# DEVELOPMENT OF LANE CHANGING DECISION MODEL FOR HETEROGENEOUS TRAFFIC OPERATION USING ADAPTIVE NEURO-FUZZY INTERFACE SYSTEM (ANFIS)

By

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# Development of Lane Changing Decision Model for Heterogeneous Traffic Operation Using Adaptive Neuro-Fuzzy Interface System (ANFIS)

BY
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A Thesis Submitted to the Department of Civil Engineering, Bangladesh University of Engineering and Technology, Dhaka, in partial fulfillment of the requirements for the degree of

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The thesis titled "**Development of Lane Changing Decision Model for Heterogeneous Traffic Operation Using Adaptive Neuro-Fuzzy Interface System (ANFIS)**", submitted by **Sudipta Sarkar**, Roll No: 040304436P, Session: April 2003, has been accepted as satisfactory, in partial fulfillment of the requirements for the degree of **Master of Science in Civil Engineering (Transportation).**

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# DECLARATION

I hereby declare that this thesis or any part of it has been submitted elsewhere for the award of any degree or diploma.

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*Development of Lane Changing Decision Model for Heterogeneous Traffic Operation using Adaptive Neuro-Fuzzy Interface System (ANFIS)*

# ABSTRACT

Lane-changing behavior models are important components of microscopic traffic simulation tools. Particularly, heterogeneity of traffic can significantly affect lane-changing behavior. The objective of this thesis is to analyze lane changing factors and related decision making sequences to develop a framework for modeling the lane-changing behavior in local traffic scenario. The intention is to provide an improved lane-changing model with a generalized and flexible structure that will be capable of providing the lane-changing behaviors of drivers in differing situations. The proposed model is generalized to overcome to a certain extent the limitations of the existing lane-changing models and fill the present gap in this arena. It is also intended to provide means to train and validate the model parameters using local traffic and behavioral data and also for cross-checking and calibration facilities. The proposed model is built using the Adaptive Neuro-Fuzzy Interface System (ANFIS).

Various membership functions of lane changing parameters were documented. Assignment of membership values for each class was done such that the obtained output gave a realistic measure of the likely outcome of different factor combinations to reflect truly as much as practicable driver level decision towards lateral movement while moving in a powered-nonpowered mix traffic stream. To train the ANFIS model the field data acquisition method was also highlighted which used varbalisation technique to quantify driver's intention towards lateral movement. Using series of input/output data set, the model constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) in combination of a least squares type of method and a backpropagation algorithm. This allows fuzzy systems to learn from the data they are modeling. In this regard, the validation, checking and calibration methodologies are also discussed. This model could be used as an embedded tool for traffic simulation software, particularly to mimic lane changing behavior utilizing local data. This model could also be used for the estimation of risks particularly for road accidents relating to lane change and also for assessing the relationships among lane change maneuvers, traffic delay and congestion phenomena.

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# CHAPTER 1

# INTRODUCTION

## 1.1 Background

In recent years, transportation is one of the emerging issues facing the cities of developing countries. Traffic congestion on urban roads is forcing city authorities to look at innovative transportation solutions. On the other hand, road accident problems in national highway are also considered as a serious problem. New road construction is no longer seen as the only solution, due to financial constraints, lack of space and environmental impacts. Transportation engineering is continually changing with an increasing emphasis on applying computers and advanced technology in order to provide solutions for maximizing the capacity of transportation networks. There is an increasing need for improved techniques for assessing traffic flow and for the appraisal of transportation projects in light of funding constraints. Advances in computer technology have provided platforms for the development of powerful microscopic simulation software, which are increasingly being used for analyzing traffic flow.

Microscopic Models are now widely accepted as providing the most appropriate analytical tool for understanding traffic capacity problems and for assessing the effectiveness of ameliorative measures. These Models can be used for a number of transportation applications, including highway and intersection design and traffic impact studies. These types of models permit the evaluation of complex driver/vehicle/network interactions that cannot be adequately quantified using analytical techniques. Conversely, research may be directed to develop key components for use within simulation models.

Lane-changing behavior models are important components of these microscopic traffic simulation tools. Lane-changing behavior can be influenced by numerous factors including lane-configurations and access control measures. Particularly, presence of non-motorized vehicles can significantly affect lane-changing behavior. This thesis presents a driver's lane-changing decision making model that has a generalized flexible structure and is applicable in all situations, including presence of non-motorized vehicles.

This chapter first presents an overview of the patterns of congestion and safety problem and the contribution of lane changing decision models in these aspects. The motivation for this research is then presented which is followed by the research objectives and the outline of the rest of the thesis.

## 1.2 Motivation

### 1.2.1 Lane change and traffic delay

One of the riskiest maneuvers that a driver has to perform in a conventional highway traffic flow system is to merge into the traffic and/or to perform a lane changing maneuvers. Lane changing/merging collisions are responsible for one-tenth of all accident-caused traffic delays often resulting in congestion. Traffic delays and congestion, in general, increase travel time and have a negative economic impact. According to the Urban Mobility Report (TTI, 2004), traffic congestion has resulted in a monetary loss of 3.5 billion hours of productivity in major US cities alone, incurring a loss equivalent to $63.2 billion in the year 2002. Though vehicle ownership is much lower in the developing countries (38 vehicles per 1,000 inhabitants compared to 585 vehicles per 1,000 inhabitants in Western Europe), the congestion situation is equally bad in most cities of the developing countries and is expected to get worse in future. These concerns make congestion alleviation a major transportation priority.

Considerable effort has been made to study different factors that cause traffic delays. Among these factors, it is suspected that Lane Change Maneuvers (LCMs) could be one source of traffic delays. To understand this conjecture, first let a single LCM be considered during congestion. For a vehicle that changes from origin lane A to destination lane B, it exits from the former and enters the latter. Intuitively, "during very high flow or queued conditions, each entering vehicle would delay the following driver and these delays would propagate upstream" (Coifman, B. et al, 2003). The extent of this influence depends on how fast the resulting disturbance propagates and whether it will dissipate before the end of the queue. On the other hand, each exiting vehicle should make it possible for the following drivers in the origin lane to accelerate and reduce their delays. This disturbance would also propagate upstream. So each LCM is expected to induce two contrary effects, causing delay in the lane the vehicle enters and reducing delay in the lane the vehicle leaves. However, the addition in delay caused by an entering vehicle might be greater than the savings in delay by an exiting vehicle in congested traffic conditions.

On congested freeway segments, if a vehicle forces its way into lane B from lane A, the vehicle that will be following the vehicle in lane B has to decelerate immediately to avoid collision; this deceleration is mandatory. However, the following vehicle in lane A does not necessarily have to accelerate immediately and take the advantage of the larger gap left by the vehicle; the acceleration is discretionary. In addition to this imbalance in the effects of entering and exiting vehicle on traffic delay, there are also likely transient effects arising from the fact that the vehicle will simultaneously occupy two lanes during the process of changing lanes, momentarily decreasing the capacity of the road link. This latter feature becomes particularly important near area of bottlenecks, potentially reducing throughput.

Traffic congestion can be viewed as an imbalance of supply and demand. Typically, traffic congestion mitigation measures have therefore been classified as either supply based or demand based approaches. The recent trend, however is to integrate both approaches and implement strategies that seek to induce demand adjustments through supply-based actions. These include Advanced Traffic Management Systems (ATMS), Advanced Traveler Information Systems (ATIS), Incident Management Systems and Managed Exclusive Lanes (HOV lanes, tolled lanes, reversible and contra-flow roadways, truck-only facilities etc.). These approaches not only make use of the transportation system to the best extent possible and increase the efficiency and reliability of the system, but also contribute to alter the driver behavior in a positive manner. This thesis focuses on driver lane changing decision making models in heterogeneous traffic environment, i.e. traffic streams in which both powered and non-powered vehicles of widely varying dimensional and operational characteristic exist as in the case in cities and towns of developing countries.

### 1.2.2 Lane change and road accident

Very recently a data mining based approach to identify potential lane change related freeway accidents was conducted. Based on the findings from Lee et al. (2006) and an extensive review of accident reports, it was concluded that all sideswipe accidents and angle accidents on inner lanes of the freeway may be attributed to lane changing maneuvers. These accidents were referred to as lane-change related accidents and are analyzed in this study. Based on variable selection procedures based on random as well as within stratum matched data it was concluded that the location specific characteristics do not have a significant effect on occurrence of a lane-change related accident.

Though it does not imply that all locations on the freeway are expected to have similar frequency of these accidents. It means that if locations with certain geometric characteristics experience more lane-change related accidents, these occurrences are better correlated with the traffic conditions existing before these accidents than the geometric characteristics that might be causing the accident prone traffic conditions. It was also noticed that the intensity of lane changes, measured in terms of overall average flow ratio (OAFR), was not significant to separate accidents from non-accident cases. It is interesting because the OAFR was successfully used to classify lane-change related accidents from rear-end accidents by Lee et al. (2006). Obviously those studies reflect the necessity of detailed analysis of lane changing decision making process for examining relationships between accidents and lateral movement of vehicles.

## 1.3 Place of Lane Change Model in Traffic Simulation Model

Simulation modeling is an increasingly popular and effective tool for analyzing a wide variety of dynamical problems which are not amenable to study by other means. These problems are usually associated with complex processes which can not readily be described in analytical terms. Usually, these processes are characterized by the interaction of many system components or entities. Often, the behavior of each entity and the interaction of a limited number of entities may be well understood and can be reliably represented logically and mathematically with acceptable confidence. However, the complex, simultaneous interactions of many system components cannot, in general, be adequately described in mathematical or logical forms.

Simulation models are designed to "mimic" the behavior of such systems. Properly designed models integrate these separate entity behaviors and interactions to produce a detailed, quantitative description of system performance. Specifically, simulation models are mathematical/logical representations (or abstractions) of real-world system, which take the form of software executed on a digital computer in an experimental fashion.

Micro-simulation models employ several sub-models, analytical relationships, and logic to model traffic flow. Detailed descriptions of each sub-model are beyond the scope of this research. Basically Simulation models include algorithms and logic to:

- Generate vehicles into the system to be simulated.
- Move vehicles into the system.
- Model vehicle interactions.

Vehicle Generation module generates vehicle into the traffic stream. At the beginning of the simulation run, the system is empty. Vehicles are generated at the entry nodes of the analytical network, based on the input volumes and an assumed headway distribution. When a vehicle is generated at the entry of the network, the simulation model assigns driver-vehicle characteristics. The following characteristics or attributes are commonly generated for each driver-vehicle unit:

Vehicle Type (car, bus, truck), length, width, maximum acceleration and deceleration, maximum speed, maximum turn radius, etc. Driver: Driver aggressiveness, reaction time, desired speed, critical gaps (for lane changing, merging, crossing), destination (route), etc. However different models may employ additional attributes for each driver-vehicle unit to ensure that the model replicates real-world conditions. Each attribute may be represented in the model by constants, functional relationships, or probability distributions. Most micro-simulation models employ statistical distributions to represent the driver-vehicle attributes. The statistical distributions employed to represent the variability of the driver-vehicle attributes and their parameters must be calibrated to reflect local conditions.

Vehicle movement module describes the process for simulating vehicle movement and how it is impacted by the physical environment. The physical environment -- the transportation network under study -- is typically represented as a network of links and nodes. Links are one-way roadways with fixed design characteristics and nodes that represent intersections or locations where the design characteristics of the links change. Simulation models have different limits on the network size (maximum number of links and nodes). Vehicles, in the absence of impedance from other vehicles, travel at their desired speed on the network links. However, their speed may be affected by the link-specified geometry (horizontal and vertical alignment), pavement conditions, and other factors. For example, the simulation model computes the actual vehicle speed as the minimum value from the desired speed and the speed computed for the specified vertical and horizontal alignment. However, not all microsimulation tools model the sensitivity of vehicle speeds to link design characteristics.

Microscopic models simulate the interactions of individual vehicles as they travel in the analytical network using car-following, lane-changing, and queue discharge algorithms. The modeling of lane changing is based on the gap-acceptance process. A vehicle may change lanes if the available gap in the target lane is greater than its critical gap. The model's lane-changing logic and parameters have important implications for traffic performance, especially for freeway merging and weaving areas.

## 1.4 Scope of the Research

Microscopic traffic simulation tools, which analyze traffic phenomena through explicit and detailed representation of the behavior of individual drivers and mimic the real world traffic situations, are ideal tools to analyze and experiment. Driving behavior models are an important component of such microscopic traffic simulation tools. These models include speed/acceleration models, which describe the movement of the vehicle in the longitudinal direction, lane-changing models, which describe drivers' lane selection and gap acceptance behaviors, etc.

The traffic movement in Bangladesh and in other developing countries is rendered more complex due to the heterogeneous characteristics of the traffic stream using the same right of way. The stream includes slow pushcarts at one extreme and the fast moving passenger cars at the other, with many intermediate types of vehicles depicting a wide variation in static and dynamic characteristics. As in mixed traffic operation no single vehicle clearly dominates the traffic stream, prediction of saturation flow is more sensitive to the vehicle mix than in western countries where traffic is largely motorized. Moreover, because of increasing number of vehicles on Bangladeshi roads and the lag in road construction, attention is to be given to traffic operation and control measures to make the most efficient use of existing road systems.

Another distinguishing feature of the traffic under study is driving behavior and specially the lack of lane discipline. In mixed traffic condition, traffic usually does not use lanes in an appropriate manner. Furthermore, lane markings on pavements along the road and near approaches are often not clear or are missing. If they exist, drivers rarely conform to them. Due to this lack of lane-discipline, the vehicles can occupy any position across the road and from a vehicle movement with no clear pattern as seen in lane-based western cities' traffic and hence the lane-based analysis breaks down.

The state-of-the-art driving behavior models do not have the capability to accommodate these special types of lane-changing behavior and hence the associated microscopic simulation tools are somehow not applicable in the analysis of mixed traffic environments.

Thus, there is a need to develop more realistic lane-changing decision models that can capture the complexity of the lane-changing process in presence of non-motorized vehicles.

### 1.5 Objectives

The purpose of this thesis is to analyze lane changing factors and decision making sequences to develop a framework for modeling the lane-changing behavior in presence of non motorized vehicles. The improved lane-changing model should have a generalized and flexible structure that is capable of capturing the lane-changing behavior in all other situations. The generalized model should overcome the limitations of the existing lane-changing models and fill the present gap in this arena. It also intended to provide means to train and validate the model parameters using local traffic and behavioral data and cross-checking and calibration facilities. Specific objectives of this research are to:

- Documenting various lane changing factors and options
- Development of a lane changing decision model in presence of heterogeneous traffic
- Formulation of calibration and validation framework for the proposed model

### 1.6 Thesis Outline

The remainder of this thesis is organized in six chapters. In Chapter 2, a literature review on research related to driver behavior and exiting lane choice models is presented. Chapter 3 presents the framework and structure of the proposed lane-changing model. Chapter 4 provides data collection procedures for model training and validation. The validation and calibration methodology developed for the model and the available data for that purpose is described in Chapter 5. The estimation results are presented in Chapter 6 followed by the calibration and validation results of the model. Finally, conclusions and directions for further research are also summarized in Chapter 7.

# CHAPTER 2

## LITERATURE REVIEW

### 2.1 Introduction

Engineers and behavioral scientists have been working together for over 50 years to understand and design efficient man-machine systems. Their research has helped transportation engineers to understand how human beings (as vehicle operators, passengers, or pedestrians) interact with vehicles and the transportation facilities they use (Shinar, 1978). The Research work modeling Driver's lane-changing behavior and associated decision include the branch of human factor in traffic engineering. Some research work related to this subject has been reviewed in this chapter. The relevant models for lane change process are discussed in this chapter along with their limitations.

### 2.2 Behavioral Research in Transportation Engineering

Behavioral research in transportation actually started in the early 1960's with the study of travel patterns, rooted in geography and engineering, aiming to find ways to spatially represent the movement of individuals and vehicles (Hensher and King, 2001). Soon after the economists entered the picture and research was focused around the Random Utility Theory. Due to a strong concern, started in the late 1970's, that the random utility paradigm does not represent the decision rules which are being used in actual travel-related choices, psychologists and sociologists offered the rules-based paradigm as an alternative. This paradigm opened up, in the early 1990's and on, opportunities to reflect the activity-based decision-making process, as developed for example, by Axhausen and Garling (1992), and Ettema and Timmermans (1997) in Europe, and by Bowman and Ben-Akiva (1997) in the U.S. During the 1990's the Differentiation and Consolidation Theory (DCT) presented by Svenson (1990), the Decision Field theory (DFT) developed in psychology by Busemeyer and Townsend (1993) and further elaborated in the transportation context by Stern (1998), and the reintroduction of the Attitude Theory by Garling et al. (1998), offered illuminating insights into the decision making process and advocated process-oriented approaches to the study of travel and driving behavior. Based on the recently published volume entitled: "Travel Behaviour Research – The Leading Edge" (Hensher, 2001), the process-oriented approach is leading the edge. It is within this framework that the European and the U.S. behavioral driving research will be surveyed.

Behavioral research in transportation is aimed to further our understanding of both travel and driving behavior. A better understanding of travel behavior will improve travel demand forecasting and the assessment of emerging transport policies, and a better understanding of driving behavior will improve our means to increase road safety. A process-oriented framework describes a series of dependencies leading from the needs and motives to travel, through travel constraints which affect a following stage of decision making. The decision making is the core of the process.

It is universal enough to provide the cognitive explanatory mechanism for a wide range of transport-related responses and/or behaviors as presented in Figure 2.1. These responses compose the various facets of both travel demand and travel/driving safety. The framework classifies these responses to six types of behaviors, ranging from the least to the most frequently practiced, as following:

- Life style behavior is the least frequently practiced response to a sever transport constraint such as, for example, a heavy recurrent congestion. It involves (in a decreasing order) a change in the individual's work load, the start of a home business and least frequently practiced, retirement. It implies the largest reduction in driving time for the individual.
- Location behavior is also a possible response to travel constraint such as congestion, and/or personal and situational constraints such as lack of public transport services, age or health limitations. It mainly concerns with changing the place of residence, work, or school. There is empirical evidence to both lifestyle and location behaviors (e.g. Mokhtarian, Raney and Salomon, 1997;

and Stern, 1998) which reflect a spatio-temporal reorganization of space and time.

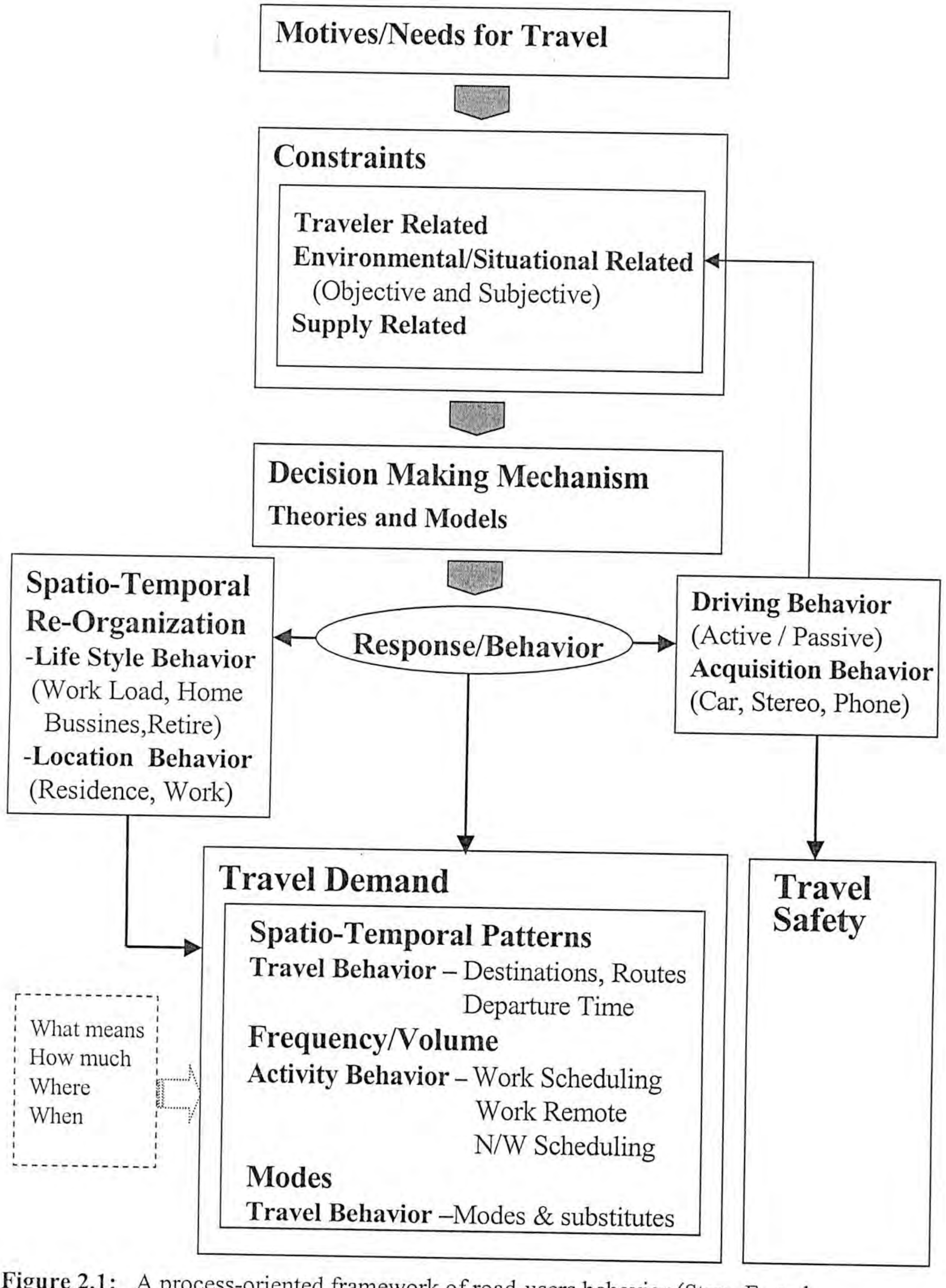



**Figure 2.1:** A process-oriented framework of road-users behavior (Stern, E., and Richardson, H. W. , 2006)

- Activity behavior refers to the change of ones daily schedule of either work or non-work activities (e.g. Stern, 1996, 2002a) as a response to non-recurrent travel constraints, either traveler or situational related. It usually changes the frequency and the volume of traffic when forecasting travel demand is concerned.

- Travel behavior includes the various choices facing the driver as regard to the choice of destination, route, departure time, and mode, including substitutes to travel (e.g. the use of telecommunication options). Both activity and travel behaviors constitute the major part of travel demand. They reflect the spatio-temporal patterns and the volumes of the various modes.

- Driving behavior actually deals with the individual's motoricity and overall actions while driving. These are responses to traveler, environmental, and situational constraints, both objective and subjectively perceived. They directly affect travel safety, but they also affect, in a dynamic way, the momentary situation on the road which may, in turn, affect the individual's decision making.

- Acquisition behavior is the most practiced reaction to traffic delays and is highly affected by traveler related characteristics (e.g. Mokhtarian et al., 1997). It concerns with the acquisition of a better car (more comfortable and better suites long trips, safer, etc.), a good stereo system (less boring while queuing), or a phone (better use of time, reduce road safety, etc.). It also affects both road safety and the momentary situation on the road.

## 2.3 Decision Making Mechanisms

Although enormous efforts were devoted by behavioral scientist over the past decades to study decision making, the efforts of transport researchers in this area remain sparse (e.g. Polak, 1998). Behavioral Decision Theory (BDT) has almost never been applied in a formal analysis or model of travel choice. Some advancement was made by Garling, Laitila and Westin who organized in 1996, in Stockholm, a conference on Theoretical Foundations of Travel Choice Modeling (Garling et al., 1998a). It was an effort to compare, internationally, the relevance of microeconomics theory, the BDT and the statistical theory to travel choice modeling. A single effort to apply BDT to travel choice was made in this conference by Stern (1998) who tried to apply Decision Field theory (Busemeyer and Townsend, 1993) to choices made by road users facing congestion. Few other efforts include production-system modeling of activity scheduling studied by Ettema et al. (1993, 1997) and by Garling et al. (1989, 1998b).

One of the major contributions of psychology to travel behavior research is the Differentiation and Consolidation (Diff Con) Theory developed by the Swedish psychologist Svenson (1992). According to the theory, the goal of a decision process is to create an alternative that is sufficiently superior in comparison to its competitors through restructuring and application of one rule only, but from a number of different rules contingent on the situation and the person. This process is named differentiation. The corresponding post-decision process in support of the chosen alternative is called consolidation. Basically it is a structural framework which illustrates how habit, general evaluation, outcome involvement, norm involvement, and ego involvement affect the decision process, the intention to implement and actual implementation of the decision. It thus calls to incorporate cultural and societal norms into the decision making process. Svenson outlines how Diff Con Theory might potentially be applied to modeling mode and other travel choices as a multi-level and multi-regime decision processes. Since behavioral decision theory has primarily been developed for describing and understanding human decision making, the main purpose has not been to predict behavior. Therefore, even the Diff Con Theory pays little attention to the cognitive and psychological processes leading the road user to a certain decision.

An important step in this direction could be better made through a process-oriented approach. This approach is explicitly concerned with how the decisions are made, as well as which decisions are made. One interesting effort in this direction was presented in a recent conference on wayfinding behavior in which American and European psychologists and geographers discussed the role of cognitive mapping in spatial navigation (see, Golledge, 1999). One of the contributions presented two complementary conceptual frameworks that explain the dynamics and high variability of persons navigating in the urban environment (Stern and Portugali, 1999). The navigation is simulated through the abovementioned Decision Field Theory (DFT) within which environmental cognition is interpreted through the concept of the inter-representational network (IRN) as developed by Portugali (1996), and Haken and

Portugali (1996). According to the IRN, a given cognitive network to interpret the navigation process is composed of elements in the mind, representing external environments, and elements in the environment, representing the mind. Urban navigation can be seen as a synergistic interplay between external and internal inputs and outputs, ordered by one or a few order parameters, which evolve in the process and enslave the interacting representational subsystems. The IRN suggests how cognitive maps, which are the basis of decision making are created, and the DFT explains the process of the decision making itself.

The Decision field theory (DFT) developed by Busemeyer and Townsend (1993), is a synthesis of two prior and independent psychological theories: approach-avoidance theories of motivation, and information-processing theories of choice response time. The theory is aimed at understanding the motivational and cognitive mechanisms that guide a deliberation process involved in making decisions under uncertainty. It integrates both information coming from the external environment and other information coming from the individual's associative memory as determinants of possible actions to be evaluated in a deliberation process. Deliberation is a time-consuming cognitive process that involves information seeking about the consequences (i.e., Events, Ei) of recognizable actions Ai, weighting of the pay-offs (Yi) of the events, and comparing the weighted consequences to establish a preference (choice) state. Several exogenous variables are assumed to affect the choice process and a threshold. In psychological theory, the threshold is expressed by an inhibitory criterion presenting a given value of a preference state. In a travel-related situation the threshold could be defined, or expressed, by actual and/or expected delay time. The result of one deliberation cycle is a momentary preference state which is chosen only when it reaches a threshold. Until then, vacillation is observed, thus activating another deliberation cycle. The smaller the distance between the preference state and the threshold, the smaller is the number of deliberation cycles.

Several empirical studies have already tested the meaning of deliberation (e.g. by the "rational relocator" which explains the "commuting paradox", Gordon, Richardson and Jun, 1991) and the effects of exogenous variables like time pressure, situation, and personality attributes on both the deliberation process and the threshold (Stern, 1999, 2001, 2002a, 2002b). Two major studies are still needed before quantification and practical modeling could proceed. First is a study aimed to find what factors govern the size and content of the individuals' associative memory; what, how much, and in which order he or she retrieve the information from that memory. Further, how these factors relate to the number of practiced comparisons? The second study must deal with the problem of using models with personality characteristics. From a practical viewpoint, personality characteristics are hard to gather and predict. The problem of using models with personality variables may be solvable if people can be classified into a small number of personality classes which can be assessed by a manageable number of attitudinal statements (see for example, Prevedouros, 1992). Such a study is therefore a must before we can proceed to quantification and modeling.

It is not, however, only these studies. As the Swiss psychologist Huguenin (1997) concluded, "Understanding the complexity of road-user behavior remains at the forefront of the problems which must be solved before useful models can be created". Therefore, the various studies on driving behavior range from empirically insufficiently comprehensible meta-theories to laboratory-tested models concerning certain aspects of the overall behavior of the driver. It still seems that none of these studies have dealt with the "source" of behavior – the cognitive mechanism behind the process of decision making.

## 2.4 Review of Some Exiting Driver's Lane Changing Model

The first lane-changing model intended for micro-simulation tools was introduced by Gipps (1986). The model considers the necessity, desirability and safety of lane-changes. Drivers' behavior is governed by two basic considerations: maintaining a desired speed and being in the correct lane for an intended turning maneuver. The distance to the intended turn defines which zone the driver is in and which of the considerations are active. When the turn is far away it has no effect on the behavior and the driver concentrates on maintaining a desired speed. In the middle zone, lane-changes will only be considered to the turning lanes or lanes that are adjacent to them. Close to the turn, the driver focuses on keeping the correct lane and ignores other considerations. The zones are defined deterministically, ignoring variation between drivers and inconsistencies in the behavior of a driver over time. When more then one lane is acceptable the conflict is resolved deterministically by a priority system considering locations of obstructions, presence of heavy vehicles and potential speed gain. No framework for rigor estimation of the model's parameters was proposed.

Several micro-simulators implement lane-changing behaviors based on Gipps' model. In CORSIM (Halati et al 1997, FHWA 1998) lane-changes are classified as either mandatory (MLC) or discretionary (DLC). MLC are performed when the driver must leave the current lane (e.g. in order to use an off-ramp or avoid a lane blockage). DLC are performed when the driver perceives that driving conditions in the target lane are better, but a lane-change is not required.

Yang and Koutsopoulos (1996) implemented a rule based lane-changing model in MITSIM where lane changes are classified as MLC and DLC. Drivers perform MLC to connect to the next link on their path, bypass a downstream lane blockage, obey lane-use regulations and respond to lane-use signs and variable message signs. Conflicting goals are resolved probabilistically using utility maximization models. DLC are considered when the speed of the leader is below a desired speed. The driver then checks the opportunity to increase speed by moving to a neighbor lane.

A similar approach is adapted in SITRAS (Hidas and Behbahanizadeh, 1998) where downstream turning movements and lane blockages may trigger either MLC or DLC, depending on the distance to the point where the lane-change must be completed. In this model, MLC are also performed in order to obey lane-use regulations. DLC are performed in an attempt to obtain speed or queue advantage, defined as the adjacent lane allowing faster traveling speed or having a shorter queue.

Ahmed et al (1996) and Ahmed (1999) developed and estimated the parameters of a lane-changing model that captures both MLC and DLC situations. A discrete choice framework is used to model three lane-changing steps: decision to consider a lane-change, choice of a target lane and acceptance of gaps in the target lane. The model framework is presented in Figure 2.2. When an MLC situation applies, the decision whether or not to respond to it depends on the time delay since the MLC situation arose. DLC is considered when MLC conditions do not apply or the driver chooses not to respond to them. The driver's satisfaction with conditions in the current lane depends on the difference between the current and desired speeds. The model also captures differences in the behavior of heavy vehicles and the effect of the presence of a tailgating vehicle. If the driver is not satisfied with driving conditions in the current lane, neighboring lanes are compared to the current one and the driver selects a target lane. Lane utilities are affected by the speeds of the lead and lag vehicles in these lanes relative to the current and desired speeds of the subject vehicle. A gap acceptance model is used to represent the execution of lane-changes.

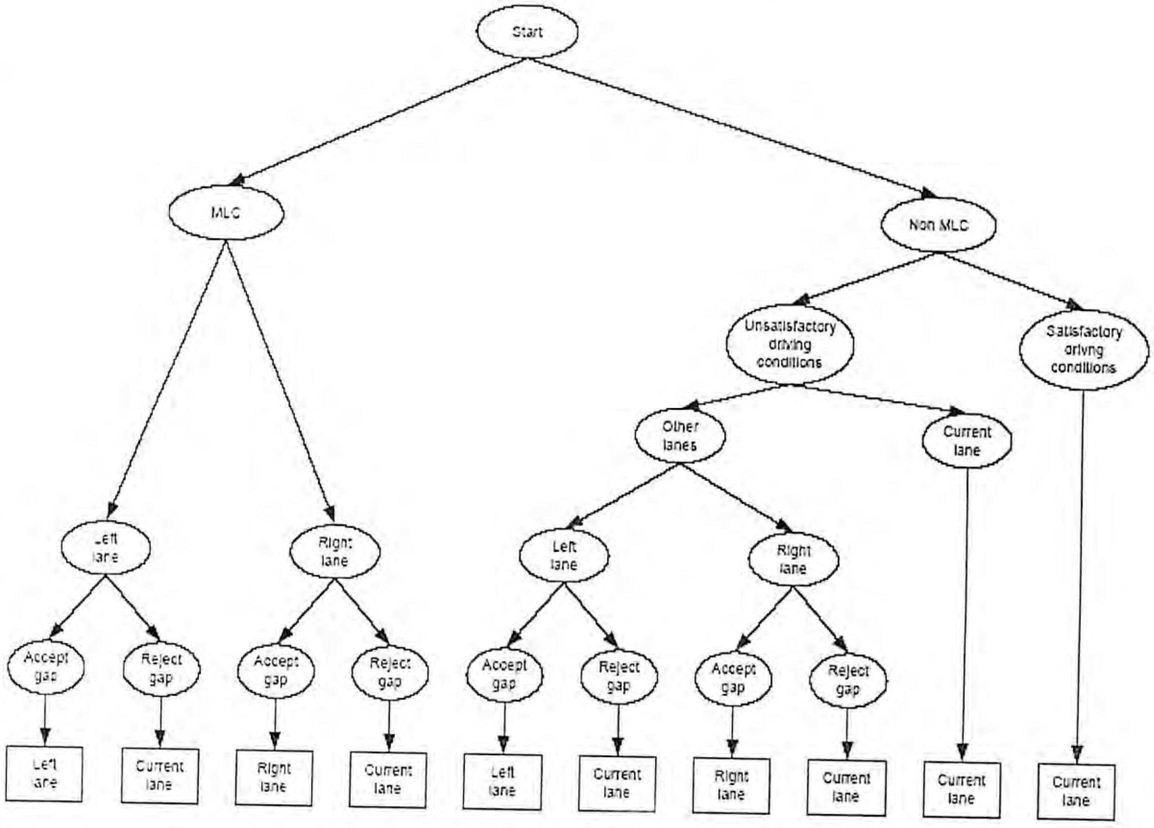



**Figure 2.2** : Structure of the Lane-changing Model Proposed by Ahmed (1999)

Ahmed estimated the parameters of this model using second-by-second vehicle trajectory data. The model however does not explain the conditions that trigger MLC situations. The parameters of the MLC and DLC components of the model were estimated separately. The MLC model was estimated for the special case of vehicles merging to a freeway, under the assumption that all vehicles are in MLC state. Gap acceptance models were estimated jointly with the target lane model in each case.

Wei et al (2000) developed a model for drivers' lane selection when turning into two-lane urban arterials. The model captured the effect of the driver's path plan on the lane choice. A set of deterministic lane selection rules were identified based on observations made in Kansas City.

Toledo (2003) developed an integrated lane-changing or lane shift model that allows joint evaluation of mandatory and discretionary considerations. In this model, the relative importance of MLC and DLC considerations vary depending on explanatory variables such as the distance to the off-ramp. This way the awareness to the MLC situation is more realistically represented as a continuously increasing function rather than a step function. The model consists of two levels: choice of a lane shift and gap acceptance decisions. The structure of the model is shown in Figure 2.3.

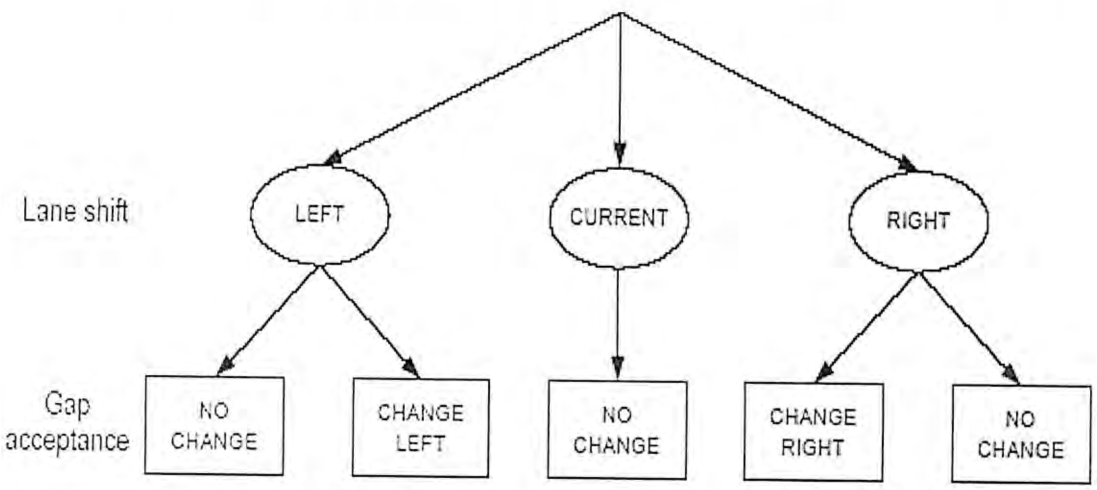



**Figure 2.3** : Structure of the lane-changing model proposed by Toledo(2003)

The first step in the decision process is latent since the target lane choice is unobservable and only the driver's lane-changing actions are observed. Latent choices are shown as ovals, observed ones are shown as rectangles. At any particular instance, the driver has the option of selecting to stay in the current lane or opting to move to an adjacent lane. The CURRENT branch corresponds to a situation in which the driver decides not to pursue a lane-change. In the RIGHT and LEFT branches, the driver perceives that moving to these lanes, respectively, would improve his condition in terms of speed and path plan. In these cases, the driver evaluates the adjacent gap in the target lane and decides whether the lane-change can be executed or not. The lane-change is executed (CHANGE RIGHT or CHANGE LEFT) only if the driver perceives that the gap is acceptable, otherwise the driver does not execute the lane-change (NO CHANGE). This decision process is repeated at every time step.

Explanatory variables in Toledo's model include neighborhood variables, path plan variables, network knowledge and experience, and driving style and capabilities. Information about the driver's style and characteristics is however not available and is captured by introducing individual specific error terms.

## 2.5 Fuzzy Logic and Neural Network Application in Transport Choice Model

The choice models developed in the last decade can be grouped into

- those labeled as **Black Box models**,
- those simulating choice according to neural **network models**,
- those known as **production rule models**, and
- those **models based on Fuzzy Set Theory**.

As summarized by Stern (1998), most conventional models are based on a utility paradigm which follows a utility maximization principle. Apart from some of their unrealistic assumptions, one of the main weaknesses of the discrete-choice models is their inability to capture many aspects of ambiguity, randomness, and uncertainty through a single random error term. The behavioral validity of the utility-maximization framework as a description of how people make decisions has continuously been questioned (e.g. Garling, 1998) and evidence from cognitive psychology (e.g. Payne et al., 1993) suggests that people apply a large range of heuristic and strategies when facing choice tasks. Moreover, the introduction of the choice mechanism in the models was incomplete and could not deal with this weakness.

Garling et al. (1994) claim that these models tend to be confined to the specification of factors that affect the final choice whereas the process resulting in the choice "is largely left unspecified". Therefore, many of the choice situations can be described as a black box (Bovy and Stern, 1990) and does not specify choice rules but only the relationship between input and output variables, not the decision process itself. The more advanced the models, the more they introduce details to explain the interior of the black box. Bovy and Stern (1990) suggested that the content of the black box is a complicated system of filters through which the information is selected and transformed. They determined two types of filters: (1) Perception filter through which the traveler's cognition of alternatives and attributes' values are processed, and (2) Evaluation filter through which the perceptions are transformed into a desirability scale. This approach enables to incorporate changes in the filters under changing realms (or situations) resulting in changes in the mix and relative weight of the attributes (Stern and Krakover, 1993). A somewhat similar black box, referred as 'driver's world', was used by Khattak et al. (1993) who revealed its internal linkages with a joint multinomial logit model, without however considering any underlying psychological process. A more recent study by Raney et al. (2000) in the U.S. also used binary logit models to estimate congestion response strategies as a function of work-family-leisure and travel related attitudes. No behavioral mechanism was used, or assumed.

A relatively new development in travel-related choice behavior was the introduction of artificial neural networks to model driver decisions. This approach was based on the assumption that there is a similarity between the process of driver decision making and the problem solving approach of neural computing (Lyons and Hunt, 1993). In principle, however, the neural network approach remains more representative of real driver decision making than a rule-based model. Rule-based decision models retain certain advantages over the neural network based approach. The operation of a rule-based model enables adjustment of rules to improve the overall performance of the model. The performance of a neural network model can be adjusted only by re-training using alternative data (e.g., Hunt and Lyons, 1995).

At the same time that the neural network approach was introduced, production rule systems emerged in the area of artificial intelligence. Basically it is a means of quantifying, codifying, and distributing expertise and opinion, aimed to develop the possibility for a decision maker to navigate in his/her representation of the environment, and to obtain the information necessary to make the relevant decision. A mathematical framework that captures the uncertainties inherent to human perceptions and the linguistic reasoning associated with human cognitive processes by means of decision rules is the fuzzy set theory. The theory was already introduced 1965 by Zadeh as a general approach to express the uncertainty in human systems. Zadeh (1973) proposed that the decision making process does not use the traditional binary valued logic, but rather a logic of fuzzy perceptions and inference rules based on approximate reasoning. The decision making framework assumes that travelers make their decisions on the basis of simple rules instead of maximizing a utility function. The decisional behavior is, accordingly, described as a series or system of IF, THEN rules. A recent effort to combine the fuzzy set approach with neural network model was presented by Vythoulkas (1994). He utilizes a fuzzy decision framework for modeling and reasoning involved in the decision process, and uses a neural network approach for calibrating the parameters of the fuzzy model. The calibration of a route choice model based on fuzzy sets and approximate reasoning was introduced by Vythoulkas et al. (1994), also through the use of a driving simulator. Similarly, Hunt and Lyons (1995) used a NEURAL DRIVER simulator to collect data for modeling lane and speed change decisions made by a driver. A more recent effort to combine fuzzy sets with microscopic simulation was introduced by Wu, Brackstone and McDonald (2000). All these models still lack a cognitive explanatory mechanism of the choice process, especially in situations where time pressure is a dominant factor.

## 2.6 Summary

There are serious limitations in application of that model to analyze mixed traffic streams. The limitations arise, on the one hand, from the deficiency of the models in handling various non-standard vehicles and behavior and, on the other, from their inability to depict the resultant stream dynamics in sufficient detail.

None of the reviewed studies related the emerging patterns to subjective constraints like perceived space, time, supply attributes, and personal limitations, or further, to cultural differences and societal norms, as possibly hidden in the emerging travel patterns and behaviors. Since the human cognitive mechanism of travel decision making is universal, idiosyncratic situations, cultural and societal norms can affect the individual's perception of constraints which will consequently affect the whole decision making process. It therefore becomes necessary to develop alternative models to overcome the limitations. In order to that, it is worthwhile to implement concept of traffic heterogeneity and issues related to it so as to gain a clear understanding on the subject and form a strong basis for alternative modeling approaches.

# CHAPTER 3

## MODEL DEVELOPMENT

### 3.1 Introduction

It has been stated in the previous Chapter that there are serious limitations in application of traditional lane changing decision models to analyze mixed traffic streams. The limitations arise, on the one hand, from the deficiency of the models in handling various non-standard vehicles and behavior and, on the other, from their inability to depict the resultant stream dynamics in sufficient details. It is therefore becomes necessary to development alternative models to overcome the limitations. In order to that, it is worthwhile to review the whole concept of traffic heterogeneity and related issues related to it so as to gain a clear understanding on the subject and form a strong basis for alternate modeling approaches.

In this chapter the conceptual framework of the proposed lane-changing decision model is presented along with the formulation of the model. The proposed model explicitly introduces the notion of traffic heterogeneity and corresponding factors that affect lane-changing process. This ensures that the model structure is flexible enough to overcome the limitations of the existing myopic lane-changing models.

### 3.2 Consideration of Heterogeneity of Traffic Stream

Knowledge of fundamental traffic flow characteristics—speed, volume and density—and associated analytical techniques are essential requirements in planning, design, and operation of transportation systems. The fundamental characteristics have been studied at microscopic and macroscopic levels. Existing traffic flow models are based on time headway, flow, time–space projectory, speed, distance headway and density. These have lead to the development of a range of analytical techniques: demand–supply analysis, capacity and level of service analysis, traffic stream modeling, shock wave analysis, queuing analysis and simulation modeling.

The focus of the major research has been homogenous traffic conditions—traffic which consists primarily of cars or motorized vehicles of similar characteristics. Situations are now where more than half of the world's population is living in megacities in the developing region. Large differences in income levels and social disparities have lead to the development of 'cities within cities'. Each level of the city, with its own level of technology and land-use patterns, exists in close geographical proximity with other cities of different patterns. This is reflected in the travel and traffic patterns existing in this region.

The same road space gets used by cars and buses, along with locally developed vehicles for public transport such as three-wheeled scooter taxis, scooters and motorcycles, bicycles, tricycle rickshaws, animal and human drawn carts. Infrastructure which is designed on the basis of homogeneous traffic models has failed to fulfill the mobility and safety needs of this traffic. Despite low levels of car ownership, accidents and congestion continue to plague. This is the right time to question the applicability of models which have been developed for a very different situation.

Traffic heterogeneity has been used mainly to describe traffic streams containing significant proportions of the heavier vehicles such as buses and trucks. However, as cited in the previous Chapter, usage of other vehicular forms in the fast streets is becoming more common. Some of the latter vehicles may exhibit extraordinary maneuvers and cause other vehicles to do the same. Detailed discussions on these abnormal maneuvers follow in the next section. Based on their behavioral characteristics and performance capabilities, two broad categories of vehicles can be defined as follows:

- Standard vehicles refer to conventional vehicles such as private passenger cars, minibuses, buses, and light and heavy trucks, which exhibit normal stream flow and queuing behaviors normally assumed in traffic analysis.

- Non-standard vehicles refer to those vehicles which exhibit or cause abnormal stream flow and queuing behaviors. They include motorcycles, scooters, mopeds and bicycles and newly innovated vehicles with similar operational characteristics. The later types of vehicles may be of different sizes, shapes and even names, depending on the country of use and can be motorized or non-motorized with two or more wheels. Examples of such vehicles include auto rickshaws and cycle rickshaws, CNG, tempos are widely used in developing countries.

A more encompassing definition of traffic heterogeneity is therefore necessary to describe flows containing both standard and non-standard vehicles. The definition should cover not only all the various vehicles types including motorized and non-motorized vehicles and taking into account their sizes and performance capabilities, but also the non-conventional behavior associated with some of them. This wider definition has been adopted in this study.

The presence of the heavier vehicles adversely affect the stream performance because they, on the one hand, have poorer acceleration and speed capabilities and hence require more time to maneuver. On the other hand, they also occupy more space and thereby limit the road capacity. Similarly, most non-standard vehicles affect the traffic negatively because of their poorer performance capabilities and non-conventional behavior exhibited or caused by some of them.

The maximum speeds most of these vehicles can achieve are restricted and range from 4 to 6 kph for pedestrian carts, 20 to 30 kph for bicycles and pedal rickshaws and 40-70 kph for motorized two wheeled vehicles like motorcycles and scooters and their three- or more-wheeled derivatives. As a result, there are increased tendencies for lateral movement by faster vehicles attempting to overtake slower ones in mixed streams containing these vehicle types. In order to model heterogeneous traffic then, it becomes imperative to adopt methods that can accommodate their poorer performance capabilities and also the non conventional behavior prevalent in such streams.

## 3.3 Non-Conventional Traffic Behavior

The movement of a vehicle from origin to destination has been characterized as a complex process involving various maneuvers and decisions which can be taken at the strategic, tactical or operational levels (Minderhound, 1999). At the strategically or tactical levels, decisions on route choice may be taken whereas actual maneuvers a vehicle undertakes are considered to be on the operational level.

At that level, the maneuvers a vehicle can undertake as it moves along can be summarized and categorized as shown in Figure 3.1. Longitudinal movement is the primary maneuver as the vehicle travels towards its destination and can involve free flow or car following conditions. The vehicle may also encounter a queue on the way and be delayed until the queue eventually clears.

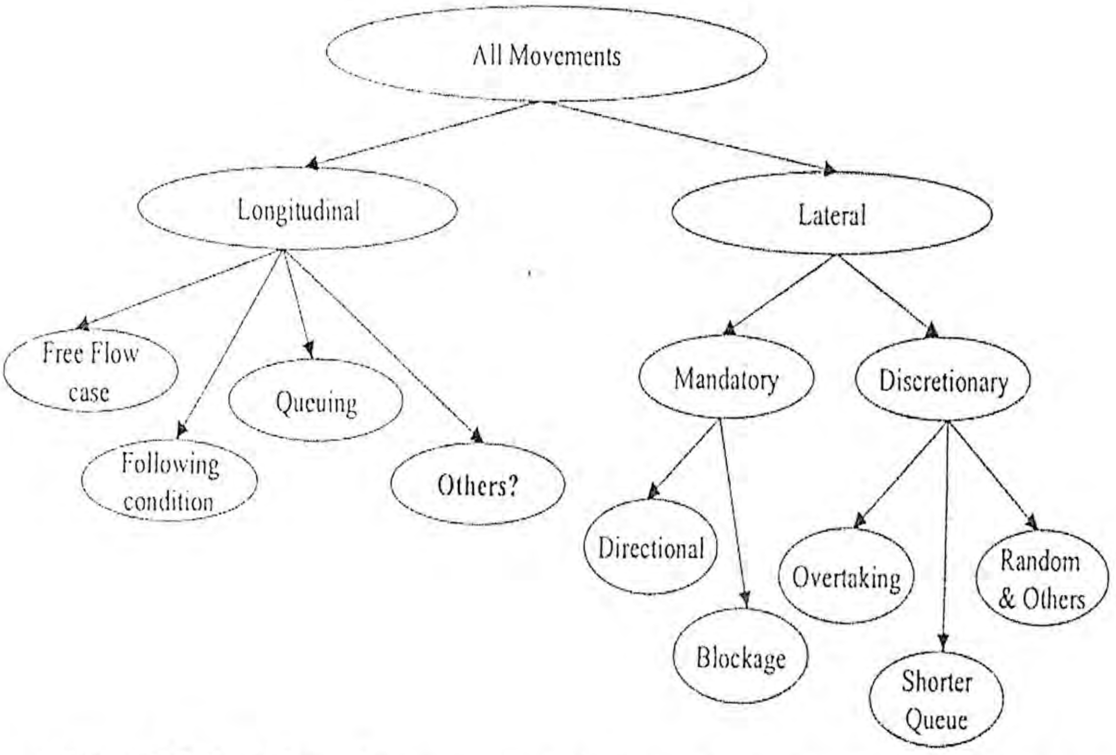



**Figure 3.1** Overview of movements a vehicle may execute under normal driving conditions. Lateral movement decisions could involve partial or complete lane change

Under normal circumstances, it will also move laterally and change lanes for a variety of reasons including those for directional requirements, need for overtaking or passing slower vehicles and or even a desire to join a shorter queue. Evidently, some of these decisions are mandatory and have to be executed within a certain time or distance limitation whereas the rest are discretionary.

In traffic modeling, these maneuvers are usually characterized by various theories including macroscopic stream models, car following rules, queuing theories, gap acceptance and rejection considerations and merging rules, the choice of the adopied theories being dependant on the detail of the model. In heterogeneous traffic it is imperative first and foremost to verify if the known characteristics of such traffic can be adequately described by the existing approaches. It also important to identify any explicit differences or phenomena which differentiate such streams from the more homogenous ones and to see how such differences could be included in revised modeling approaches.

Specific characteristics of heterogeneous traffic differ with locality and the prevailing traffic conditions such as the level of heterogeneity of the stream but some of these characteristics are common and wide spread and are known to influence the overall stream performance. Common examples include non-lane based travel, abnormal queuing behavior exhibited by bicycles and motorcycles, the tendency for competing vehicles to initiate some contact leading to unpredictable driving patterns and random stopping of some vehicle types at undesignated areas to drop and pick passengers. These factors are discussed in detail in the following sections.

### 3.3.1 Non-lane based Travel

It is normally assumed that all vehicle movements occur within the confines of a single lane but this is not always so. Vehicles often use two lanes simultaneously either during lane changing maneuvers or even during normal travel. In the first instance, the non-lane based travel is temporal and lasts only during the lane change maneuver whereas in the second instance, it may take a longer time until such a time as the vehicle is forced to change its path of straight movement. Although it has been recognized in many newer model (Minderhound, 1999, Van Aerde *et al,* 1996, Hoogendoom, 1999) that the lane changing process ultimately affects flows on a vehicle's present as well as target lanes, there is hardly any detailed consideration given to prolonged simultaneous usage of two lanes. This latter case is more prevalent in traffic streams containing high percentages of non-standard vehicles and as observed in (Gunay, 1998), it is common in many parts of the world. Non-lane based travel is affected by a variety of factors such as the condition of the road surface, existence and clarity of the lane demarcations, and the presence of narrow vehicles like bicycles and motorcycles. A non lane based modeling approach is therefore necessary to analyze such mixed streams.

### 3.3.2 Queuing Patterns of Motorcycles and Bicycles

Queuing analysis forms an important part of traffic analysis especially at intersections where vehicles have to wait for their right of way. It is through this that queue lengths and duration and consequently delays are calculated and modeled and the level of service of the facility determined. At intersections, the bulk of queuing analysis techniques assumes first in first out (FIFO) discipline for a single channel or multi-channel server (Huber and Gerlogh, 1975, May 1990).

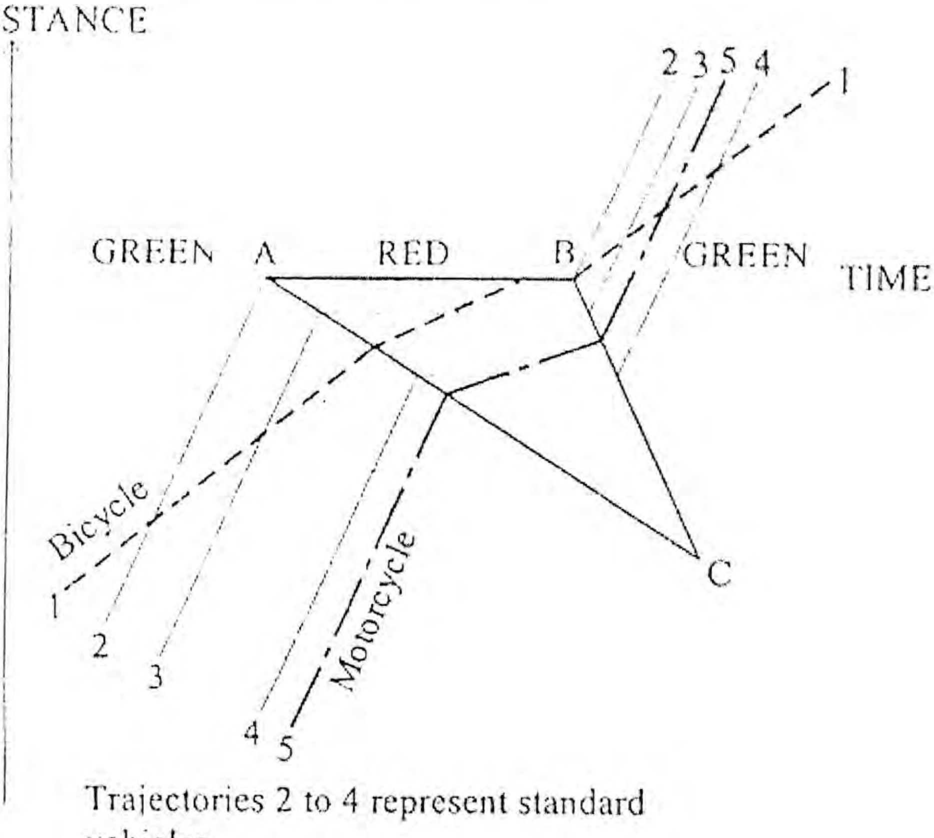



**Figure 3.2**: Time distance diagram showing seepage of two-wheeled vehicles (Powel,1998)

However, mixed streams containing narrow vehicles show somewhat different queuing disciplines. Bicycles, scooters and motorcycles (i.e. two wheelers) do not normally remain at the position at which they arrive at the queue but, rather, they usually creep at reduced speeds towards the front as illustrated by the time distance diagram in Figure 3.2. These movements shall be henceforth reflected to as seepage action. It can be seen in the Figure that vehicles1 and 5 creeps towards the front upon meeting the queue, line AC, whereas the rest wait until the departure wave, line BC. Although this phenomenon has been used in estimation of passenger car unit (pcu) values for motorcycles (Powel, 1998), its overall effect on the traffic performance has not been quantified.

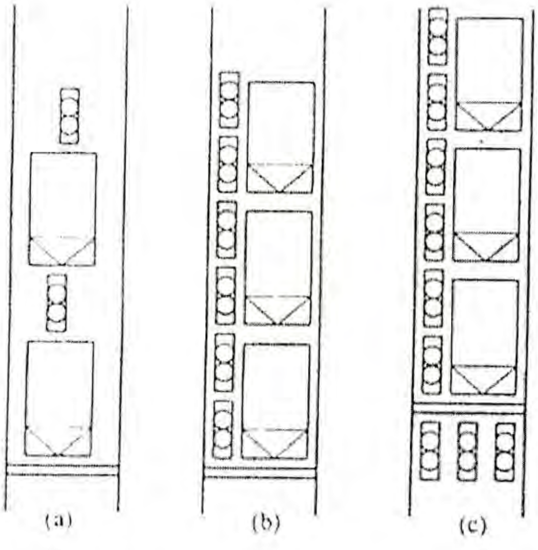



**Figure 3.3**: Possible queuing disciplines for mix traffic streams

At stand still, narrow vehicles queue side by side to the standard vehicles or to one another. There are different possibilities of queuing disciplines as shown in Figure 3.3. The conventional discipline 3.3(a) would obviously result in erroneous results as it is likely to predict higher delays and queue lengths. The most commonly observed discipline follows the pattern in 3.3(b) but as the composition of narrow vehicles become more predominant, some of the narrow vehicles, particularly the motorized ones, spill over to the area immediately beyond the stop line 3.3(c). At the beginning of the green period, they quickly clear the area since they possess high acceleration rates.

### 3.3.3 Initiation of Contact between Drivers

Of significance to traffic operations is the interaction of vehicles within a single stream of traffic or of two separate traffic streams. These interactions take place virtually all over the traffic network when a driver changes lane, merges into a traffic stream or crosses a traffic stream, and inherent to these maneuvers is the concept of gap acceptance. A driver wishing to engage in any of the above maneuvers searches for, accepts or rejects gaps in the conflicting traffic streams according to his own perception of safety. It is on that basis that delay that is incurred and the queues that build up are analyzed. Both intrapersonal and inter-personal variations plays significant role in the size of accepted or rejected gaps. Faced with similar traffic situations at different times, a driver may accept different gaps depending on several factors. One such factor is the waiting time before an acceptable gap becomes available.

Although little quantitative analysis has been carried on the subject, it is generally known that drivers who have suffered longer delays tend to accept smaller gaps than they would normally do (Young et al, 1989, Van Aerde et al,1996). The work of Polus et al, 1996, also reinforced this view by showing that drivers generally grow impatient after some time of waiting. In heterogeneous traffic, the same principle may apply where a vehicle wishes to change lanes but can not obtain a gap of sufficient length. It is common for such a vehicle to try to initiate some form of contact with other competing vehicles to give them preference. This implies that the vehicle can start the maneuver without sufficient gaps or that the second vehicle no longer moves according to car following rules but rather in accordance to some unspecified patterns.

### 3.3.4 Other factors

There are further external factors which affect the overall stream performance. Some of these factors are a consequent of driving disciplines whereas others come about as a result of the chaotic traffic situations associated with heterogeneity. The most common situations include:

- Random stopping of vehicles at undesignated places to drop and pick passengers thereby reducing capacities depending on the frequency and duration of each stopping. Prior studies have shown that blockages by buses can cause up to 30% loss in capacity depending on the frequency and duration of the stop and also on the number of lanes available (TRB, 1985). However, stopping by buses are predictable and occur at the designated positions.

- Partial or complete blockage of travel lane. This is common as a result of either roadside activity causing drivers to become apprehensive and steer laterally. In addition, it could result from badly parked vehicles or broken down vehicles blocking part of the travel lane. Taragin (1955) reported lateral displacements of vehicles of 0.6 to 1.0 m as a result of objects placed at the side of the road but what is unknown is the overall effect such kind of maneuvers have on the traffic performance.

Although these factors are known to reduce capacity and hence result in lower speeds, they are hardly incorporated in traffic models and their effects have not been quantified in enough detail to enable drawing of clear relationships between them and the resulting traffic performance.

### 3.4 Greater Insight into Lane Changing in Non-Lane Based Operation

Lane changing process in the non-lane based mixed traffic operation is different from that of lane based case in the following respects (Hoque M S, 1994)

i) Lane changing and overtaking behavior utilizing all the available road space is probably the most significant characteristic which differentiate the non-lane based traffic from the lane based traffic. Because of wide variations in lane occupancy by different categories of vehicles and freedom in lateral movements, whenever a follower gets a sufficient side gap, the driver tends to move laterally rather than follow the lead vehicle.

ii) Unlike traffic in lane based conditions where, in order to overtake a front slow leader, vehicles move completely one lane laterally, in the non-lane based case this overtaking operation is made by clearing only the obstructed portion with the preceding vehicle.

iii) As in the lane based case where average speed of traffic stream is relatively higher and overtaking need be made in one attempt i.e. after taking decision of lane changing, the vehicle should be able to move from its own lane to the adjacent lane completely in one operation and not in-between the lanes or partially, overtaking decision is very sensitive to the gap acceptance criteria. On the contrary, in the mixed traffic operation to overcome obstructed portion there is no need to do it in one operation rather it happens gradually i.e. strip by strip depending on the availability of the opportunity. In addition, as in the mixed traffic operation average speed of traffic stream is relatively low, the strip changing decision is not so sensitive to the gap acceptance model. As a result, in non-lane based operation lane changing and overtaking is a gradual and continuous process.

iv) Since in the lane-based traffic operation, the vehicle remaining in its lane has a priority over a vehicle joining that lane, usual lane changing criteria is that after moving to a new lane it must not force the rear vehicle to reduce its speed. In contrast, in the mixed traffic operation, since the lane concept does not exist and hence the above priority(as the lack of lane discipline brings about a feeling of superiority for a leading vehicle over the vehicles behind it), any vehicle can change to the desired strip so long as this can be done safely i.e. satisfying non-collision criterion.

v) For overtaking purpose both sides are desirable although motorized vehicles prefer the right side, as the left part of the road is used by the slow moving non-motorized vehicles. From the field survey it has been observed that the left turning motorized vehicles as well as the right turning non-motorized vehicles start correcting their positions only when they reach very near to the stop line and based on the queue length in the desired direction.

In the mixed traffic operation, as at the upstream non-motorized vehicles usually occupy the left part of the road, in order to avoid conflicts with these slow moving vehicles the left turning motorized vehicles do not come to that side early. Similarly, due to the high speed difference with the right side motorized vehicles, at upstream the right turning non-motorized vehicles stay in the left part of the road. Another interesting feature of the non-lane based mixed traffic operation is that in order to make left turn when motorized vehicles come to the left side of the road, they use horn to warn the non-motorized vehicles so that they can get enough space to pass through.

## 3.5 The Concept of Taxonomic Model of Driving and Driver Decision Making

This section attempts to contextualize the concept of taxonomic model of drivers' on-road performance and behavior. A taxonomic model of drivers' sensory, mental and psychomotor functions is presented in Table 3.1. This is an attempt to move beyond the overly simplistic IPDE/SIPDE (identify, predict, decide, execute/scan, identify, predict, decide, execute) models. The targeted categories in this model mainly represent stages of information processing and outputs that take place while driving. Immediate, real-time processing takes place continuously, in routine situations, and discontinuously, as the occasional detection, perception and evaluation of potential hazards, and the decisions and actions taken in response (Figure 3.4). These categories can be seen as families of related skills that serve related purposes and call upon related underlying capacities.

Given a particular situation evaluation, final authority for action (or inaction) rests with the driver's decision skills, which weight the optional courses of action, selecting and timing responses. Decision skills are pivotal in this and any other plausible driver model. A clear definition of decision making is provided by McWhirter et al. (1994): Decision-making is a goal-directed sequence of affective and cognitive operations that leads to adaptation of behavioral responses to external and internal challenges or demands. A clear link exists between deficits in decision-making skills and high-risk behavior.

**Table 3.1:** A Taxonomic Model of Drivers' Sensory, Mental and Psychomotor Functions

| Skill Category | Definition | Importance |
|---|---|---|
| Knowledge | **Cognitive/memory:** Experiences, facts, rules, principles and expectations stored in long-term memory | Provides the background against which all the perceptual and cognitive functions take place |
| Attention | **Cognitive/perceptual:** Controlling, dividing and switching focus | Real-time management of cognitive resources and perceptual channel-capacity, screening out Distractions |
| Detection | **Sensory /pre-attentional:** Fixation, formation of images | Identifies changes in the environment that may need identification and Evaluation |
| Perception | **Sensory/cognitive:** Processing images to extract meaning and produce schemata | Creates awareness and understanding of constantly-changing Situations |
| Evaluation | **Cognitive/affective:** Risk analysis of situation to produce outcome expectations, attributions | Estimates consequences and probabilities of alternative actions in the Situation |
| Decision | **Cognitive/affective:** Matching options and motives | Selects optimal response: risk acceptance or Rejection |
| Motor Skill | **Perceptual-motor**: Integrating control actions | Execution of intended Maneuvers |
| Imagination | **Cognitive:** Safety margin, anticipatory responses | Time, speed and space Choices |
| Motivation | **Affective/social:** Transient objectives, drives, needs, emotions | Prioritizes and balances a large and often conflicting set of goals and values |
| Responsibility | **Cognitive/affective/cultural:** Executive "policy" skills | Chooses goals and values, directs self-monitoring, consistently controls Transient states |

Decision skills include identifying and weighing optional courses of action, and selecting and timing responses to optimize the driver's personal benefit-cost equations. Although strongly connected and influenced by evaluations, decision skills are clearly distinct and autonomous. In real-time driving continuous, evaluation and decision are seen as necessary because few of the elements that are perceived require any action. But continuous real-time driving decisions are only a part of the driver skill picture. Drivers' decision skills can be seen as a hierarchy with various levels ranging from the operational to the strategic (Ranney, 1994). From the human-reengineering perspective, it is clear that they even reach beyond into the realm of self-management decisions and values-consistency skills.

Even the real-time decision skills are based in complex, highly variable cognitive processes. They depend on and are influenced by the driver's knowledge and motivation, and they are strongly affected by impairments such as alcohol and fatigue. Clearly, the motivational influence on decision-making is critically important (e.g., a consistently evaluated hazard may be acted upon differently if someone get angry). In recognition of this importance, a major portion of intensive, high-performance training (as in military and commercial aviation) is to practice decision-skill responses so heavily that they become less susceptible to disruption by transient motivational and emotional states. The driver's motivation will influence not only the choice of action but also the timing of action. A risk-accepting, inappropriate choice will often result. Since many potential hazards do not develop and often are chosen to delay response.

This may be a kind of skill in its own right; it would be inefficient, and maybe even unsafe, to react to every possible hazard as soon as it is perceived. A critical failure of this skill occurs when a decision is delayed until safe correction of the problem is no longer certain or even possible. Both the choice of appropriate response and the choice of appropriate timing of response are critical skills.

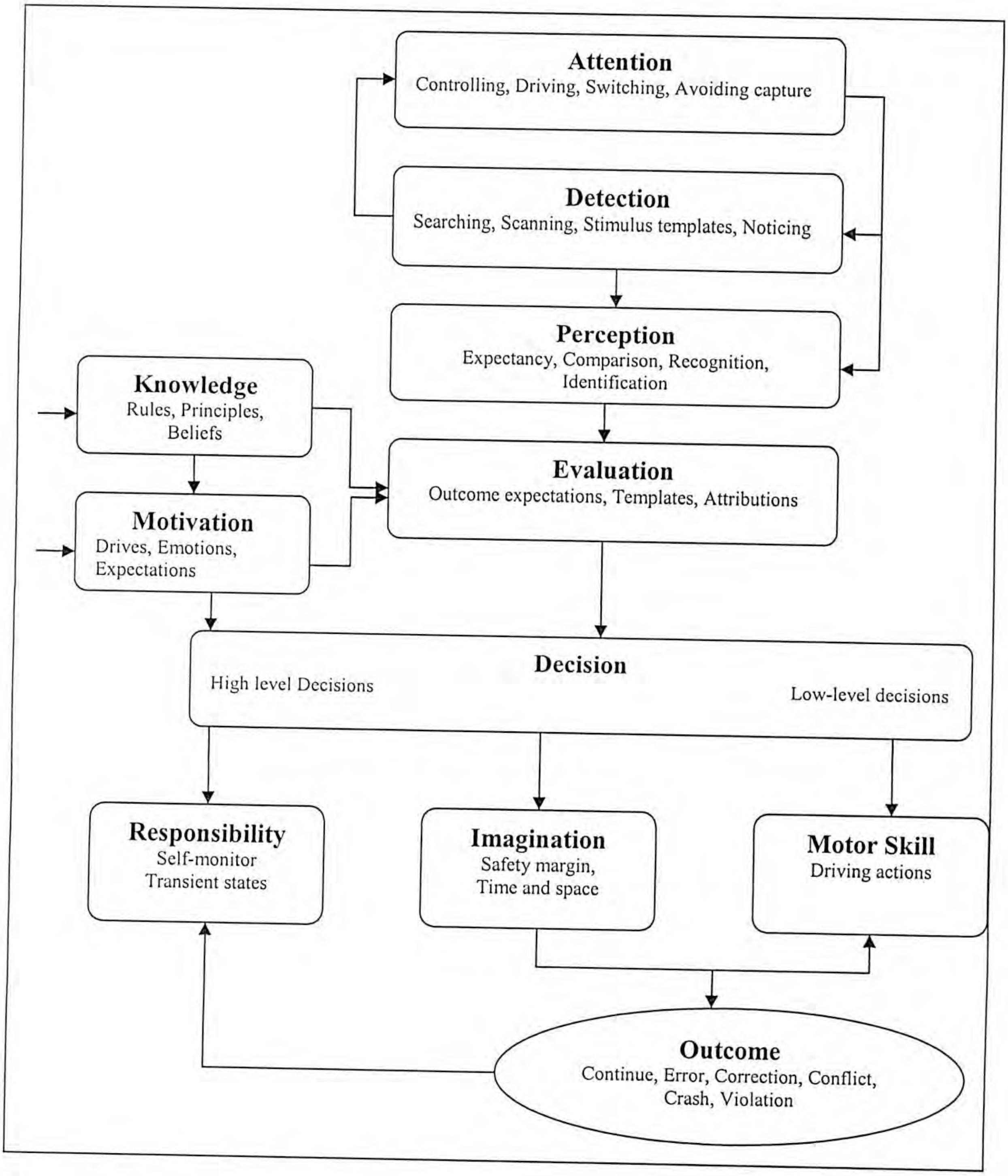



**Figure 3.4** Stages of Information Processing and Outputs that Take Place While Driving.

## 3.6 Application of Fuzzy Logic in Modeling Driver's Behavior

Fuzzy inference (or simply "fuzzy logic") is a powerful problem-solving methodology with wide applications in industrial control and information processing. It provides a simple way to draw definite conclusions from vague, ambiguous or imprecise information. It resembles human decision making with its ability to work from approximate data and find precise solutions. Fuzzy logic is a feasible method for modeling human behavior and human perception. Fuzzy logic can be used to model uncertain processes in science and engineering and a host of literature is available on the subject (eg. Beien, 1995, Kosko 1992, 1997, Kahlert 1993, Klir 1995). Its application to traffic engineering is recent and has dwelt particularly with car following modeling (Kikuchi et al 1992, Rekersbrink 1994) and lately with traffic signal optimization (Niittymaki, 2000). It can be applied in modeling decisions in lateral movement to assess the measure of the desire to carry out any particular action. Follows are the some advantages of Fuzzy Logic:

- *Fuzzy logic is conceptually easy to understand.* The mathematical concepts behind fuzzy reasoning are very simple. What makes fuzzy nice is the "naturalness" of its approach and not its far-reaching complexity.

- *Fuzzy logic is flexible.* With any given system, it's easy to massage it or layer more functionality on top of it without starting again from scratch.

- *Fuzzy logic is tolerant of imprecise data.* Everything is imprecise if it being looked closely enough, but more than that, most things are imprecise even on careful inspection. Fuzzy reasoning builds this understanding into the process rather than tacking it onto the end.

- Fuzzy logic can model nonlinear functions of arbitrary complexity. You can create a fuzzy system to match any set of input-output data. This process is made particularly easy by adaptive techniques like Adaptive Neuro-Fuzzy Inference Systems (ANFIS), which are available in the Fuzzy Logic Toolbox.

- Fuzzy logic can be built on top of the experience of experts. In direct contrast to neural networks, which take training data and generate opaque, impenetrable models, fuzzy logic lets you rely on the experience of people who already understand your system.

- Fuzzy logic can be blended with conventional control techniques. Fuzzy systems don't necessarily replace conventional control methods. In many cases fuzzy systems augment them and simplify their implementation.

- Fuzzy logic is based on natural language. The basis for fuzzy logic is the basis for human communication. This observation underpins many of the other statements about fuzzy logic. The last statement is perhaps the most important one and deserves more discussion. Natural language, that which is used by ordinary people on a daily basis, has been shaped by thousands of years of human history to be convenient and efficient. Sentences written in ordinary language represent a triumph of efficient communication. This is generally unaware of because ordinary language is of course, something is used for every day life. Since fuzzy logic is built atop the structures of qualitative description used in everyday language, fuzzy logic is easy to use.

## 3.7 Application of Neural Network

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between elements. A neural network can be trained to perform a particular function by adjusting the values of the connections (weights) between elements. Commonly neural networks are adjusted, or trained, so that a particular input leads to a specific target output. Such a situation is

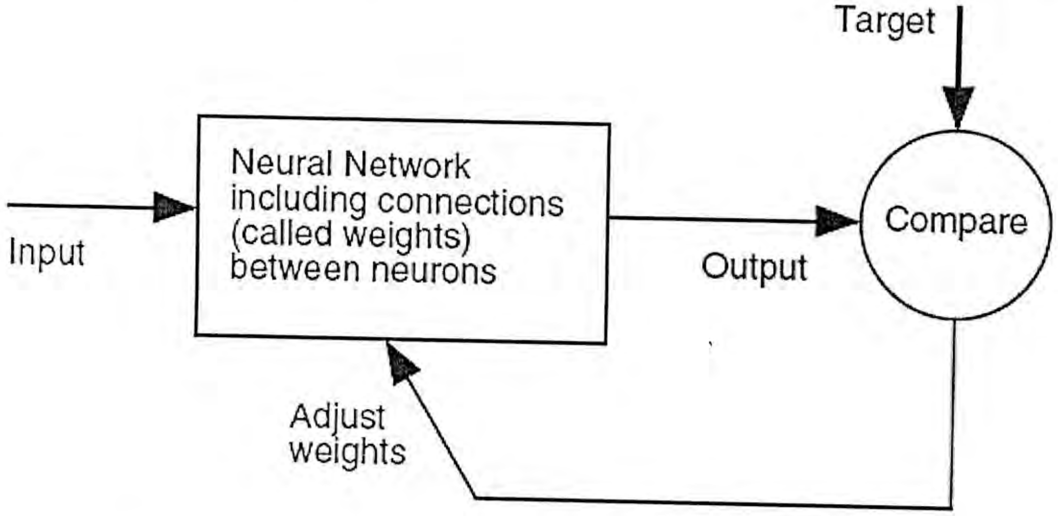



**Figure 3.5:** Typical Neural Network Modeling Framework

shown below. There, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically many such input/target pairs are used, in this supervised learning, to train a network.

Batch training of a network proceeds by making weight and bias changes based on an entire set (batch) of input vectors. Incremental training changes the weights and biases of a network as needed after presentation of each individual input vector. Incremental training is sometimes referred to as "on line" or "adaptive" training. Neural networks have been trained to perform complex functions in various fields of application including pattern recognition, identification, classification, speech, vision and control systems.

Today neural networks can be trained to solve problems that are difficult for conventional computers or human beings. The supervised training methods are commonly used, but other networks can be obtained from unsupervised training techniques or from direct design methods. Unsupervised networks can be used, for instance, to identify groups of data. Certain kinds of linear networks and Hopfield networks are designed directly. In summary, there are a variety of kinds of design and learning techniques that enrich the choices that a user can make. The field of neural networks has a history of some five decades but has found solid application only in the past fifteen years, and the field is still developing rapidly. Thus, it is distinctly different from the fields of control systems or optimization where the terminology, basic mathematics, and design procedures have been firmly established and applied for many years.

## 3.8 Application of MATLAB Toolbox of ANFIS

MATLAB® is a high-performance language for technical computing. It integrates computation, visualization, and programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notation. Typical uses include Math and computation Algorithm development Data acquisition Modeling, simulation, and prototyping Data analysis, exploration, and visualization of Scientific and engineering graphics Application development, including graphical user interface building MATLAB is an interactive system whose basic data element is an array that does not require dimensioning. This allows solving many technical computing problems, especially those with matrix and vector formulations, in a fraction of the time it would take to write a program in a scalar noninteractive language such as C or Fortran. The name MATLAB stands for matrix laboratory. MATLAB was originally written to provide easy access to matrix software developed by the LINPACK and EISPACK projects. Today, MATLAB engines incorporate the LAPACK and BLAS libraries, embedding the state of the art in software for matrix computation. MATLAB has evolved over a period of years with input from many users. In university environments, it is the standard instructional tool for introductory and advanced courses in mathematics, engineering, and science.

In industry, MATLAB is the tool of choice for high-productivity research, development, and analysis. MATLAB features a family of add-on application-specific solutions called toolboxes. Very important to most users of MATLAB, toolboxes allow the users to learn and apply specialized technology. Toolboxes are comprehensive collections of MATLAB functions (M-files) that extend the MATLAB environment to solve particular classes of problems. Areas in which toolboxes are available include signal processing, control systems, neural networks, fuzzy logic, wavelets, simulation, and many others. The MATLAB system consists of five main parts: Development Environment. This is the set of tools and facilities that help the users with MATLAB functions and files. Many of these tools are graphical user interfaces. It includes the MATLAB desktop and Command Window, a command history, an editor and debugger, and browsers for viewing help, the workspace, files, and the search path. The MATLAB Mathematical Function Library: this is a vast collection of computational algorithms ranging from elementary functions, like sum, sine, cosine, and complex arithmetic, to more sophisticated functions like matrix inverse, matrix eigenvalues, Bessel functions, and fast Fourier transforms.

The MATLAB Language is a high-level matrix/array language with control flow statements, functions, data structures, input/output, and object-oriented programming features. It allows both "programming in the small" to rapidly create quick and dirty throw-away programs, and "programming in the large" to create large and complex application programs. MATLAB has extensive facilities for displaying vectors and matrices as graphs, as well as annotating and printing these graphs. It includes high-level functions for two-dimensional and three-dimensional data visualization, image processing, animation, and presentation graphics. It also includes low-level functions that allow the users to fully customize the appearance of graphics as well as to build complete graphical user interfaces on MATLAB applications. The MATLAB Application Program Interface (API): this is a library that allows writing C and FORTRAN programs that interact with MATLAB. It includes facilities for calling routines from MATLAB (dynamic linking), calling MATLAB as a computational engine, and for reading and writing MAT-files

### 3.9 Conceptual Framework

#### 3.9.1 Recognizing the process of lane changing

Many lane change models attempt to simplify the decision process by forming a decision tree and asking questions of overriding importance first. Other models do so by categorizing broad possibilities of the intended actions and following each of them through various steps. That is achieved by assessing the general conditions which may necessitate those actions and facilitate their execution. The process could also be approached from a different perspective.

Recognizing that all of the questions that can be asked will translate into a couple of possible alternatives only, the process could be turned into that of presenting the vehicle with a list of alternatives to choose from. It becomes roughly analogous to buying an item of clothing; the driver first chooses those alternatives meeting some broad set of criteria-(identifying phase), it then puts the chosen alterative under further scrutiny-(fitting) and eventually comes up with one final choice. Whether or not one gets to actually buy the item depends on its "price" and the money the buyer has. This, in the case of a vehicle wishing to move laterally, translates into safety consideration which is measurable by the size of the available gap. What is needed, therefore, is to identify these alternatives, to define for each a broad set of conditions that must be satisfied to warrant its choice and finally to develop a method of evaluating the alterative to facilitate a final choice.

### 3.9.2 Steps of lateral movements

The lateral movement model should not only check that the appropriate set of conditions for each action has been satisfied but also consider to what degree this has been done. It should further evaluate other external constraints influencing desirability and the urgency of the particular action. This calls for an evaluation method that is sensitive to the continuously changing position and speed of the vehicle on the one hand, and to the activities of its interacting partners on the other. The whole process was consequently achieved in the following four steps, each of which is discussed in greater detail in the subsequent sections:

*Step 1:* Recognition of the need to move laterally and identification of available options;

*Step 2:* Evaluating whether or not there is enough incentive to carry out the maneuver at the present time and choosing between the alternative options if more than one is available;

*Step 3:* Checking for safety criteria (available gaps) before embarking on the actual maneuver;

*Step 4:* Actual carrying out of the lateral movement (that is lateral movement dynamics)

### 3.9.3 Model structure

The first task is to define all the possible lateral movement actions a driver may take and the basic conditions necessitating the actions. Each action has its own specific conditions that govern it, although most, if not all, may be subject to certain general restrictions. One such restriction is that the lead vehicle or an object, such as a stop line, must be within sight distance of the follower. It has also been shown that there is a limit to the distance at which-following vehicle can react to the perceived action of the lead vehicle and this is suggested to be in the region between 80 to 100m (Wiedemann 1974). The actions are listed below together with a description of the set of conditions necessitating them.

**Avoidance of Obstruction:** Obstruction to be avoided can be a stopped vehicle, a very slow moving vehicle whose maximum speed falls below certain speed or even an object blocking part or the whole lane. End of a lane (e.g. an acceleration lane) forcing vehicles to merge into a neighboring lane is also generally considered under this category since it is analogous to having a permanent physical blockage at that point.

**Directional Lane Change:** A vehicle will change lane when it realizes that the travel lane does not lead to the intended travel direction. The decisions on the choice of the correct lane could begin earlier, especially where the vehicle is conversant with the network. Even if the actual targeted lane is not available yet, like in the case of a short turning lane, the vehicle may change to an adjacent lane long before the stop line. An upper limit of 300 m from the stop line has been set for these decisions.

**Overtaking Action:** Overtaking can occur anywhere along the link, when a lead vehicle is moving at a slower speed than what the follower desires. Those that involve the use of two lanes simultaneously at some point are only attractive if the new lane is faster than the present lane. A third condition is that some fraction of vehicles will still not initiate an overtaking maneuver even when the previous conditions do exist. This traction has been set at 40% of all vehicles. Lastly, a vehicle has to be within a certain distance behind the lead vehicle before starting the overtaking maneuver.

**Lane Change for shorter Queue Length:** A vehicle will change lanes to be on a shorter queue if the one on the present lane is longer than the one on the new lane, provided that both lanes lead to the same travel direction.

**Lane Changing due to loading and Unloading:** A vehicle will change lanes at selected locations due to loading and unloading particularly in urban scenario.

**Random Lane Change:** Finally, a vehicle can also change lane at random particularly from the inner faster lanes to slower outer one. Further still, it assumed that the slow vehicles will generally use the outer lane and will also desire to change to the outermost lanes in case they find themselves in the inner ones.

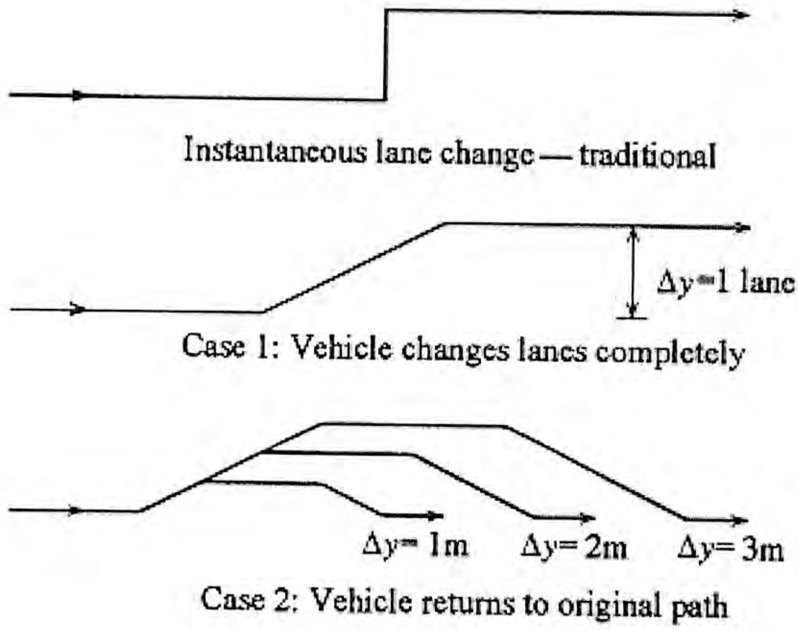



**Figure 3.6:** Types of Lateral Movement

The listed actions are simplified and cover the obvious lateral movement actions that would normally be expected in urban environments. They represent only the basic conditions used to identify the possible alternatives and there are additional exogenous factors affecting the final choice of alternative. The actions can be classified as mandatory or discretionary. The first two actions (avoidance of obstruction and directional lane change) are mandatory and must be carried out before the vehicle reaches a certain critical point. The rest actions arc discretionary and can be abandoned altogether at either step two or three, depending on the prevailing circumstances. A summary of these actions are given in Table 3.2.

Each alternative has been listed in an active perspective whereby it causes a vehicle to leave the present lane for a new one. It can however act passively too, in which case it tends to deter a vehicle from leaving the present lane even if there are other incentives to do so. An example of this latter situation is the case in which a vehicle contemplates overtaking a slower one. Now suppose that the present lane leads to the vehicle's intended travel direction and that the overtaking maneuver would involve changing to a lane that leads to a different direction. The overtaking action is therefore active whereas the directional requirement acts passively to keep the vehicle on its present lane. Such kind of conflicts necessitates the formulation of an evaluation procedure.

Table 3.2: List of Active Lateral Movement Actions and Associated Factors

| Possible Action | Type[a] | Case[b] | Lateral Displacement | Exogenous constraints and factors affecting desire/urgency for action |
|---|---|---|---|---|
| 1. Lane change to avoid obstruction<br>End of lane | M | 2<br><br>1 | Varies<br><br>1 lane | Distance to obstruction (or end of lane), available time |
| 2. Lane change due for directional requirements | M | 1 | 1 lane | Distance to critical point, available time, number of lanes to target lane |
| 3. Overtaking a slower<br>- standard vehicle<br>- narrow vehicle | <br>D | <br>1<br>2 | <br>1 lane<br>Varies | Distance to stop line, desired speed, actual speed, speed of slower vehicle |
| 4. Change lane to shorter queue | D | 1 | 1 lane | Distance to present queue, difference in queue length, available time |
| 5. Random lane change to slower lane | D | 1 | 1 lane | Distance to stop line, available time |

*Notes:*

[a] *M: Mandatory Action;* *D: Discretionary Action*

[b] *Case involves a complete lane change and case 2 involves returning to the previous lane as specified in Figure 3.6*

### 3.9.4 Evaluation of options using Fuzzy Logic

The need to evaluate options exists not only in case of multiple conflicting ones but also where only one alternative is available. In the first instance, a vehicle needs to choose the most critical alternative when faced with several viable options. For example, it may recognize the need to get in lane for the desired travel direction and at the same time wish to overtake a slower vehicle ahead. The vehicle must somehow decide which of the two actions is more desirable. In the second instance, the existence of exogenous constraints may give it some sense of urgency in starting and completing the intended action. This is clearly demonstrated by the same vehicle recognizing that it must change to the correct lane before reaching the stop line, and the urgency to do so increases as it approaches the stop line.

Several factors are known to influence the lane changing process (Gipps 1986, Schnittger 1991) and an attempt must be made to distinguish those basic ones necessitating the action in the first place from those that only influence their urgency. The latter factors include distance to the critical point, the perceived available time within which the maneuver must be completed, the number of lanes to be traversed to reach the target, difference in queue length and difference in actual speed and desired speeds as shown in the last column of Table 3.2. The available time is a function of the instantaneous speed and the distance to the critical point. These factors can influence at least one of the options as can be seen in the Table.

The ability to measure the sense of urgency for each action based on the prevailing factors is therefore necessary. However, simple ways of doing so do not exist because the factors change rapidly with vehicle movements and traffic situation and the perceptions of different drivers also vary greatly. Secondly, information is not available on definite relationships between these factors on the one hand and driver behavior on the other and only rudimentary patterns of responses can be drawn when the factors approach some limiting values. These considerations necessitate the use of approaches like fuzzy logic, which are suitable in modeling uncertain processes.

### 3.10 Model Component

In conventional (crisp) set theory, an individual in a universal set $X$ can belong to a certain crisp set or not. *A* value of 0 of 1 is assigned to the individual to denote membership or non-membership of the set in consideration. In fuzzy sets on the other hand, an individual can have varying grades of membership defined by the membership function. For a fuzzy set A belonging to the universal crisp set $X$, the membership function $\mu_A$ can be denoted by:

$$\mu_A: X \longrightarrow [0, 1] \qquad \text{(3-1)}$$

This means that the membership grade of an individual in $X$ can be a member of set $A$ by various grades ranging from 0 to 1 defined by the function. This kind of imprecise representation is necessary in modeling uncertain situations in real life. In this study The Fuzzy Logic Toolbox (MathWorks, Inc, 2004) is used in which a collection of functions is built on the MATLAB® numeric computing environment. It provides tools to create and edit fuzzy inference systems. The fuzzy process can be divided into three sections, defining the membership functions and associated rule and fuzzification. The fuzzification part simply refers to the process in which the system to be modeled is represented using appropriate fuzzy sets. Individual parameters can have variable membership grades to a fuzzy set as determined by the assigned membership function. Although the choice of membership functions is subjective, it should nevertheless be logical and lead to consistent results.

In MATLAB Fuzzy logic toolbox, the FIS Editor handles the high-level issues for the system: number of input and output variables and their names. The Fuzzy Logic Toolbox doesn't limit the number of inputs. The Membership Function Editor is used to define the shapes of all the membership functions associated with each variable. The Rule Editor is for editing the list of rules that defines the behavior of the system. The Rule Viewer and the Surface Viewer are used for looking at, as opposed to editing, the FIS. They are strictly read-only tools.

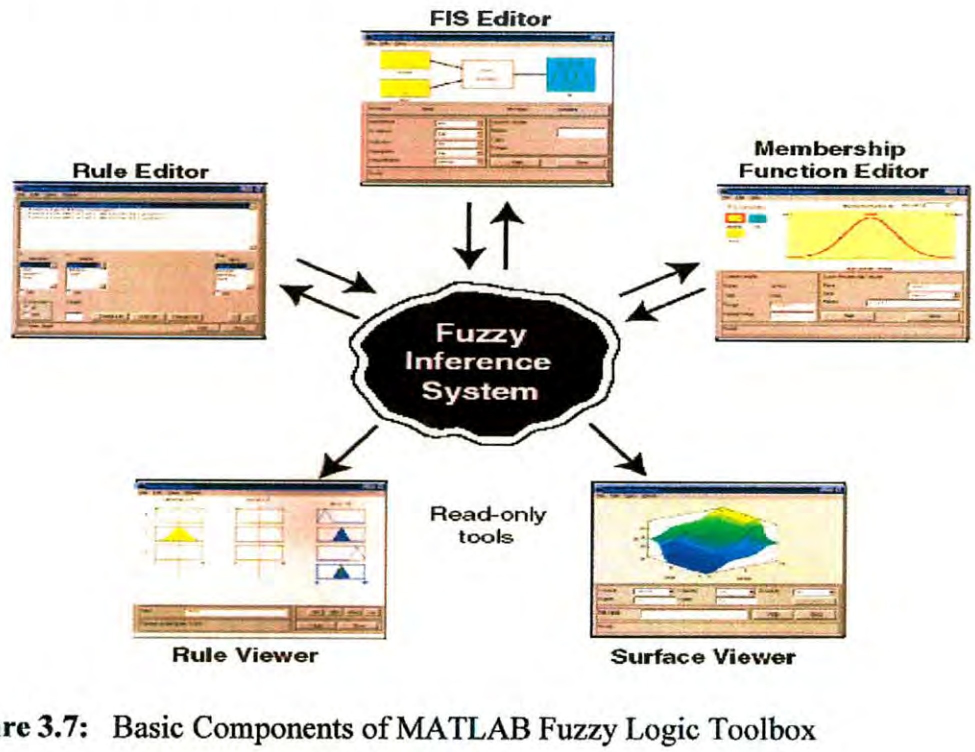



**Figure 3.7:** Basic Components of MATLAB Fuzzy Logic Toolbox

In this analysis, the factors of distance to critical point, available time, difference in speeds and difference in queue length, distance of coming vehicle etc were classified simply as small, medium and large, and appropriate values assigned to define the demarcation for each class. The membership functions for the different parameters used in lateral movement modeling are shown in Figure 3.8.

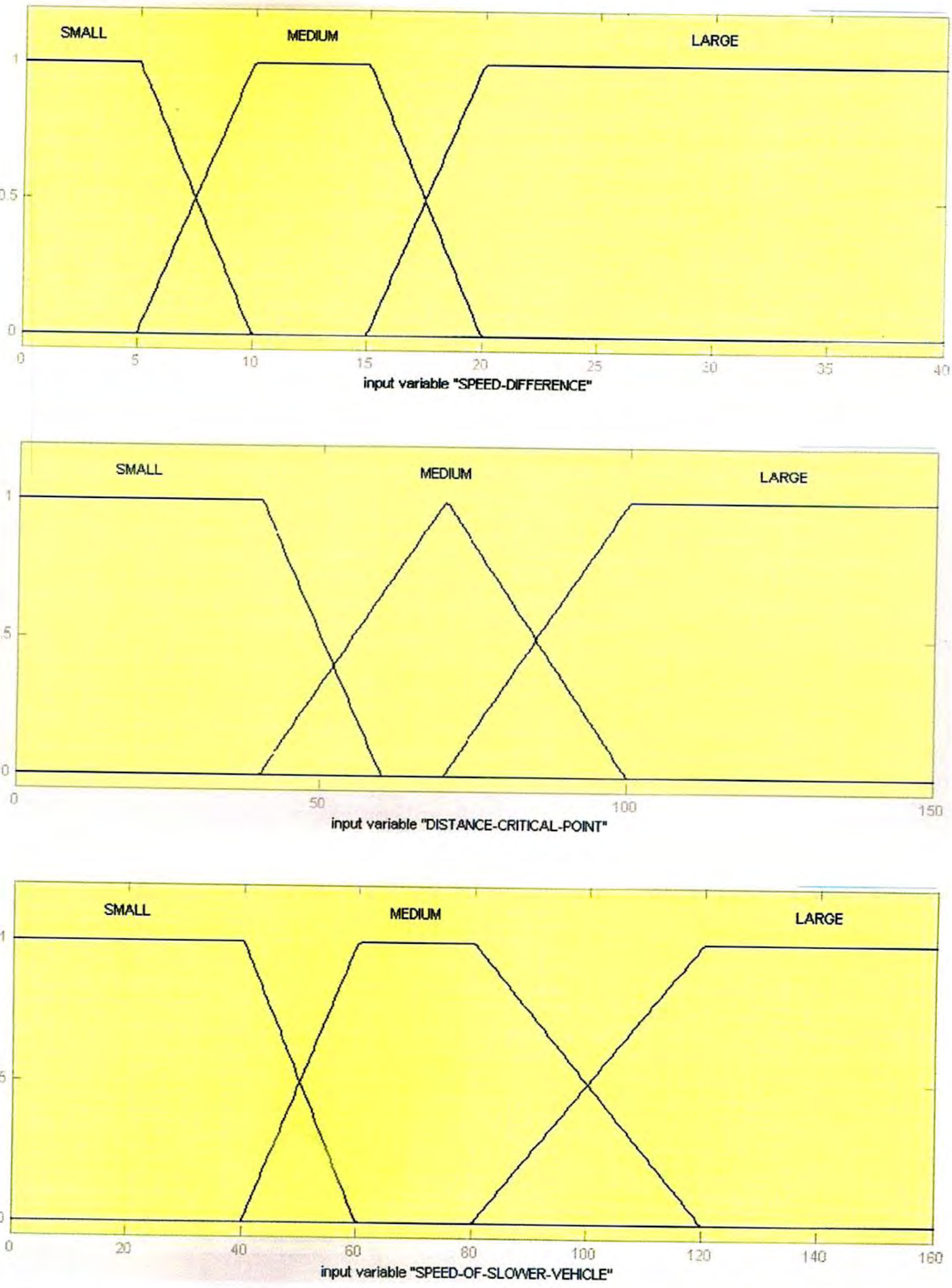



**Figure 3.8**: Fuzzy Membership Functions for the Different Parameters (contd..)

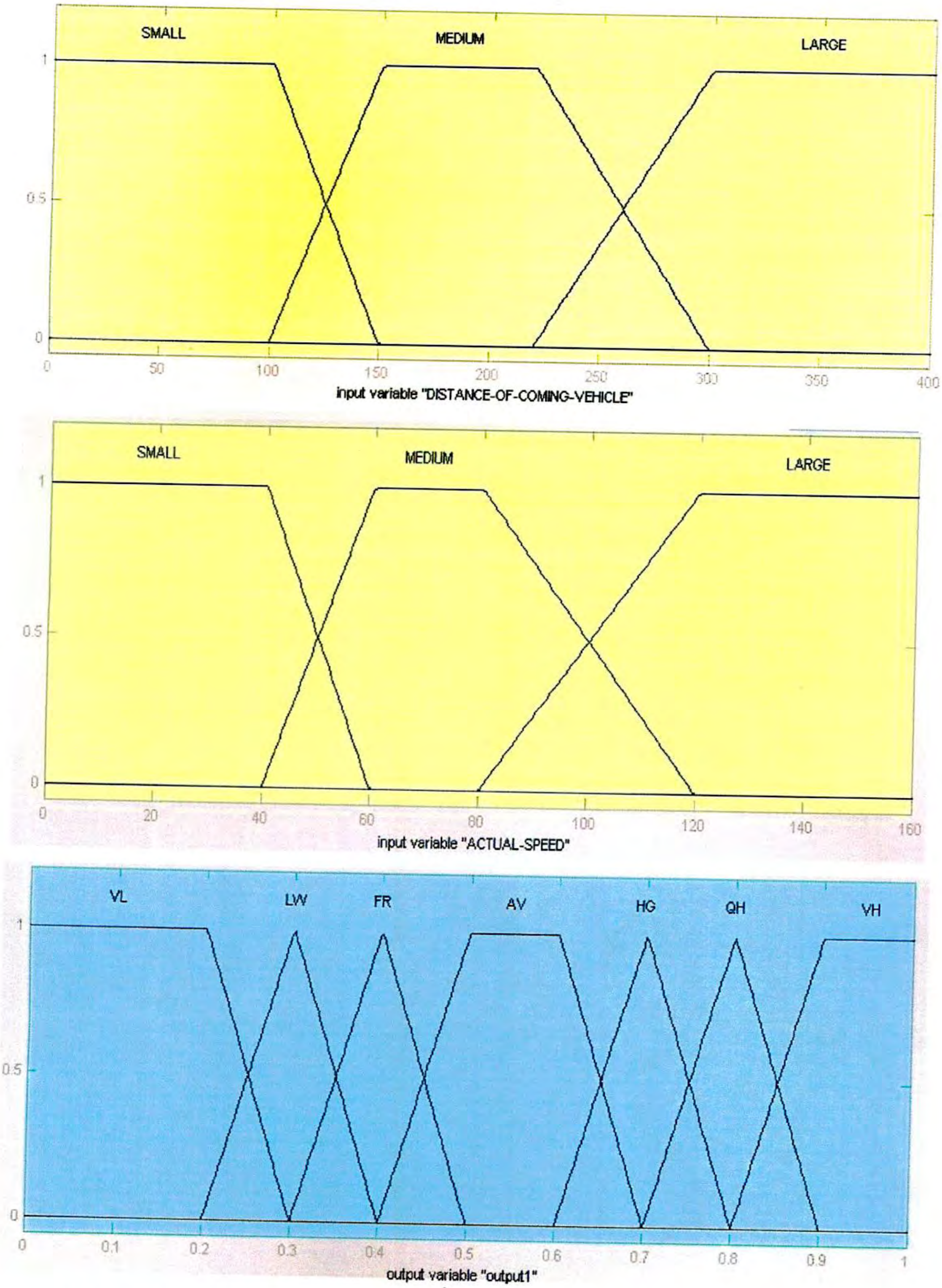



**Figure 3.8**: Fuzzy Membership Functions for the Different Parameters

The second part, commonly referred as fuzzy inference, specifies the rules governing the whole process by combining two or more of the parameters. The aim is to infer what would happen to the component of the system governed by the rules when two or more of the parameters are combined. Rules can be defined for some or all possible combination of factors including the intermediary situations when the parameters are medium or high.

In this case, each action is governed by a specific combination of two factors with membership functions as shown in Figure 3.8. In defining the rules, the boundary conditions of the factors governing each action are considered. The other combinations define intermediary situations between these two extremes. A summary of these boundary conditions are presented in Table 3.3. The corresponding rules for each combination are tabulated in Table 3.3.

**Table 3.3**: Boundary Conditions in Drawing Fuzzy Rules for Lateral Movements

| | **Possible Action** | **Factor 1** | **Factor 2** | **Drive when both factors are** | |
|---|---|---|---|---|---|
| | | | | **Small L** | **Large** |
| 1 | Lane change to avoid obstruction | Available Time | Distance to obstruction | Very high | Fair |
| 2 | Lane change due to directional requirements | Available Time | Distance to stop line | Very high | Fair |
| 3 | Overtaking action | Speed difference | Distance to stop line | Very low | Quite high |
| 4 | Change lane to shorter queue | Queue difference | Distance to queue | Very low | Quite high |
| 5 | Random lane change to slower lane | Available Time | Distance to stop line | Very low | Quite high |

Fuzzy sets are also subject to operations just like the conventional sets in Boolean algebra. Given two fuzzy sets $A$ and $B$, their standard intersection and standard union in relation to a parameter $x$ are defined as:

$$\begin{aligned}&\forall x \in X;\\&(A \cap B)_x = \min[\mu_A(x), \mu_B(x)]\\&(A \cup B)_x = \max[\mu_A(x), \mu_B(x)]\end{aligned} \qquad \text{.................................} 3.2$$

$X$ is the universal set, $\mu_A(x)$ and $\mu_B(x)$ are the membership grades of $X$ in sets $A$ and $B$ respectively. The two operators are the most widely used basically because they are relatively straightforward to understand and apply. In particular, the "and ($\cap$) Operator" was adopted in the study.

A method of storing and representing fuzzy rules is through the use of Fuzzy Associated Memory (FAM) matrix. Each FAM matrix entry is an output of a fuzzy set that is a consequent of a fuzzy rule. There is a specific rule for each possible combination of different parameters. In the example above the combinations results into fuzzy sets VH, VH, QH and HG respectively. A summary of the rules for different actions and their respective factors is given in the Table 3.4.

**Table 3.4:** Fuzzy Associated Memory Matrix Showing Output Rules for Different Combinations of Factor

| Distance to critical point | Available Time | | |
|---|---|---|---|
| | Small | Medium | Large |
| Small | VH | VH | QH |
| Medium | QH | HG | AV |
| Large | AV | AV | FR |

(a) For mandatory actions (1 and 2)

| Distance to critical point | Difference in speed | | |
|---|---|---|---|
| | Small | Medium | Large |
| Small | VL | VL | LW |
| Medium | LW | FR | AV |
| Large | FR | AV | QH |

(b-i) For overtaking action

| Speed of Slower Vehicle | Distance of Coming Vehicle | | |
|---|---|---|---|
| | Small | Medium | Large |
| Small | L | QH | VH |
| Medium | L | AV | HG |
| Large | VL | LW | FR |

(b-ii) For overtaking action

| Actual Speed | Distance of Coming Vehicle | | |
|---|---|---|---|
| | Small | Medium | Large |
| Small | VL | VL | FR |
| Medium | L | AV | HG |
| Large | AV | QH | VH |

(b-iii) For overtaking action

| Difference in queue length | Available Time | | |
|---|---|---|---|
| | Small | Medium | Large |
| Small | VL | LW | FR |
| Medium | AV | AV | AV |
| Large | HG | QH | QH |

(c) For shorter queue

| Distance to critical point | Difference in speed | | |
|---|---|---|---|
| | Small | Medium | Large |
| Small | VL | VL | LW |
| Medium | LW | FR | AV |
| Large | FR | AV | QH |

(d) For random lane change

*Notes: VL: Very low, LW: Low, FR: Fair, AV: Average, HG: High, QH: Quite high, VH: Very high*

The third section is the defuzzification process and is concerned with obtaining a final crisp output from the fuzzy system. This can be done by different methods but the three most commonly used ones include:

- The maximum criterion method
- The mean maximum method
- The centre of gravity

The fuzzy similarity approach is also gaining popularity in recent years (Nittimaki, 2000). The centre of gravity method has been adopted in this study. It involves computing the centroid of the regions defined by overlapping membership functions contained in the FAM matrix. The area of each region is weighted by the results of the combination process (in this case the "and operator"). Calculation of the centroid can be simplified by the equation below.

$$\text{Fuzzy\_output} = \frac{\sum_{i=1}^{n} c_i . w_i . A_i}{\sum_{i=1}^{n} w_i . A_i} \qquad \text{.................................} \textit{(3-3)}$$

*Where:*

| | |
|---|---|
| $A_i$ | *is the area defined by rule;* |
| $c_i$ | *is the centroid of Ai;* |
| $w_i$ | *is the weighting factor for area;* |
| $n$ | *is the number of active areas;* |

Assignment of membership values for each class was done such that the obtained drive gave a realistic measure of the likely outcome of different factor combinations. Each output of drive for any action assumes a value within the range 0 to 1.0. The magnitude of the driver reflects the urgency or suitability of the action and is used in the evaluation exercise.

### 3.11 Application of Adaptive Neuro Fuzzy Interface (ANFIS) in Modeling

In the preceding sections the model maps input characteristics to input membership functions, input membership function to rules, rules to a set of output characteristics, output characteristics to output membership functions, and the output membership function to a single-valued output or a decision associated with the output. Membership functions have been considered as fixed, and somewhat are chosen arbitrarily. Also, fuzzy inference has been applied to modeling systems whose rule structure is essentially predetermined by the user's interpretation of the characteristics of the variables in the model. The function anfis and the ANFIS Editor GUI is one of the Fuzzy Logic Tools and apply fuzzy inference techniques to data modeling. The acronym ANFIS derives its name from *adaptive neuro-fuzzy inference system.* Using a given input/output data set, the toolbox function anfis constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using either a backpropagation algorithm alone, or in combination with a least squares type of method. This allows fuzzy systems to learn from the data they are modeling.

### 3.11.1 Modeling scenario

ANFIS can be applied to a system for which a collection of input/output data is known. It is not necessarily have a predetermined model structure based on characteristics of variables in system. There will be some modeling situations in which it is difficult to set pattern of data and to discern what the membership functions should look like. Rather than choosing the parameters associated with a given membership function arbitrarily, these parameters could be chosen so as to tailor the membership functions to the input/output data in order to account for these types of variations in the data values. This is where the so-called *neuro-adaptive* learning techniques incorporated into ANFIS in the Fuzzy Logic Toolbox can help.

### 3.11.2 Model learning and inference through ANFIS

The basic idea behind these neuro-adaptive learning techniques is very simple. These techniques provide a method for the fuzzy modeling procedure to learn information about a data set, in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data. This learning method works similarly to that of neural networks. The Fuzzy Logic Toolbox function that accomplishes this membership function parameter adjustment is called ANFIS.

An adaptive FIS usually consists of two distinct modifiable parts: the antecedent part and consequent part. These two parts can be adapted by different optimization methods, one of which is the hybrid learning procedure combining gradient descent and least squares estimator. The antecedent part or If–part contains nonlinear parameters of membership functions that can take many different forms (Gaussian, triangular, trapezoidal, etc.). Membership function can be any function with range in [0, 1] if human experts find them appropriate to represent their knowledge. Gradient decent method is used to adjust nonlinear parameters. The consequent part or Then-part contains output's linear parameters, which can be tuned with least squares estimator.

A network-type structure similar to that of a neural network, which maps inputs through input membership functions and associated parameters, and then through output membership functions and associated parameters to outputs, can be used to interpret the input/output map. The parameters associated with the membership functions will change through the learning process. The computation of these parameters (or their adjustment) is facilitated by a gradient vector, which provides a measure of how well the fuzzy inference system is modeling the input/output data for a given set of parameters. Once the gradient vector is obtained, any of several optimization routines could be applied in order to adjust the parameters so as to reduce some error measure (usually defined by the sum of the squared difference between actual and desired outputs). In this modeling work, ANFIS uses a combination of least squares estimation and backpropagation for membership function parameter estimation.

Fundamentally, ANFIS is a graphical network representation of Sugeno-type fuzzy systems, endowed with neural learning capabilities. The network is comprised of nodes and with specific functions, or duties, collected in layers with specific functions. The fuzzy inference system with two input $x$ and $y$ and output $z$ *is considered*. For a first-order Sugeno fuzzy model, a common rule set with two fuzzy if-then rules is the following:

*Rule 1: If* $x$ *is* $A_1$ *AND* $y$ *is* $B_1$, *then* $f_1=p_1x+q_1y+r_1$,

*Rule 2: If* $x$ *is* $A_2$ *AND* $y$ *is* $B_2$, *then* $f_2=p_2x+q_2y+r_2$.

ANFIS can construct a network realization of rules. Figure 3.9 illustrate the reasoning mechanism for this Sugeno mode and the corresponding equivalent ANFIS architecture, where nodes of the same layer have similar functions, as described next.

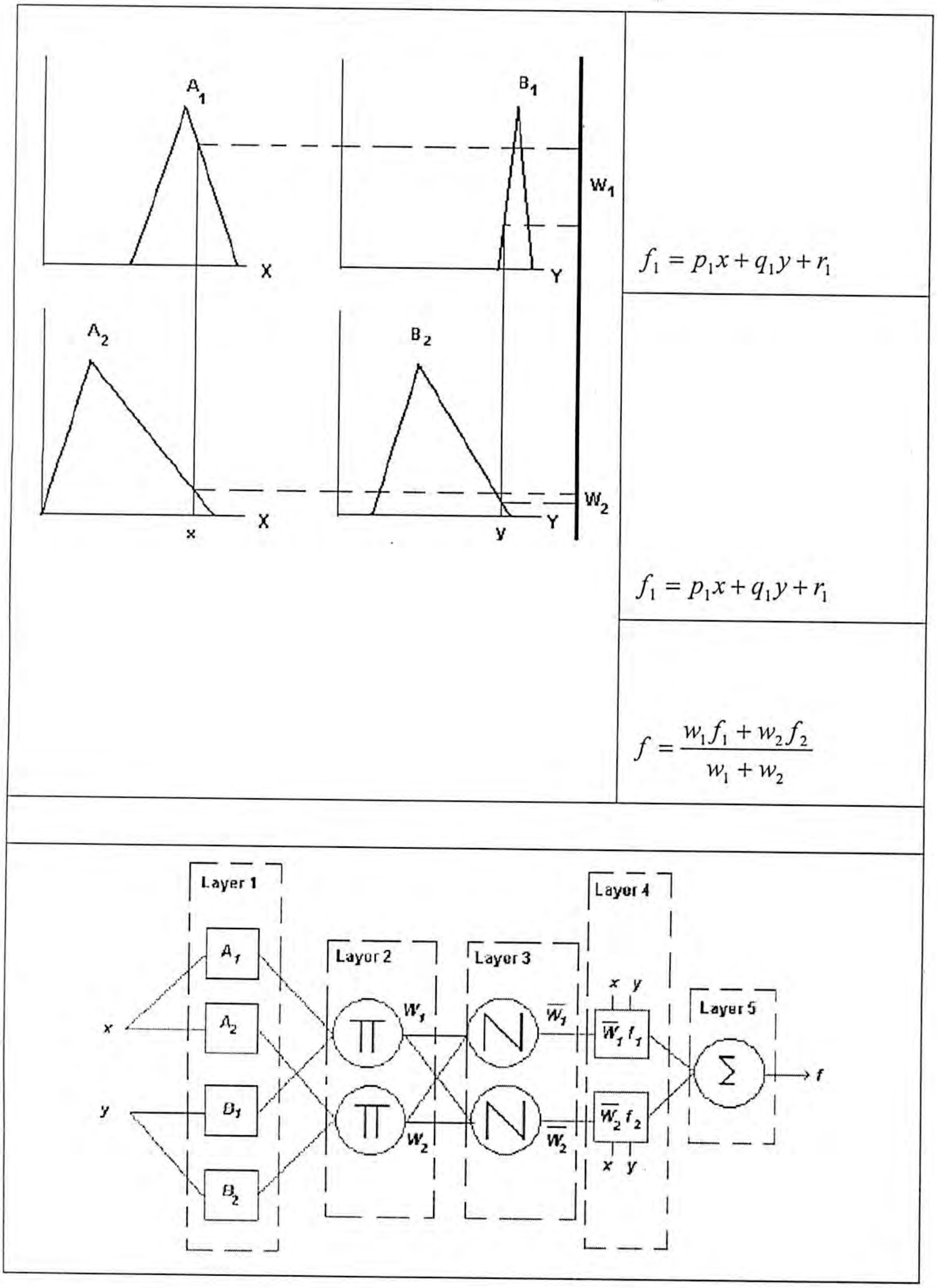



**Figure 3.9:** Evaluation of A Network Realization of Rules(Top) and The Corresponding ANFIS Architecture(Bottom)

**Layer 1.** Every node in this layer is an adaptive node with a node function

$$O_i^1 = \mu_{Ai}(x), \text{for i=1,2, or} \quad \text{.......................................} \; (3.4)$$

$$O_i^1 = \mu_{Bi-2}(y), \text{ for i=3.4} \quad \text{.......................................} \; (3.5)$$

Where $x$ (or $y$) is the input to node i and $A_i$ (or $B_{i-2}$) is a linguistic label (such as "small" or "large") associated with this node. In other words, i is the membership grade of a fuzzy set A (=$A_1$, $A_2$, $B_1$ or $B_2$) and it specifies the degree to which the given input $x$ (or y) satisfies the quantifier A.

**Layer 2.** Every node in this layer is a fixed node labeled $\Pi$, whose output is the product of all the incoming signals. Each node output represents the firing strength of a rule.

$$O_i^2 = w_i = \mu_{Ai}(x) \times \mu_{Bi}(y), \quad i=1,2 \quad \text{.......................................} \; (3.6)$$

**Layer 3.** Every node in this layer is a fixed node labeled N. The *i*-th node calculates the ratio of the *i*-th rule's firing strength to the sum of all rule's firing strengths. Outputs of this layer are called **normalized firing strengths.**

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2}, \quad i=1,2 \quad \text{.......................................} \; (3.7)$$

**Layer 4.** Every node *i* in this layer is an adaptive node which has a node function

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i) \quad \text{.......................................} \; (3.8)$$

Where $\overline{w}_i$, is the output of layer3 and $\{p_i, q_i, r_i\}$ is the parameter set. Parameters in this layer will be referred to as the consequent parameters.

**Layer 5.** The single node in this layer is a fixed node labeled $\Sigma$, which computes the overall output as the summation of all incoming signals.

$$O_i^5 = overall\_output = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad \text{.......................................} \; (3.9)$$

### 3.11.3 Hybrid Learning Algorithm

From ANFIS architecture shown in the Figure 3.9, we observe that the values of the premise parameters are fixed, the overall output can be expressed as a linear combination of the consequent parameters. In symbols, the output *f* in the Figure 3.9 can be rewritten as

$$
\begin{aligned}
f &= \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 \\
&= \overline{w}_1 (p_1 x + q_1 y + r_1) + \overline{w}_2 (p_2 x + q_2 y + r_2) \qquad \text{.........} (3.10) \\
&= (\overline{w}_1 x) p_1 + (\overline{w}_1 y) q_1 + (\overline{w}_1) r_1 + (\overline{w}_2 x) p_2 + (\overline{w}_2 y) q_2 + (\overline{w}_2) r_2
\end{aligned}
$$

*Which is linear in the consequent parameters* $p_1, q_1, r_1, p_2, q_2$ *and* $r_2$.

$S$ = *set of total parameters,*

$S_1$ = *set of premise (nonlinear) parameters,*

$S_2$ = *set of consequent (linear) parameters*

The learning algorithm for ANFIS is a hybrid algorithm which is a combination between gradient descent and least-squares method. More specifically, in the forward pass of the hybrid learning algorithm, node outputs go forward until layer 4 and the consequent parameters are identified by the least-squares method. In the backward pass, the error signals propagate backward and the premise parameters are updated by gradient descendent. The next Table summarizes the activities in each pass.

**Table 3.5**: Two Passes in the Hybrid Learning Procedure for ANFIS

| Items | Forward pass | Backward pass |
|---|---|---|
| **Premise parameters,** $S_1$ | Fixed | Gradient descent |
| **Consequent parameters,** $S_2$ | Least-squares estimator | Fixed |
| **Signals** | Node outputs | Error signals |

The consequent parameters are identified optimal under the condition that the premise parameters are fixed. Accordingly, the hybrid approach converges much faster since it reduced the search space dimensions of the original pure backpropagation method.

### 3.11.4 Adjustment for ANFIS Structure

In order to formulate ANFIS model following constraints are considered

- Be first or zeroth order Sugeno-type systems.

- Have a single output, obtained using weighted average defuzzification. All output membership functions must be the same type and either be linear or constant.
- Have no rule sharing. Different rules cannot share the same output membership function, namely the number of output membership functions must be equal to the number of rules.
- Have unity weight for each rule.

Taking into account all those limitations output function for all types of lateral movement are taken as constant. Output membership functions for each type are classified as Very Low(VL), Low(LW), Fair(FR), Average(AV), High(HG), Quite High(QH) and Very High(VH) with parameters 0.15,0.3,0.4,0.6,0.7,0.8, and 0.95 respectively. Output functions quantify driver's decision for lane change.

Rules that define boundary conditions or the rules which specifically identify membership function relationship are used for ANFIS. The rules are selected in such a way to avoid the rule sharing and have unit weight. The follow Figures (Figure 3.10, 3.11, 3.12) show basic membership parameters for the fuzzy interface system, associated rules and ANFIS structure

For example for overtaking action difference in speed, distance to critical point (normally for urban scenario, distance from intersection), speed of slower vehicle, distance of coming vehicle and actual speed of the vehicle is taken as input variables. Their membership functions are previously shown in Figure 3.8. Four rules are used. ANFIS model structure for overtaking action shows that input function speed of slower vehicle, distance of coming vehicle and actual speed don't shows connection through rules as their precise relationships to output function is not known precisely. However training of ANFIS establish any relationships if exists.

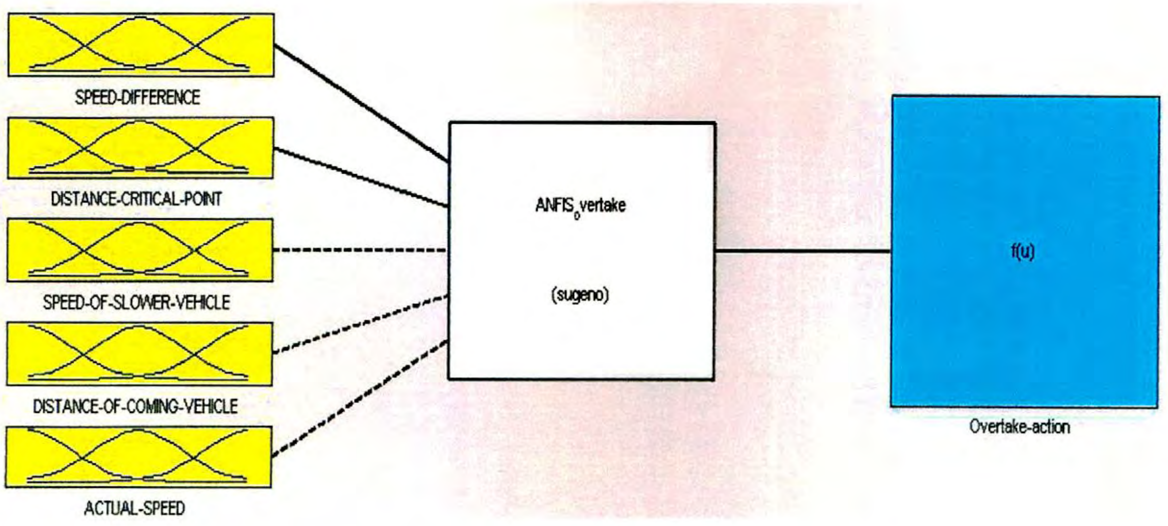



**Figure 3.10**: Model Structure for Overtaking Action

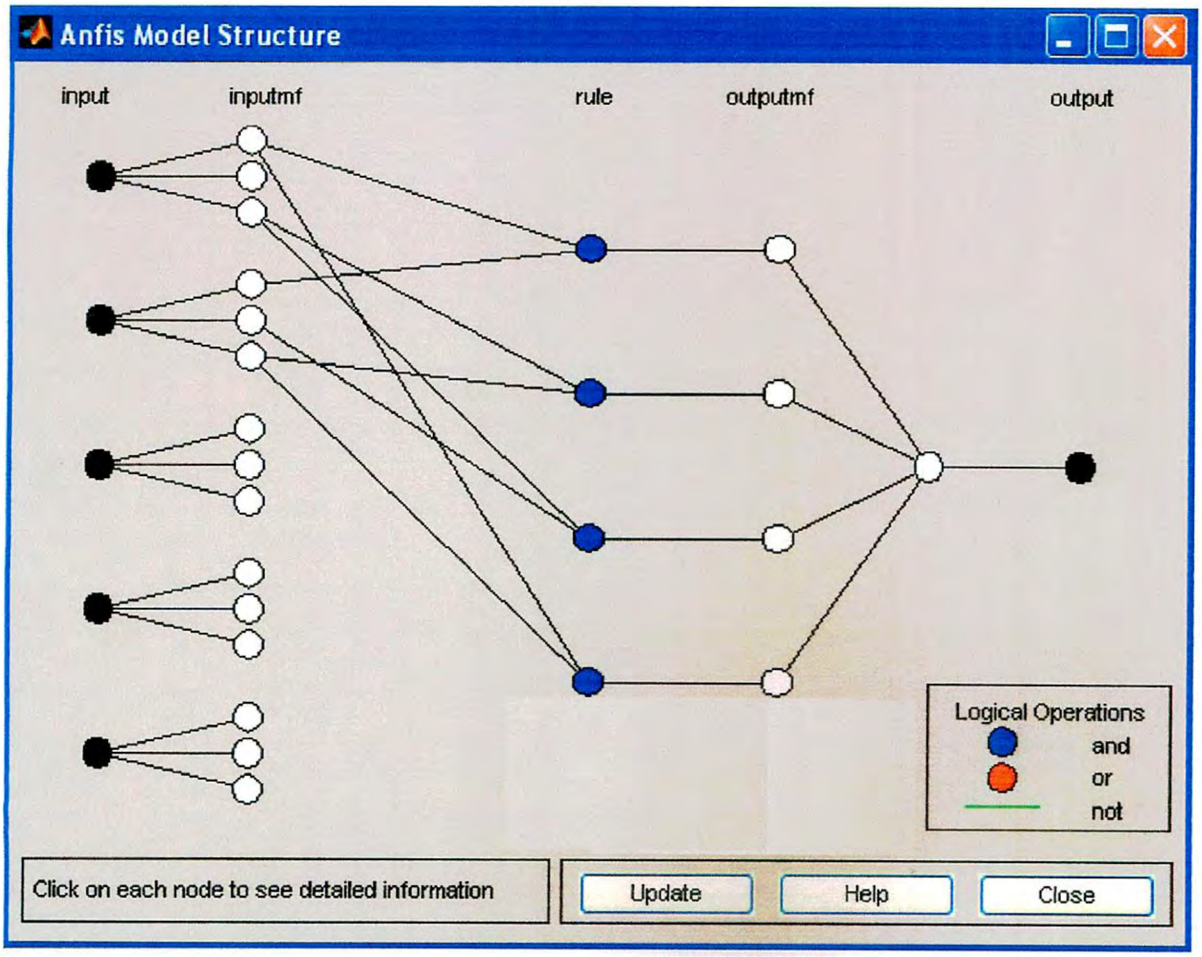



**Figure 3.11**: Model Structure for ANFIS for Overtaking Action

1. If (SPEED-DIFFERENCE is SMALL) and (DISTANCE-CRITICAL-POINT is SMALL) then (Overtake-action is VL) (1)
2. If (SPEED-DIFFERENCE is LARGE) and (DISTANCE-CRITICAL-POINT is LARGE) then (Overtake-action is QH) (1)
3. If (SPEED-DIFFERENCE is LARGE) and (DISTANCE-CRITICAL-POINT is MEDIUM) then (Overtake-action is AV) (1)
4. If (SPEED-DIFFERENCE is SMALL) and (DISTANCE-CRITICAL-POINT is LARGE) then (Overtake-action is FR) (1)

**Figure 3.12**: Rule Associated with ANFIS model Structure for Overtaking Action

## 3.12 Summary

Leading a research field from infancy to maturity and technological deployment is a particularly difficult task, and crucial methodological developments obtained through the insight and intuition make a difference. In this Chapter, mathematical formulations of the different components along with methodological aspects of the proposed lane change decision model have been presented. Various lane changing variables are considered and various linguistic variables and driving behavior are expressed in numeric term which is very much essential for modeling purpose. This framework of model utilize the adaptive neuro fuzzy interface which provides the platform for training, testing and checking with existing data and therefore gives most reliable soft computing tool.

# CHAPTER 4

## DATA COLLECTION METHODS

### 4.1 Introduction

Driver behavior has seen a resurgence of interest over the recent years, as it has increasingly become apparent that a detailed understanding of how we drive is essential for both the design and assessment of new driving models and for the development of microscopic simulation models.

### 4.2 Basic Considerations

To formulate lane changing decision model, more insights into the behavior of drivers - particular how drivers interact (cooperate, negotiate) with each other and with the environment - is required. Research at this microscopic level requires a high detail of data collection in order to be useful. Empirical study of driver behavior is not possible without real-life data that consist of complete vehicle trajectories recorded at a long roadway stretch and at a high frequency, as well information on the vehicles themselves. Longitudinal and lateral positions are thus to be collected very precisely in order to determine the exact lane changing of the vehicles.

The availability of these data is limited and dated (Treiterer and Myers, 1974). From the perspective of model validation and calibration, the large number of unobservable microscopic parameters, and their complex and non-linear relation with the resulting macroscopic flow characteristics, yields that indirect model calibration using macroscopic data may not always be good practice. For this reason, Brackstone and Mac-Donald (1995,1998) argue that calibration of microscopic simulation models requires detailed information on dynamic behavior of vehicle pairs. Also the existence of stable or meta-stable traffic states in congested circumstances and the behavioral hypotheses postulated to explain these phenomena (Kerner,1999) can also be studied in detail when detailed microscopic information is available.

## 4.3 Data Collection Methods

### 4.3.1 Driving simulator

Driving simulators are used to create realistic driver sensations in laboratory environments. They are widely used for experiments on, for example, driver behavior, vehicle characteristics, road design or the use of new technical equipment. One of the main advantages is that it is possible to conduct safe experiments with equal conditions for all test drivers. Driving simulators uses computer models to calculate the movements of the driving simulator vehicle corresponding to driver's use of the steering wheel and the pedals. They also include some kind of scenario module that controls the surroundings, e.g. the road design, trees, houses, events etc and a visual system that presents the surroundings on some sort of screen. Some driving simulators utilize real vehicle cabs and advanced motion systems that support the driver's visual impression of the vehicle's movements.

**Figure 4.1:** Typical Driving Simulator

Since one of the main ideas of experiments in driving simulators is to create a safe environment that resembles driving in real traffic systems as closely as possible, it is obvious that trustworthy ambient traffic is needed. Realistic traffic is specially needed in studies where the traffic intensity and composition has a large influence on the driver's ability to drive the vehicle. Simulation of surrounding traffic for a driving simulator can be made using models of microscopic simulation of traffic. Micro-simulation is a useful and very popular tool in studies of traffic systems. Road network descriptions, origin-destination matrices and information about driver characteristics are the main inputs in such simulations.

The models are able to generate information, for example, about average speeds and traffic flows on different road sections. The simulation is performed at a microscopic level, which implies detailed modeling of vehicle characteristics and driver behavior. This is done by using behavioral models for behaviors such as car-following, speed adaptation, lane-changing and overtaking. Micro-simulation is mainly used to obtain outputs at a macroscopic level. The desired results are often measurements such as average flow, speed, or queue lengths and calibration and validation are therefore usually done at a macroscopic level. However, when simulating surrounding traffic for a driving simulator, the simulator driver's experience of the ambient traffic is at the micro-level. It is therefore important to calibrate and validate the model at a microscopic level.

### 4.3.2 Using instrumented vehicle

An instrumented car can be used in the lane changing experiment. The instrumented vehicle is equipped with a GPS-based navigation system and an advanced on-board trip computer for recording travel time, distance, speed, etc. lidar sensors and video cameras are installed to observe surrounding objects in both front and rear sides. Software installed on a portable laptop computer can log all information infused from those equipments at a certain frequency.

## 4.4 Experimental Setup and Data Requirements

As discussed on the preceding sections lane-changing behavioral data can best be collected using instrumented vehicle or driving simulator to calibrate and validate the fuzzy sets and systems.

However in absence of those equipments, manual experiment setup has been designed. The basic concept of data collection methodology for Fuzzy model development was taken from the reference (Wu, J.P et al, 2000). The following sections describe such arrangements. Two -lane undivided section was considered. In order to obtain dynamic lane-changing data in a range of circumstances, against which the model can be calibrated two vehicles have been taken for data acquisition. First vehicle gathers information from driver about his lane changing decision and also to collect information regarding speed and distances of lead and following vehicles. Second vehicle normally follow the first one and purpose of this vehicle is to gather backup data and data regarding traffic environment, and particularly to document first vehicle's lane changing maneuver.

Each vehicle is equipped with video cameras, front, back and sides (preferably right side) and data has been collected using video technology. All cameras have been set from same time frame. Video data is basically used for reference point selection purpose. The vehicle is also equipped with GPS device for recording distance and speed information against time of drive. The driver was asked by an observer to give spontaneous subjective assessments of their following distance/relative speed using the verbal terms used to describe the fuzzy sets (the so called 'verbalisation technique').

About every half minute, the observer asked about his intention. The interval between questions was carefully controlled in order to ensure that the driver did not suffer 'task overload'. Any response given after 1 second was discarded in order to ensure that the statements given were instinctive and not subject to prejudgment. Each successful lane change was classified according to its purpose as discussed in Section 3.9.3

Following steps of work are required for the whole job:

- On-board equipment
- Driver's behavior recording
- Measurements of vehicle parameters
- Data collection
- Synchronizations of the various data

**Table 4.1:** Sample Data Recoding Table for Model Training

| Time | Type of lateral movement | Input variables | | | | | | | Output | Remarks |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Distance to critical point | Actual Speed | Speed of the slower vehicle | Difference in speed | Distance to present queue | Difference in queue length | Distance of the coming vehicle | Decision of lane-change | |
| 11:15:30 | Overtake | - | 70 | 65 | 15 | - | - | 200 | QH | Rural section |
| | | | | | | | | | | |

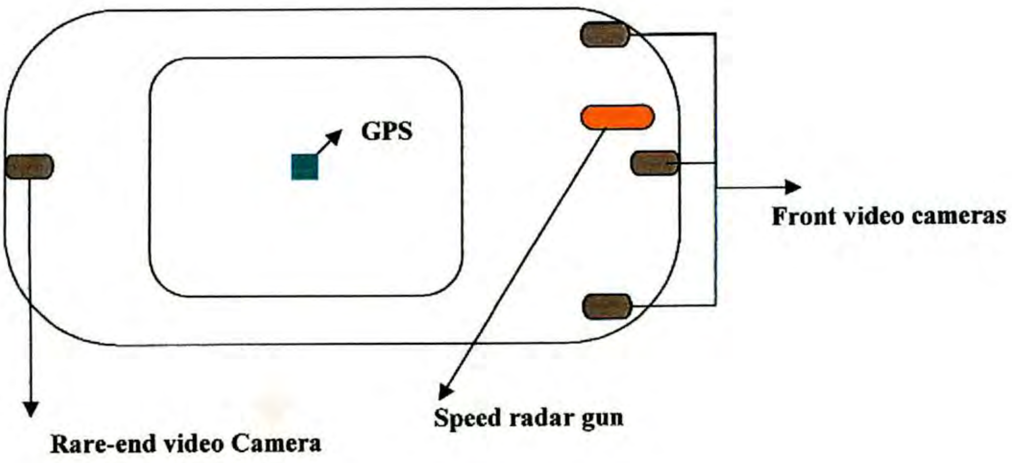



**Figure 4.2:** Instrument Setup of Data Collection Vehicle

## 4.5 Other Issues

Collecting data for validation is most conveniently done simultaneously with data collection for inputs. The use of the same or closely related data for both input and validation is an issue that is rarely confronted. The conventional wisdom is that such dual-use of the data is "forbidden". In fact, it can be done but how to attach computable uncertainties, essential to producing fully reliable results, is not straightforward. This issue is under study by a research team at NISS and Duke University; a Bayesian approach based on Bayarri and Berger (1999) holds great promise for producing methodology to treat the issue.

A problem as yet not addressed is assessing the impact of data of inferior quality. The problem is complicated by the need to specify the "brunt of the impact"; quantify scenarios of alternative collections of data; and design, execute and analyze computational experiments to measure the consequences, or sensitivities, of model output to wrong data inputs including incorrect signal settings or drifts in signal timing. This issue is not unique to transportation studies and research; it permeates virtually all of science.

## 4.6 Summary

Data is a major requirement for tuning and calibrating a model. Estimation is treated of inputs to the model directly from field data. When model output are used, either alone or with field data, to determine input parameters the process is often called calibration Tuning is a phrase commonly associated with adjusting input parameters to match model output. Formally the same as calibration the term, tuning, is frequently reserved for cases where the input parameters are unobservable or represent physical (and other processes) which the model does not (or cannot) adequately incorporate.

The practice of tuning is not only common but is often essential, especially for long range study of the model and its associated phenomena. Some input parameters may neither be well-specified, nor capable of being estimated from the field data (for example, driver aggressiveness in our test-bed). Some assumptions about input parameters may be found to be erroneous after viewing the data and their modification may produce "better" simulations. Ultimately, what becomes problematic is the validation accompanying such tuning. The following chapter discuss various issues related to validation and calibration and training of ANFIS model.

# CHAPTER 5

## CALIBRATION AND VALIDATION FRAMEWORK

### 5.1 Introduction

This Chapter gives an overview of the overall validation and calibration framework for the lane change decision model. The data requirements for estimating, calibrating and validating the model parameters have been summarized in this regard.

The process involves two types of data: training data and checking data. Those data have been collected from two separate collection sites. The characteristics of the two datasets are described in this connection.

### 5.2 Training Data and Training Error

The training data is a required argument to ANFIS model. Each row of data file is a desired input/output pair of the target system to be modeled. Each row starts with an input vector and is followed by an output value. Therefore, the number of rows is equal to the number of training data pairs, and, since there is only one output, the number of columns of data file is equal to the number of inputs plus one.

The training error is the difference between the training data output value, and the output of the fuzzy inference system corresponding to the same training data input value, (the one associated with that training data output value). The training error records the root mean squared error (RMSE) of the training data set at each epoch.

The ANFIS Editor GUI will plot the training error versus epochs curve as the system is trained.

### 5.3 Checking Data And Checking Error

The checking data is used for testing the generalization capability of the fuzzy inference system at each epoch. The checking data has the same format as that of the training data, and its elements are generally distinct from those of the training data.

The checking data is important for learning tasks for which the input number is large, and/or the data itself is noisy. Since the model structure used for ANFIS is fixed, there is a tendency for the model to overfit the data on which is it trained, especially for a large number of training epochs. If overfitting does occur, the fuzzy inference system cannot be expected to respond well to other independent data sets, especially if they are corrupted by noise. A validation or checking data set can be useful for these situations. This data set is used to cross-validate the fuzzy inference model. This cross-validation is accomplished by applying the checking data to the model, and seeing how well the model responds to this data.

When the checking data option is used with ANFIS the checking data is applied to the model at each training epoch. The FIS membership function parameters computed using the ANFIS Editor GUI when both training and checking data are loaded are associated with the training epoch that has a minimum checking error. The use of the minimum checking data error epoch to set the membership function parameters assumes that the checking data is similar enough to the training data that the checking data error will decrease as the training begins and the checking data increases at some point in the training, after which data overfitting has occurred.

The checking error is the difference between the checking data output value, and the output of the fuzzy inference system corresponding to the same checking data input value, (the one associated with that checking data output value). The checking error records the RMSE for the checking data at each epoch. This gives the snapshot of the FIS structure when the checking error is at its minimum. The ANFIS Editor GUI will plot the checking error vs. epochs curve as the system is trained.

## 5.4 Familiarity Breeds Validation: Knowing Data

The modeling approach used by ANFIS is similar to many system identification techniques. First, a parameterized model structure has been hypothesized (relating inputs to membership functions to rules to outputs to membership functions, and so on). Next, input/output data in a form that is usable by ANFIS for training has been collected. Then ANFIS is used to train the FIS model to emulate the training data presented to it by modifying the membership function parameters according to a chosen error criterion. In general, this type of modeling works well if the training data presented to ANFIS for training (estimating) membership function parameters is fully representative of the features of the data that the trained FIS is intended to model. This is not always the case, however. In some cases, data is collected using noisy measurements, and the training data cannot be representative of all the features of the data that will be presented to the model. This is where model validation comes into play.

## 5.5 Model Validation Using Checking and Testing Data Sets

Model validation is the process by which the input vectors from input/output data sets on which the FIS was not trained, are presented to the trained FIS model, to see how well the FIS model predicts the corresponding data set output values. This is accomplished with the ANFIS Editor GUI using the so-called testing data set, and its use is described in a subsection that follows. This other type of validation data set is referred to as the checking data set and this set is used to control the potential for the model overfitting the data. When checking data is presented to ANFIS as well as training data, the FIS model is selected to have parameters associated with the minimum checking data model error.

One problem with model validation for models constructed using adaptive techniques is selecting a data set that is both representative of the data the trained model is intended to emulate, yet sufficiently distinct from the training data set so as not to render the validation process trivial. This problem could be overcame using large amount of data, hopefully this data contains all the necessary representative features, so the process of selecting a data set for checking or testing purposes is made easier.

The basic idea behind using a checking data set for model validation is that after a certain point in the training, the model begins overfitting the training data set. In principle, the model error for the checking data set tends to decrease as the training takes place up to the point that overfitting begins, and then the model error for the checking data suddenly increases.

## 5.6 ANFIS Training

The two ANFIS parameter optimization method options available for FIS training are hybrid (the default, mixed least squares and backpropagation) and backpropa (backpropagation). Error Tolerance is used to create a training stopping criterion, which is related to the error size. The training will stop after the training data error remains within this tolerance. This is best left set to 0 it is not known how training error is going to behave. To start the training,

- optimization method is set as hybrid.
- training epochs is fixed to 40; under the Epochs listing on the GUI
- and then start train session

The following should appear on screen.

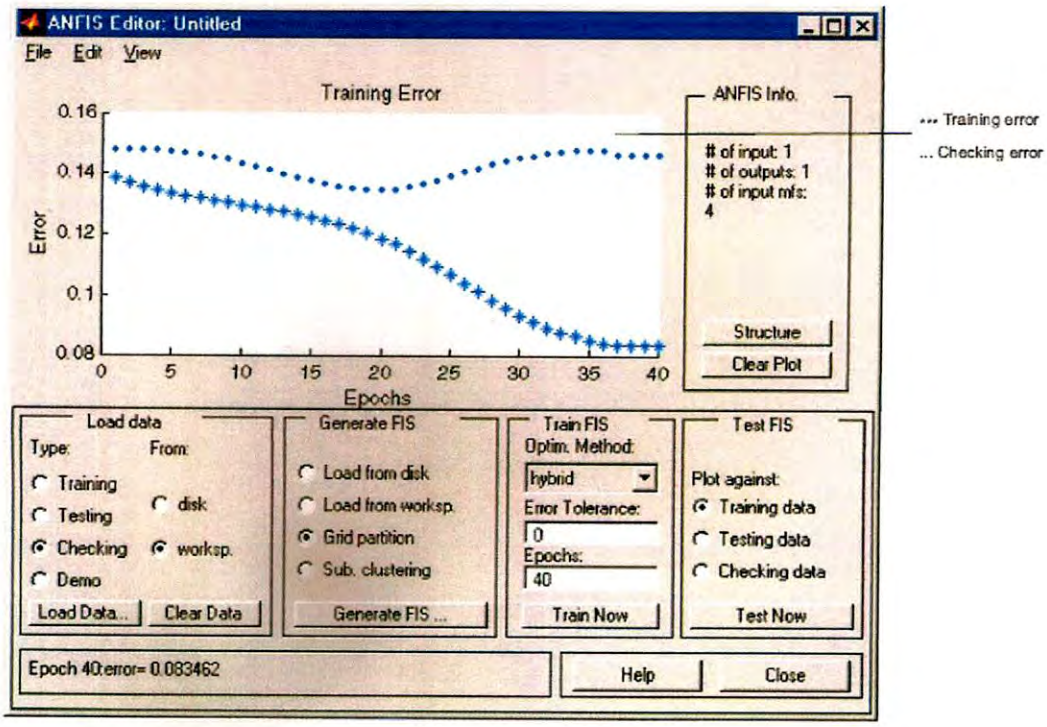



**Figure 5.1**: Plot of Training and Checking Error

If checking error decreases up to a certain point in the training and then it increases. This increase represents the point of model over fitting. ANFIS chooses the model parameters associated with the minimum checking error (just prior to this jump point). This shows the importance of checking data option of ANFIS. To test FIS against the checking data, the Checking data check box is selected in the Test FIS portion of the GUI. Good and representative training shows quite a bit of similarity. For example Figure shows the checking data against the FIS, it looks pretty good.

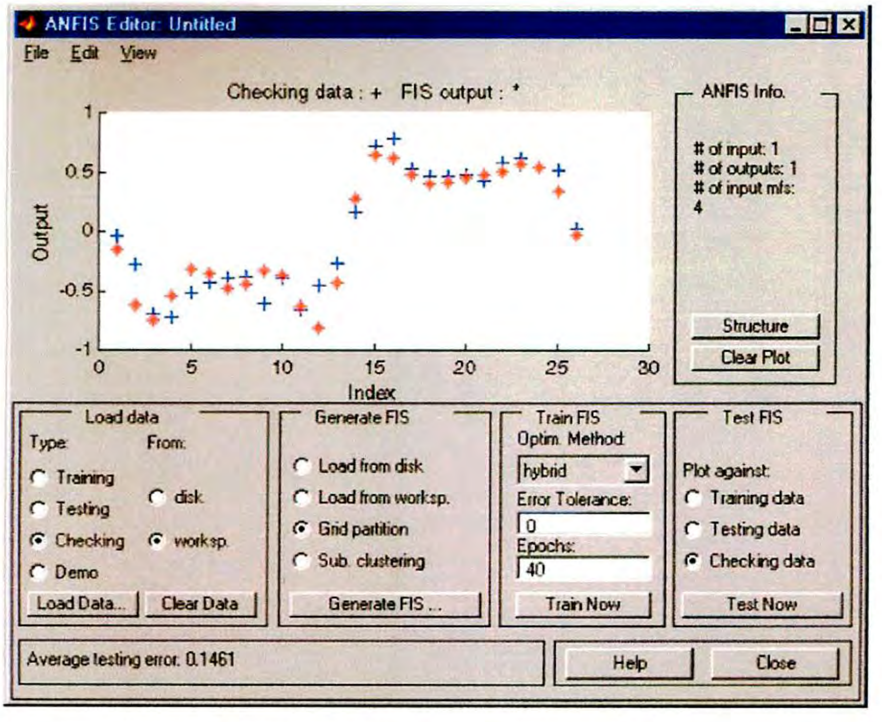



**Figure 5.2**: Plot of Checking Data and FIS Output.

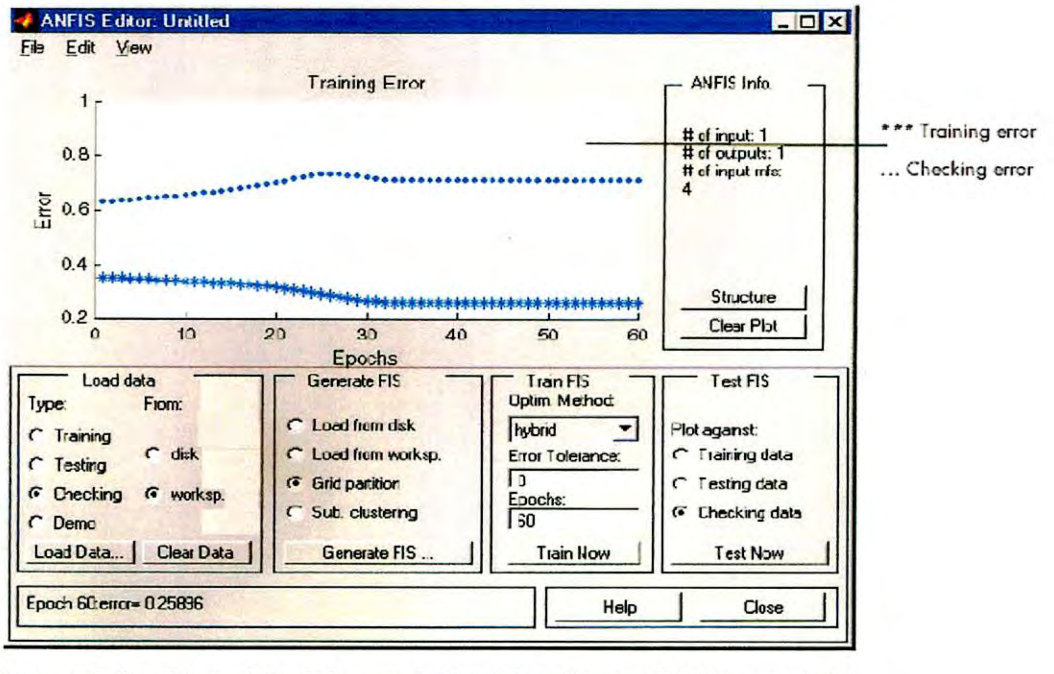



**Figure 5.3**: Plot of Training and Checking Error with inappropriate

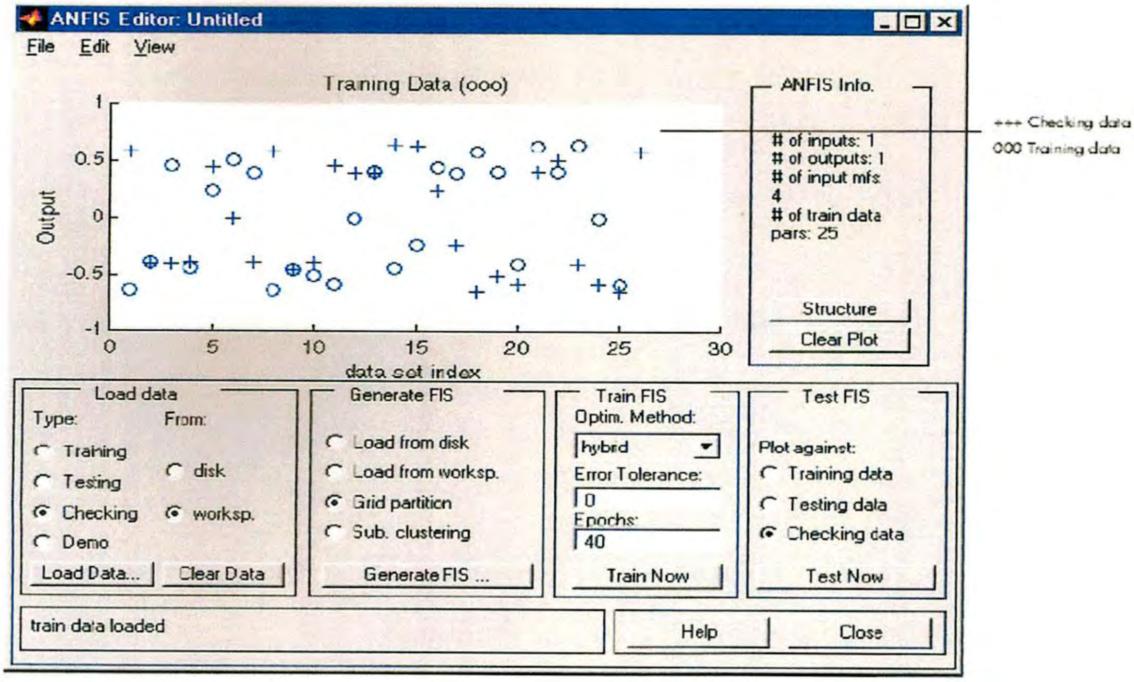



**Figure 5.4**: Plot of Training and Checking Data with inappropriate Membership Functions

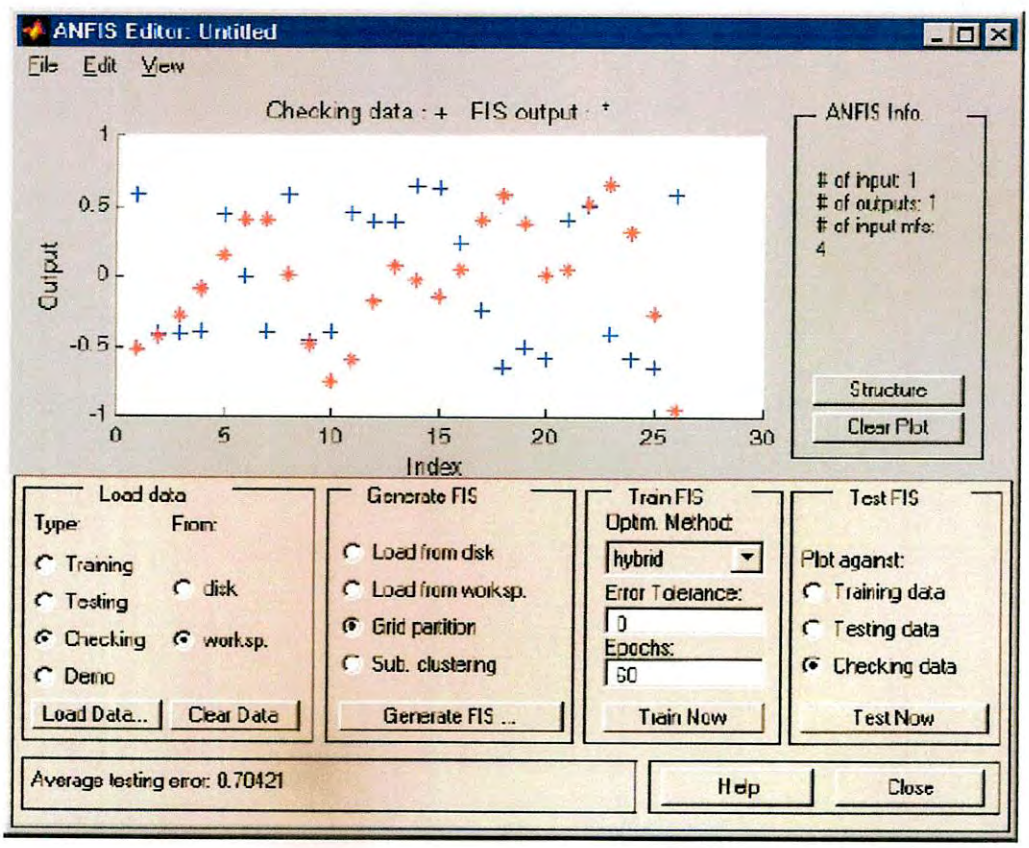



**Figure 5.5**: Plot of Checking Data and FIS Output with inappropriate Membership Functions

On the other hand Figure 5.3 shows the checking error is quite large. The following plot (Figure 5.4, 5.5) in the GUI indicates that there is quite a discrepancy between the checking data output and the FIS output.

It appears that the minimum checking error occurs within the first epoch. It is previously mentioned that using the checking data option with ANFIS automatically sets the FIS parameters to be those associated with the minimum checking error. Clearly this set of membership functions would not be the best choice for modeling the training data. This example illustrates the problem discussed earlier wherein the checking data set presented to ANFIS for training was sufficiently different from the training data set. As a result, the trained FIS did not capture the features of this data set very well. This illustrates the importance of knowing the features of data set well enough during the process of selecting training and checking data. In this example, the checking error is sufficiently large to indicate that either more data needs to be selected for training, or it might necessary to modify membership function choices (both the number of membership functions and the type). This is known as calibration. In view of these, following validation and calibration sequence has been used for proposed decision model

## 5.7 Summary

The validation aspect in the development of any model is of utmost importance. If such validation is insufficient, little confidence can be placed on the results. But owing to the complexity of the site selection and data collection, and also for the time constraint proper validation was not possible. But it is always possible to do validation work when sophisticated field data will available. It will help to do further refinement of the parameters used and help to raise the confidence level of this model. However, it can be used as a research tool for studying driver behaviour during the process of lane change. In the next Chapter some experimental results will be documented to show the use and applicability of the proposed model.

# CHAPTER 6

## MODEL OUTPUT AND RESULTS

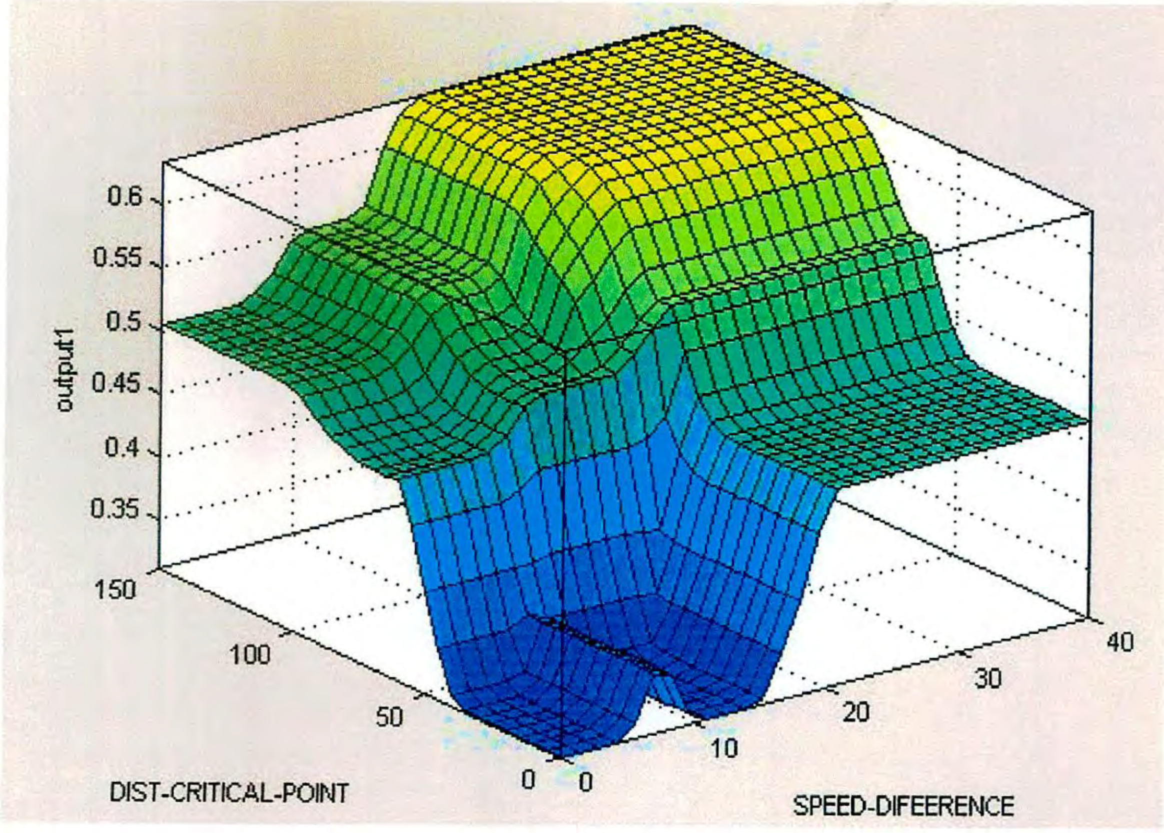
### 6.1 Introduction

Successfully developed model is used to acquire result relating to driver's decision. The decision value encompasses the effect of various exogenous factors and their membership functions and rules that combine those factors. Besides this the ANFIS training has also influenced the model outputs.

This Chapter contextualizes some model outputs and results. MATLAB surface viewer and rule viewer are used to generate those outputs.

### 6.2 Model Output

Rule based fuzzy logic model produces the following decision surface which illustrates the relationships of different membership functions and parameters. In this Chapter results of lane change for overtaking action are documented. Similar model could easily be developed based on the same methodology with different factors and membership functions (Section 3.9).



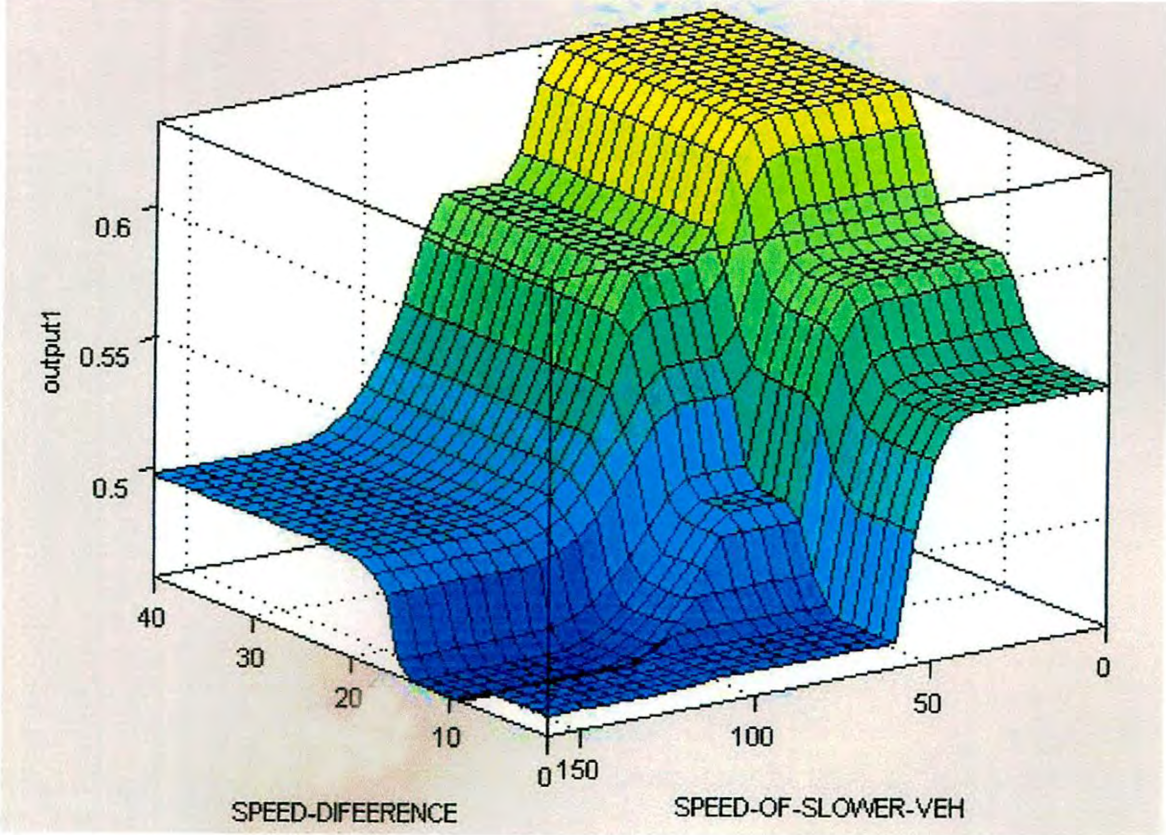
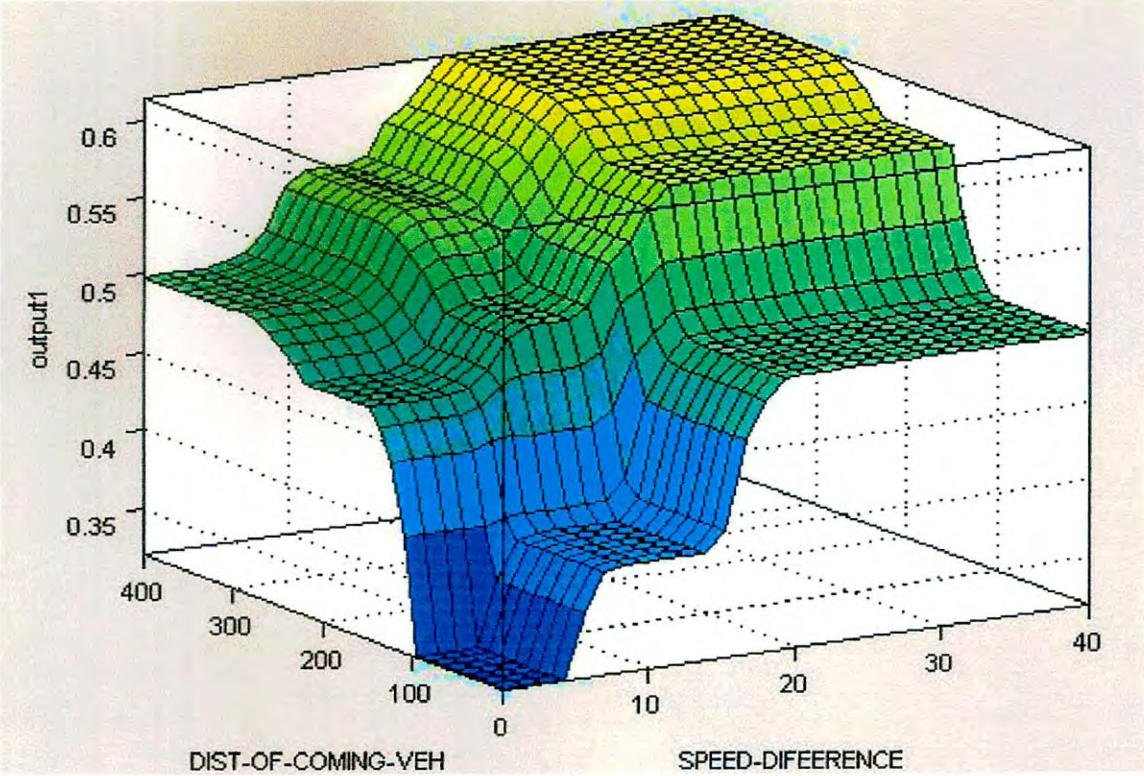




**Figure 6.1:** Decision Surface of Rule Based Fuzzy Interface System for Various Parameters (cont.)



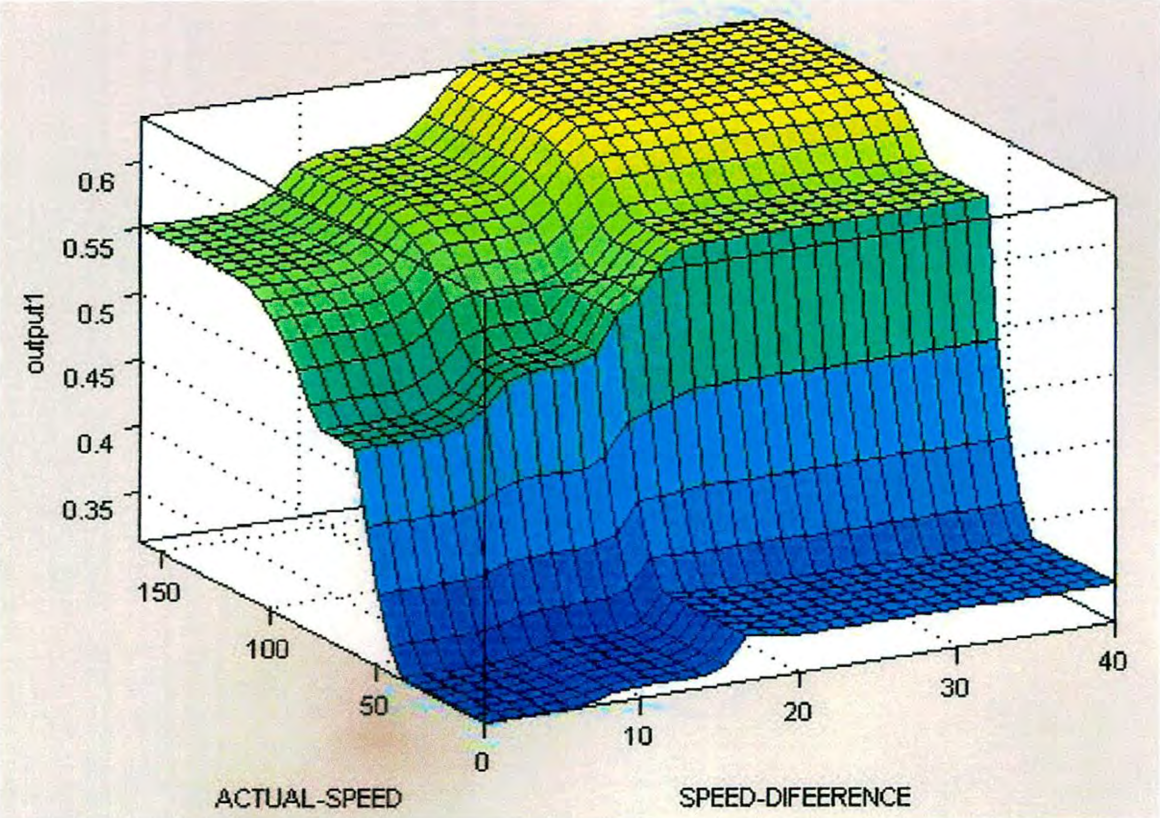




**Figure 6.1:** Decision Surface of Rule Based Fuzzy Interface System for Various Parameters (cont.)

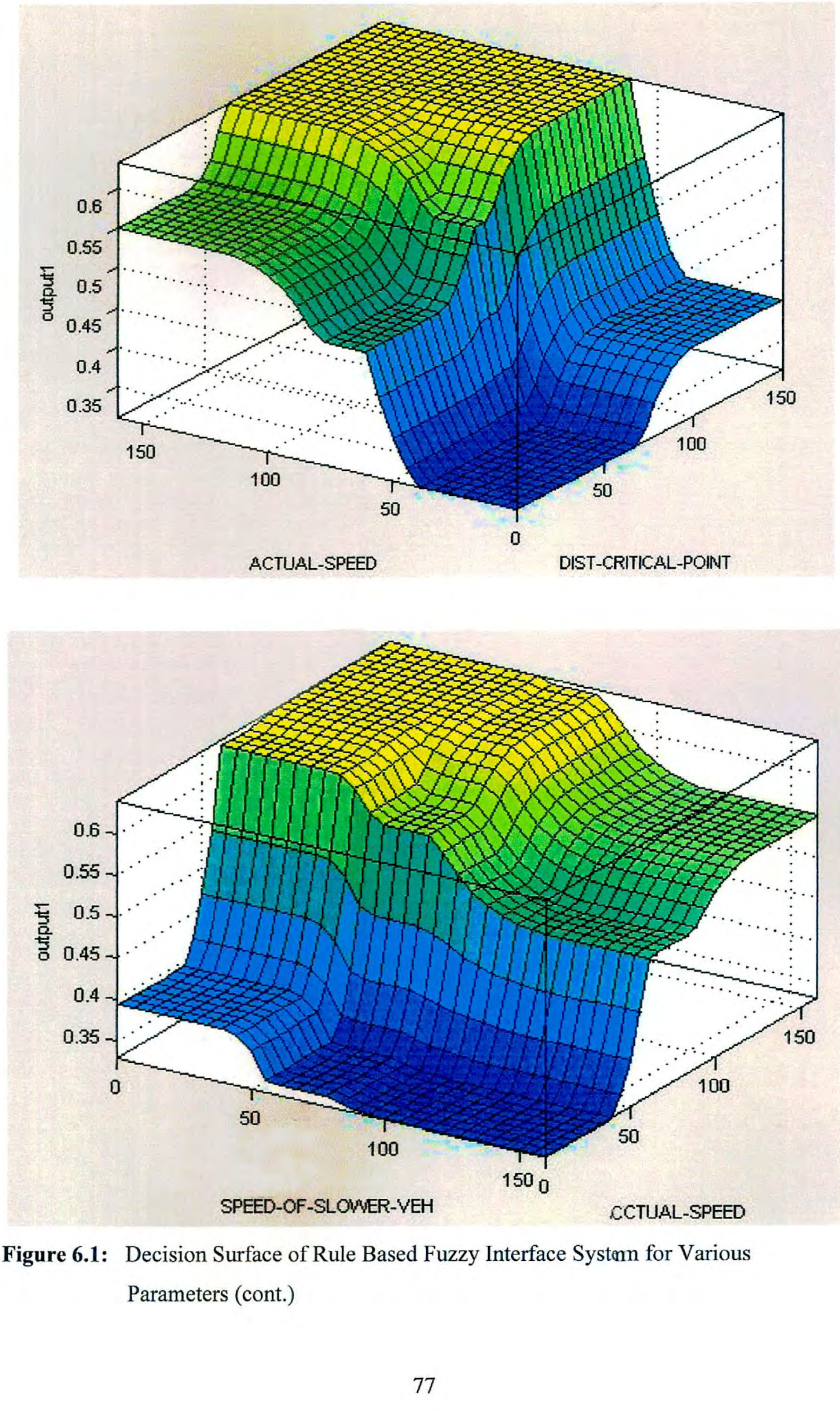



**Figure 6.1:** Decision Surface of Rule Based Fuzzy Interface Systam for Various Parameters (cont.)

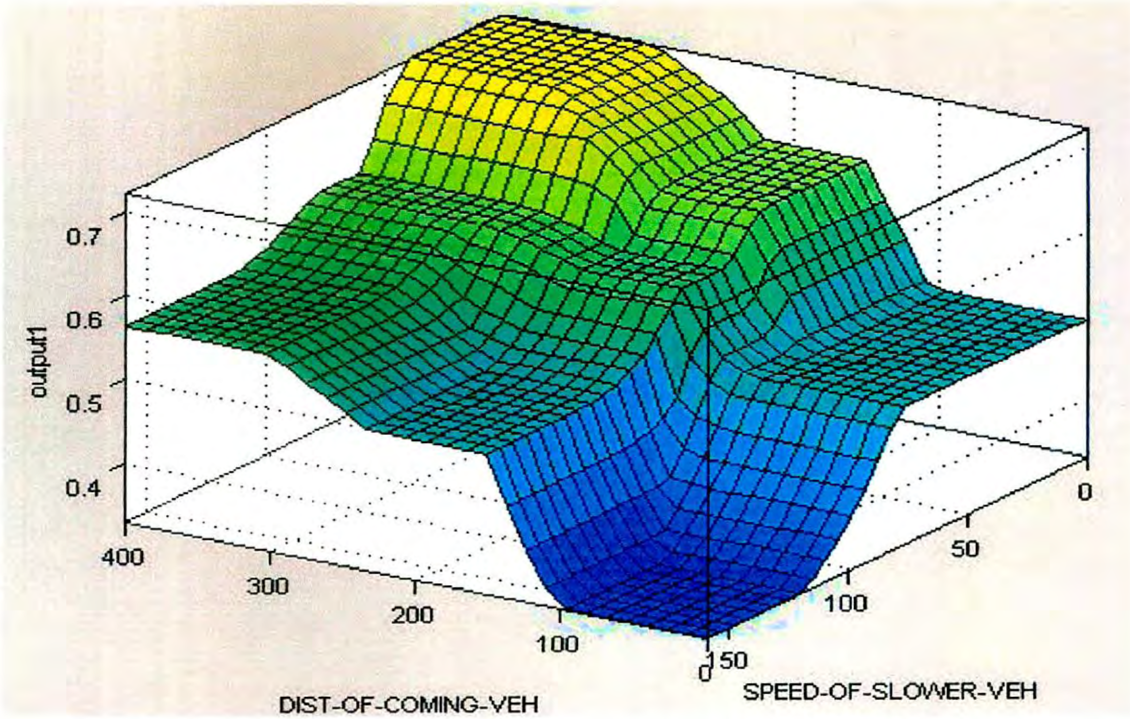



**Figure 6.1:** Decision Surface of Rule Based Fuzzy Interface System for Various Parameters

The rule viewer is used to interpret the entire fuzzy interface process. Here, it shows how the shape of certain membership functions influences the overall result.

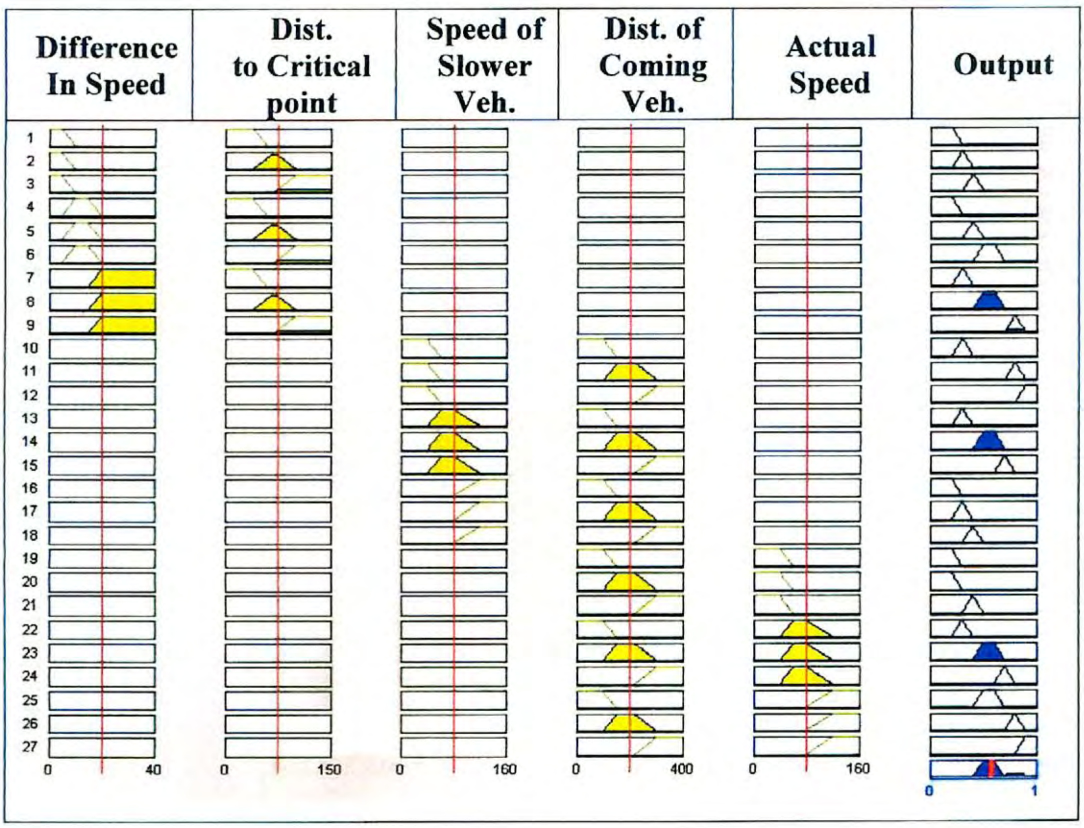



**Figure 6.2:** Rules of Fuzzy Interface System for Various Parameters and Associates Outputs

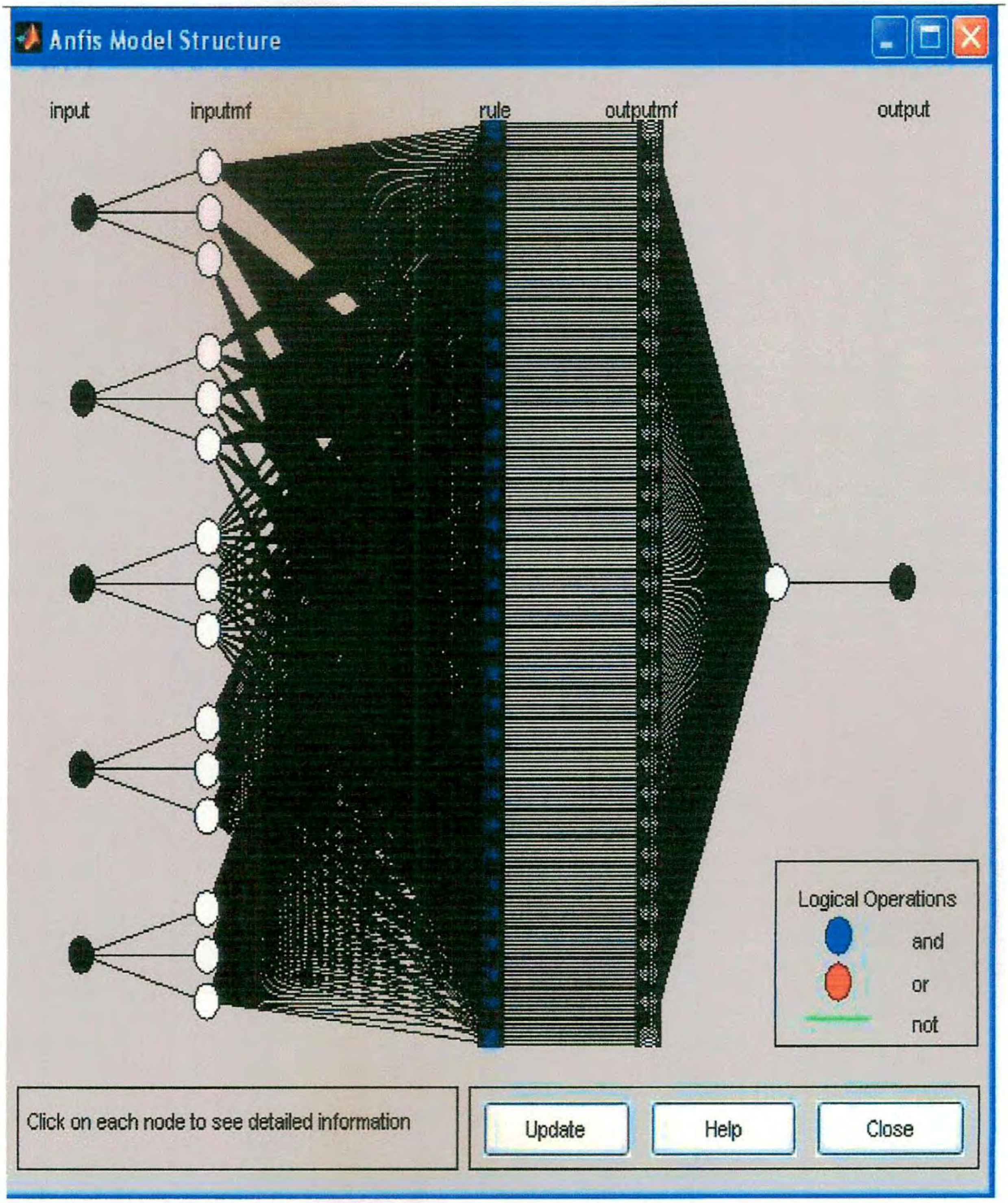



**Figure 6.3:** ANFIS Model Structure During the Process of Training

ANFIS model was developed initially with simple structure (Figure 3.11) and after training it has changed to following complex net. Here only limited data is used for training and checking purpose. For example, followings are the properties of trained ANFIS.

*ANFIS info:*

*Number of nodes: 524*

*Number of linear parameters: 1458*

*Number of nonlinear parameters: 60*

*Total number of parameters: 1518*

*Number of training data pairs: 100*

*Number of checking data pairs: 22*

*Number of fuzzy rules: 243*

*Warning: number of data is smaller than number of modifiable parameters*

Using the limited data the model was trained as discussed previously in Chapter 4. The Figure 6.4 shows the decreasing trend of training error. As indicated previously, here the number of training and checking data is less than the number of modifiable parameters; the trained ANFIS is quite incomplete in structure. However, complete training is beyond the scope of this research. This could easily be done by collecting more sets of data for training.

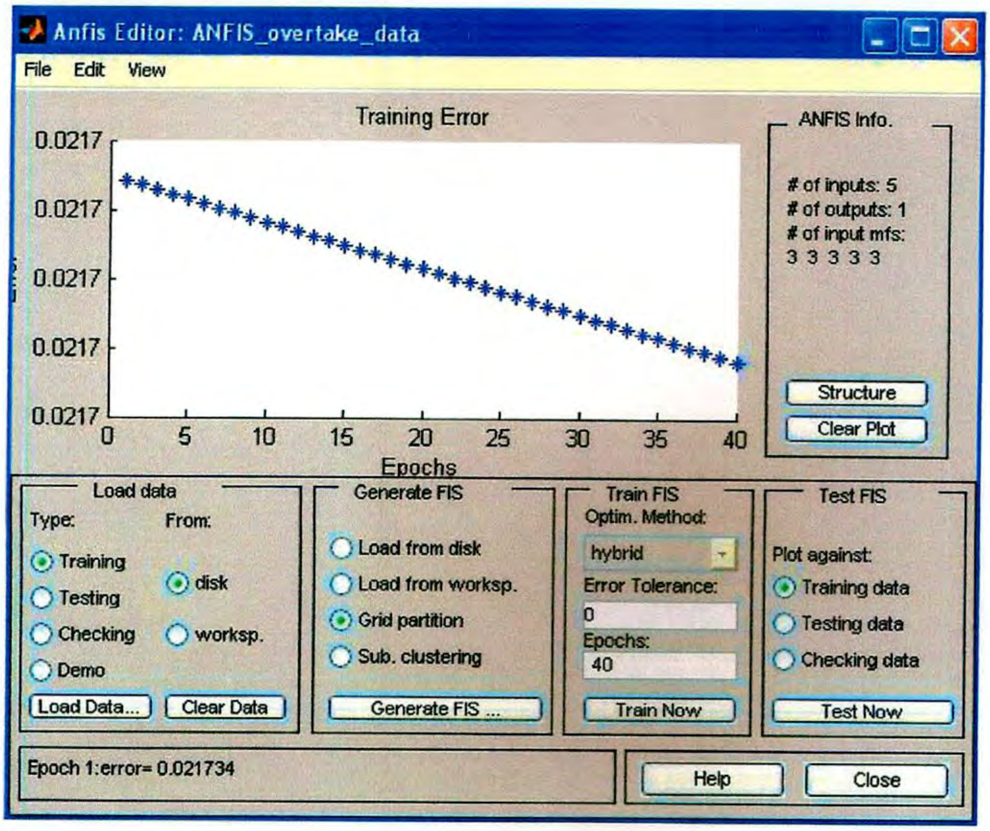



**Figure 6.4:** Plot of ANFIS training Error

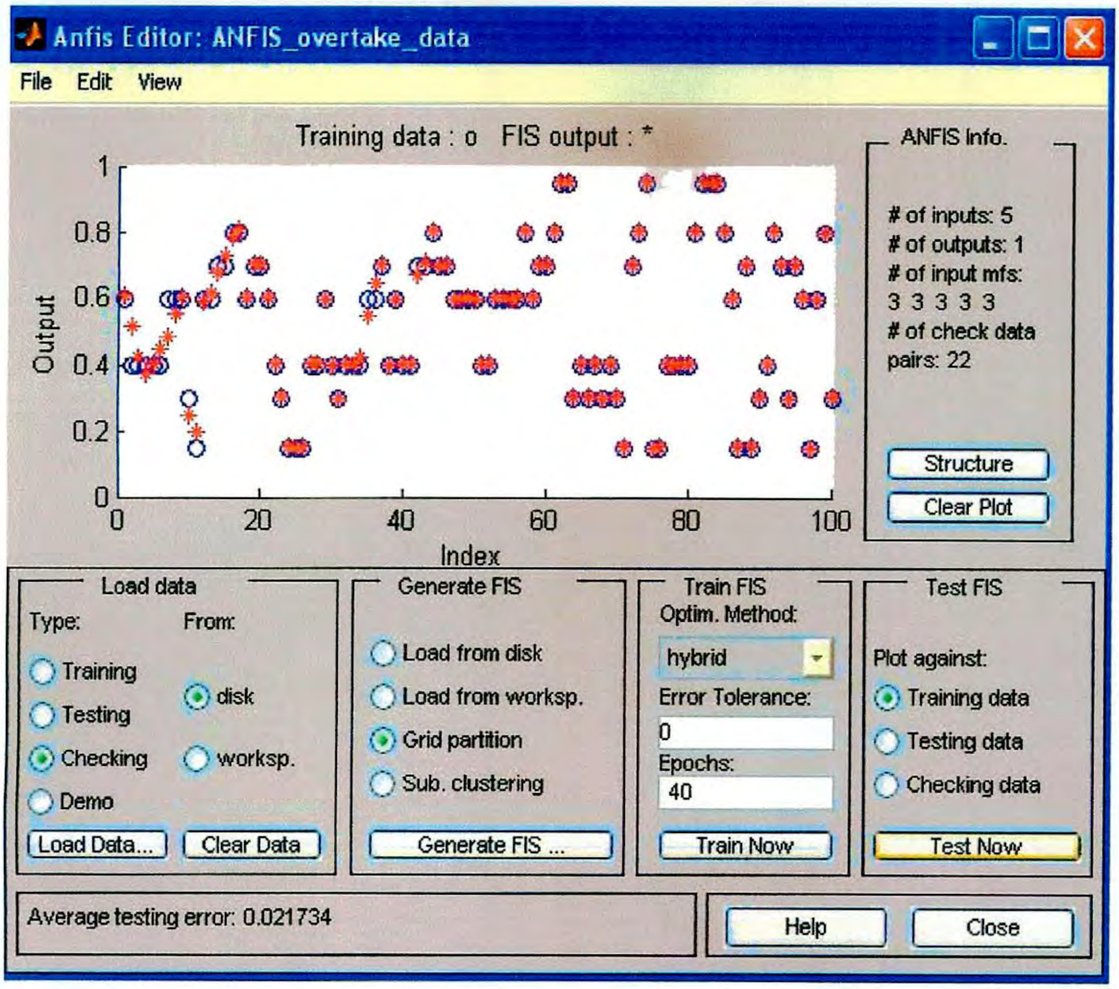



**Figure 6.5:** Plot of training data against FIS output

To check the validation of the proposed model, the training data was plotted against the FIS (Fuzzy Interface System) output. Here (Figure 6.5) Checking data against the FIS looks pretty good.

## 6.3 Modification of Membership Functions

After ANFIS training the initial membership functions which are shown in Figure 3.8 has changed and following modified membership functions are created. Using gradient descent the membership functions of the left hand side of rules are turned better to reflect the characteristics of the model.

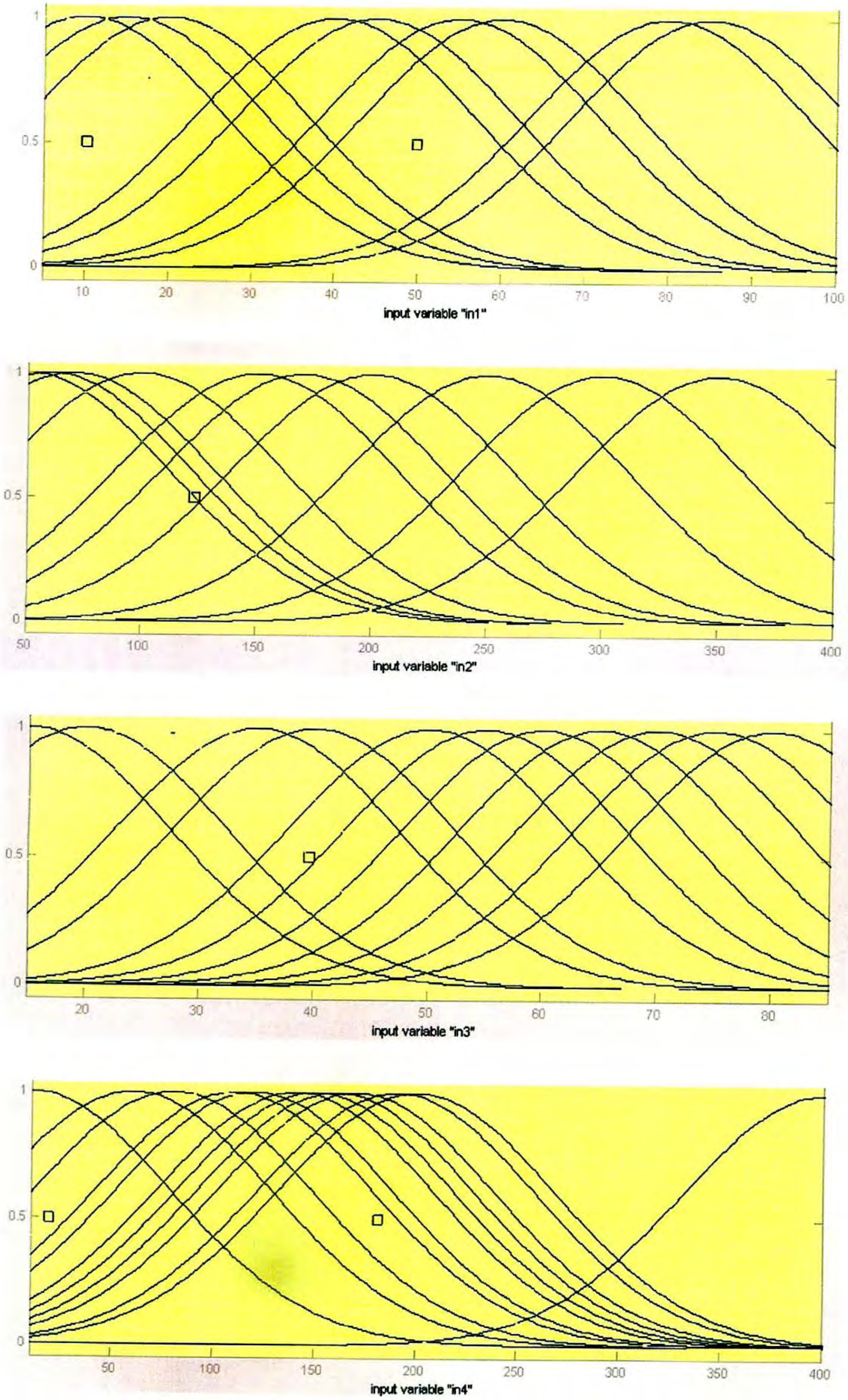



**Figure 6.6:** Modified Membership Functions (cont.)

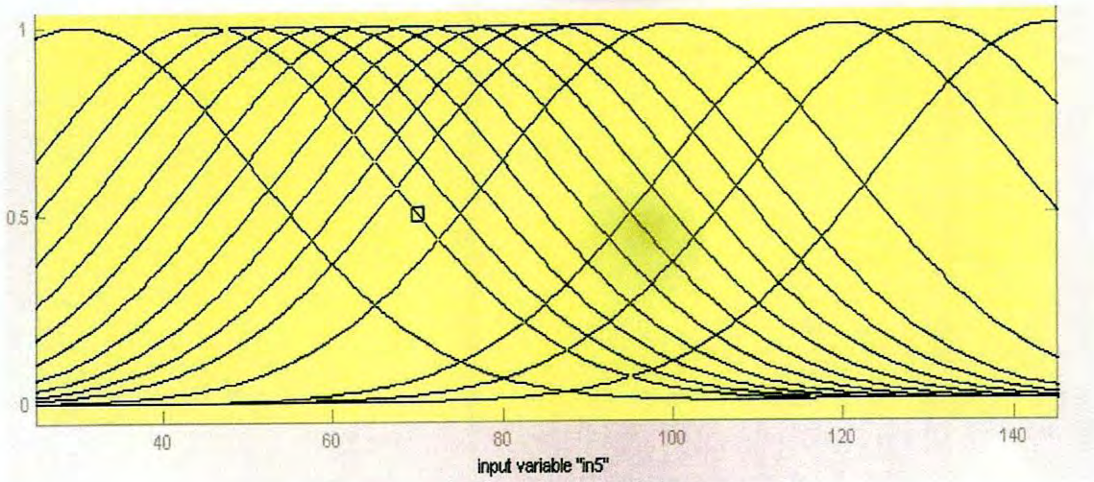



**Figure 6.6:** Modified Membership Functions

### 6.4 Summary

This Chapter gives an overview of various model outputs. It also lists Rules of Fuzzy Interface System for Various Parameters and Associates Outputs. Plot of training data against FIS output is use to check the accuracy of the proposed model. Lastly the modified membership functions are shown with diagrams.

# CHAPTER 7

## CONCLUSIONS AND RECOMMENDATIONS

### 7.1 Introduction

This chapter summarizes the research reported in this thesis and highlights the major contributions. The scope of applications of this research in various related field are also documented. Directions for future research are suggested in the end.

### 7.2 Research Contributions

The objective of this research was to develop a lane-changing decision model. This thesis contributes to state-of-the-art in lane-changing models in the following respects:

- A new lane-changing decision model is proposed which is the first of its kind and unique tool which uses the both concept of Fuzzy Logic and Artificial Neural network with training facilities. This model is based on the notion that the drivers make lane-changing decisions based several interlinked parameters.

- Based on the concepts of driver behavior lane model structure is developed. This model structure is flexible enough to accommodate any further parameter and training particularly to reflect the local condition and traffic behavior.

- The membership functions parameters for different types of lane change are estimated and corresponding rules are documented.

- The research work also reviews the existing literature regarding driver behavior and lane change model. It also documents the development process of various lane change model, their applicability and existing limitations.

- One of the most important contributions of this research is to provide a calibration and validation framework along with data acquisition methodology to quantify driver's decision during lane changing process.

## 7.3 Scope of Applications

- This model can be used as part of traffic simulation model

- This can also be used to quantify the lane changing behavior which is essential to evaluate the effect of lane change in relation to traffic congestion and delay.

- In some extent, it can be used to quantify the risk of accidents due to lane changing maneuver.

- Overall, it is useful to get insight of human behavior and traffic flow which is in many respects still unexplored.

## 7.4 Recommendation on Further Research Works

Detailed trajectory data from sites was not available during this research and it was not possible to estimate separately the effects of variables affecting the driver's decisions.

As only very limited data was available for training the model the ANFIS output may not be reliable. In this regard, the experimentation could be done with large set of training and testing data from different road locations to acquire more sophisticated results and parameters.

Modeling the cooperative lane-changing behaviors (e.g. courtesy yielding) has not been included within the scope of this research. Future research should capture the effects of cooperation among driver, particularly in the merging areas near the on ramps.

The interaction between the lane-changing and acceleration behavior of the driver is also ignored in the current model whereas, in real world, drivers are likely to accelerate and decelerate based on their tactical short-term plan to reach their target lane. Hence, there is the need to develop more detailed driving behavior models based on the concept of generalized target lane capable of capturing interdependencies between lane-changing and acceleration behaviors.

It is also important to experiment in various diversified situations especially in situations where time pressure is a dominant factor. As Bowman and Ben-Akiva (1997) pointed out, the choice models "can be challenged as to the validity of their decision protocol". Even the fuzzy set theory neither explains the mechanism nor accounts for the high variability which results from personality and momentary changes in driving styles and increasing internal aggression due to time pressure.

More specific emerging topics for future research include the factors that govern the size and content of the individuals' associative memory; what, how much, and in which order the individual retrieves the information from that memory. Further, how such factors relate to the number of practiced comparisons? These possible research directions require, above all, the development of methods to obtain data on choice processes in an unobtrusive way. So there is a lot scope to work further in this arena.

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