Department of Civil and Environmental Engineering. His research interests include lane changing behavior, artificial intelligence, smart cities, intelligent transportation systems, and infrastructure security.

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