TRAFFIC ACCIDENT PREDICTIONS BASED ON FUZZY LOGIC APPROACH FOR SAFER URBAN ENVIRONMENTS, CASE STUDY: İZMİR METROPOLITAN AREA

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Ömer SELVİ

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İzmir

We approve the thesis of **Ömer SELVİ**

Assist. Prof. Dr. Yavuz DUVARCI
Supervisor

Prof. Dr. Gökmen TAYFUR
Co-Supervisor

Assist. Prof. Dr. Ömür SAYGIN
Co-Supervisor

Prof. Dr. Cemal ARKON
Committee Member

Prof. Dr. Güneş GÜR
Committee Member

Assist. Prof. Dr. Yıldırım ORAL
Committee Member

Assist. Prof. Dr. Erkal SERİM
Committee Member

03 July 2009

Assoc. Prof. Dr. Semahat ÖZDEMİR
Head of the City and Regional Planning Department

Prof. Dr. Hasan BÖKE
Dean of the Graduate School of Engineering and Sciences

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ABSTRACT

TRAFFIC ACCIDENT PREDICTIONS BASED ON FUZZY LOGIC APPROACH FOR SAFER URBAN ENVIRONMENTS, CASE STUDY: İZMİR METROPOLITAN AREA

Dissertation has dealt with one of the most chaotic events of an urban life that is the traffic accidents. This study is a preliminary and an explorative effort to establish an *Accident Prediction Model* (APM) for road safety in İzmir urban environment.

Aim of the dissertation is to prevent or decrease the amount of possible future traffic accidents in İzmir metropolitan region, by the help of the developed APM. Urban traffic accidents have spatial and other external reasons independent from the vehicles or drivers, and these reasons can be predicted by mathematical models.

The study deals with the factors of the traffic accidents, which are not based on the human behavior or vehicle characteristics. Therefore the prediction model is established through the following external factors, such as traffic volume, rain status and the geometry of the roads.

Fuzzy Logic Modeling (FLM) is applied as a prediction tool in the study. Familiarizing fuzzy logic approach to the planning discipline is the secondary aim of the thesis and contribution to the literature. The conformity of fuzzy logic enables modeling through verbal data and intuitive approach, which is important to achieve uncertainties of planning issues.

ÖZET

GÜVENLİ KENTSEL ÇEVRELER İÇİN BULANIK MANTIK YAKLAŞIMI İLE TRAFİK KAZALARI TAHMİNİ, ÖRNEK ÇALIŞMA: İZMİR METROPOLİTAN ALANI

Bu tez kentsel yaşamın kaotik olaylarından biri olan trafik kazaları ile ilgilidir. Bu çalışma, İzmir'in yol güvenliğine bir katkı sağlamak için hazırlanmış kaza tahmin modellemesi yönünde atılan ilk adımdır.

Tezin amacı İzmir metropolitan alanı özelinde geliştirilecek bir kaza tahmini modeli ile, gelecekte beklenen olası kazaların engellenmesi ya da kaza sayısının azaltılması yönünde bir çaba ortaya koymaktır. Kent içi trafik kazalarının taşıtlardan ve sürücülerden bağımsız, mekansal ve diğer dışsal nedenleri vardır ve bu nedenler matematiksel modellerle tahmin edilebilir.

Çalışmanın öncelikle hedefi, trafik kazalarını etkileyen sürücü ve otomobil özelliklerinden bağımsız, dışsal faktörleri ortaya çıkarmaktır. Bu nedenle tahmin modeli trafik hacmi, yağmur durumu ve yol geometrisi gibi dışsal faktörlerden kurulmuştur.

Çalışmada Bulanık Mantık Modelleme yaklaşımı tahmin aracı olarak kullanılmıştır. Tezin bir diğer amacı ve literatüre katkısı da, planlama bilim alanında modelleme aracı olarak kullanımına rastlanmayan bulanık mantık yaklaşımına dikkati çekmektir. Sözel değişkenlerle ve sezgisel yaklaşımlarla model kurulmasına imkan sağlayan bulanık mantık sistemin, belirsizliklerle dolu planlama bilim alanına uygunluğu vurgulanmıştır.

to my beloved mother, Fatma SELVİ,
whose invaluable effort and support has taken me to the present

sonsuz emeği ve desteğiyle bugüne gelmemi sağlayan
sevgili annem Fatma SELVİ'ye

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LIST OF ABBREVIATIONS

AAA	Annual All Accidents
AADT	Average Annual Daily Traffic
AAHTL	Annual Average Hourly Traffic per Lane
AHRT	Annual Hourly Rain Total
AID	Automatic Incidence Detection
ANN	Artificial Neural Networks
APM	Accident Prediction Models
BS	Number of Bus Stops
CoA	Center of Area
CoG	Center of Gravity
DUMAS	Developing Urban Management and Safety
FIS	Fuzzy Inference System
FNM	Fuzzy-Neural Model
GIS	Geographical Information Systems
GLM	Generalized Linear Modeling
HSIS	Highway Safety Information System
HTBR	Hierarchical Tree Based Regression
ITS	Intelligent Transportation Systems
LOSS	Level of Service of Safety
MA	Number of Minor Access
MBF	Membership Function
MLP	Multi Layer Perceptron
MMI	Metropolitan Municipality of İzmir
NB	Negative Binomial
PDO	Property Damage Only
PM	Percent of Median
RENB	Random Effect Negative Binomial
RW	Road width
SJ	Number of Signalized Junctions
SPF	Safety Performance Function
TIDI	Traffic Inspection Department of Izmir
VMT	Vehicle Miles Travelled

CHAPTER 1

INTRODUCTION

One of the most essential aim of City (or Transport) Planner is to accommodate safe environments for the city dwellers. In the world, average 3,480 people die in a day because of a simple urban activity that is transportation (WHO-World Health Organization). In our country, 4,228 people were killed and 183,841 people were injured because of traffic accidents, in the year 2008. The material loss of the traffic accidents to the national economy is about 350,000 TL in a year (TÜİK-Turkey Foundation of Statistics).

Reducing the amount and of course the severity of the traffic accidents will require safer roads and provide major savings for the society. Safer roads mean safer urban environments so this issue is relevant to the field of City Planning Discipline.

1.1. Motivation

Technological development enables more control on society. As seen in every emerging fact this innovation has also brought its supporters and the opponents.

This argumentative process can be used on roads, which is one of the most dangerous components of an urban, to provide safer environments. It is possible to improve transportation theory and practice through these technological tools. This dissertation defends a control on dangerous machines on roads which cause to kill people and give material loss to the society. Hence, machine control mechanisms would work especially on transport systems, all modes of which, except walking, are machine-based.

The ability to predict the possibility of accident occurrence is very important to transportation planners and engineers, because it can help in identifying hazardous locations and sites which require treatment. Besides, the determination of the safe roads which will also be deducted from the prediction model could help the urban designers to produce safer roads or junctions.

Road safety has three major components: the road system, the human factors, and the vehicle elements (Peled, et al. 1996). Human factors and the vehicle elements are assumed as a fact in this study. Therefore the dissertation deals with the factors of the traffic accidents, which are independent from the human and vehicle elements, and aims to develop an accident prediction model through these external factors.

1.2. Aim and Scope of the Study

In general, there are two different approaches to prevent the risk of the accidents. One is AID (Automatic Incidence Detection) systems that run just after the accidents and the other one is based on the APM (Accident Prediction Models) that depend on the statistical modeling. The major function of AID is to warn the authorities to prevent the traffic jam after the accidents and to inform and direct the drivers to the alternative routes (Day 2005). The other approach APM can be stated as the estimation of the probability of an accident at the known segment of a road.

The aim of this dissertation is to develop an alternative accident prediction model for the selected urban roads of İzmir metropolitan area, to prevent or decrease the possibility of "future accidents". The main objective of the study is to reveal the *accident generating factors* of İzmir urban roads. The boundary of the case study area is given in Figure 1.1.

Main contribution of the model results to the road safety issue is to expose the safety/risky conditions for the selected roads on certain times.

Fuzzy Logic Approach seems a convenient model for dealing with uncertainty phenomena. Traffic accidents have similar reasons such as the road factors, features of the traffic, whether conditions, etc. Some of the factors may be static (geometry of the road) and some may be dynamic (traffic density).

Primary aim of the thesis is to expose the environmental factors of the traffic accidents in İzmir case. The most effective factors will be the *"input variables"* of the fuzzy logic model.

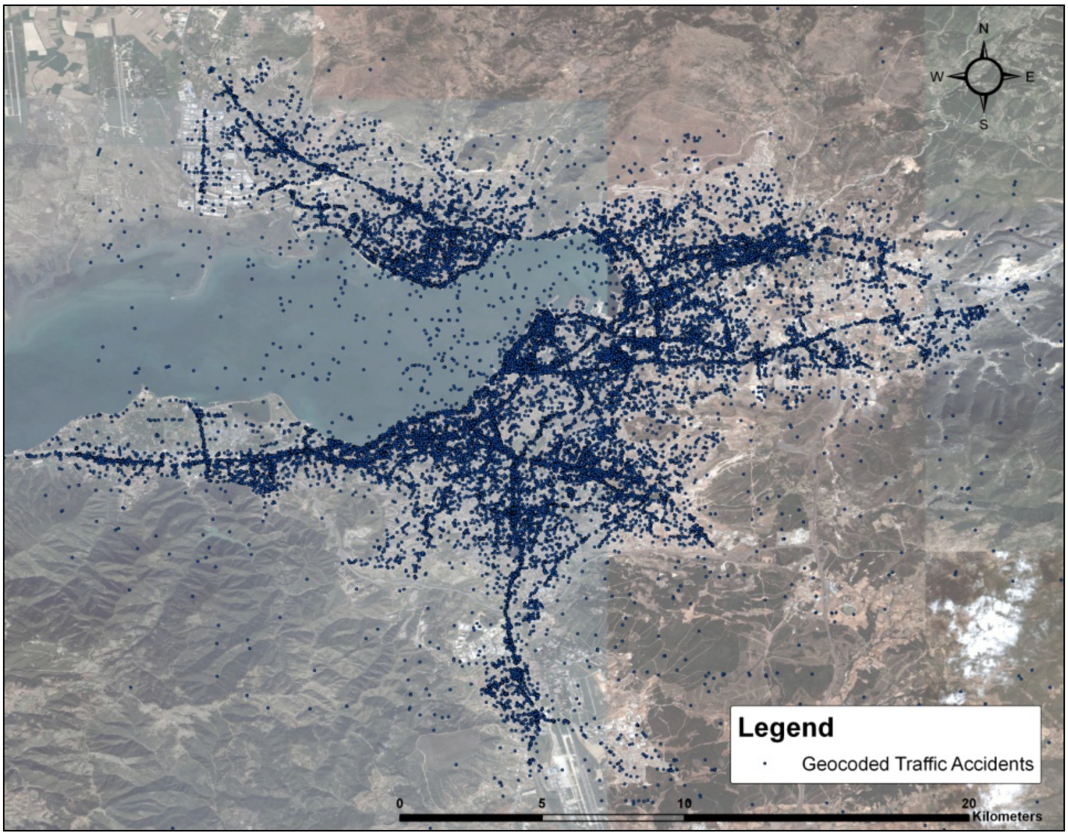

Figure 1. 1. Spatial scope of the case study area İzmir Metropolitan Region

Methodological approach is given in the following flow chart in Figure 1.2. Comprehensive literature survey is performed to compare the applied techniques on *road safety, accident prediction models, and accident analysis and prevention title.* Through the literature and according to the data obtained from the foundations or surveys, the modeling technique is selected and the variables are defined.

Required traffic accident data was obtained from Traffic Inspection Department of İzmir (TIDI). Traffic counts were obtained from the Metropolitan Municipality of İzmir (MMI). Geometric variables of the roads and bus stops were obtained from maps, and the rain data was obtained from the State Meteorological Service.

Due to the limitations of the data gathering, the spatial analysis and fuzzy modeling were performed with different set of data. The accident records of the year 2005 was used for spatial analysis by the help of the software ArcGIS 9.2, and records of the year 2007 was used for fuzzy modeling study by the help of the software MATLAB 7.4.0.287.

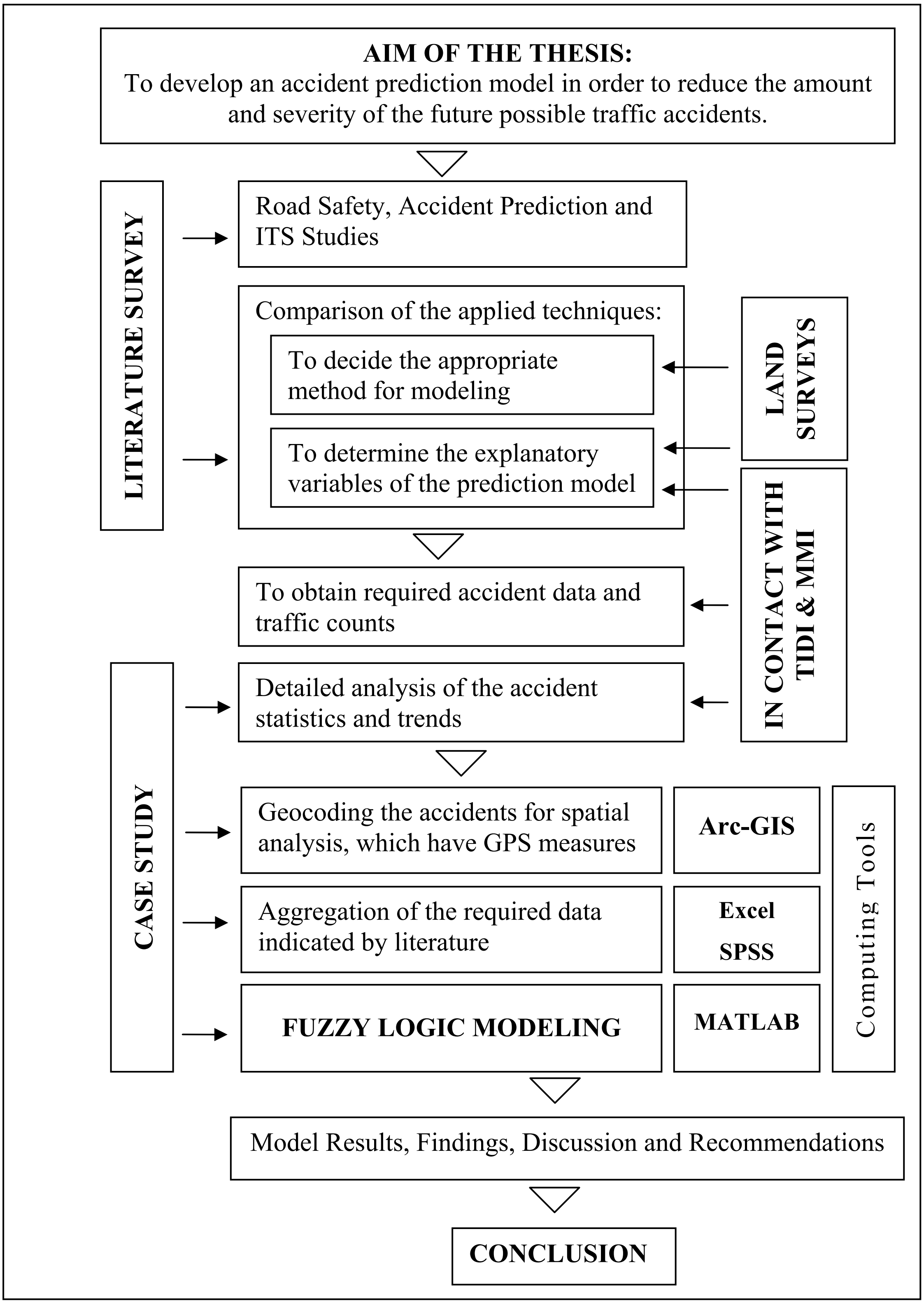

Figure 1. 2. Methodology of the Dissertation

1.3. Dissertation Organization

This dissertation consists of five chapters in addition to the appendices and bibliography. Organization of the chapters is as follows;

Chapter 1, the current chapter, contains the motivation, aim and scope of the study and the main hypothesis of the study as an introduction.

In chapter 2, traffic accident prediction models in the literature were examined, and it was recognized that statistical and probabilistic methods such as Generalized Linear Modeling (GLM) and Negative Binomial (NB) Models were used widely. Artificial intelligence methods such as ANN were also coincided for recent years. As a result, the use of fuzzy logic method was decided to establish accident prediction model.

In chapter 3, fuzzy logic approach, its theory and practical applications were dealt with. A simple fuzzy modelling was realized to indicate its availability in planning discipline.

In chapter 4, spatial analyses were made by using GIS tools. As a result of analyses, the streets that produced the most accidents were defined. However, required permission for traffic counts could not be taken on selected streets. Instead, traffic counts of MMI made for 19 main arterials in 2007, were obtained. Thus, this data was used to establish the fuzzy logic model. Then, the results of the model and findings were discussed. As a result of modeling, four main safety levels were determined.

Last chapter discussed the contribution of the dissertation to the City and Transportation Planning area of science and recommendations for further studies.

CHAPTER 2

DEBATES ON TRANSPORTATION PLANNING AND NEED FOR ROAD SAFETY

Development of transportation planning is parallel with urban planning. However unlike urban planning, for 40 years, it has been away from theoretical debates that spread from social sciences. According to Yiftachel this may be related to two factors; (Banister 1994)

- transportation planning includes engineers, economists and social scientists in its theoretical structure, so it is difficult for any of them to debate with the others
- critics are from outside of transportation planning

In 1960s the dominant view was that; urban planning operates for public interest. This view was questioned in 1970s. Marxists claimed that planning had helped capital accumulation of that system. From Weberian point of view state was providing many social benefits by using planning as a tool. According to corporatists, there was an agreement between state and companies, so the benefits they provided were for each other (Banister 1994).

Such socialist view did not find a response in transportation planning, because the state had a strong role in all stages of transportation planning (investments, operating, control etc.), and the transportation was perceived as a public good. In transportation planning, the origins of theoretical debates were emerged from the increase of cars and roads in 1960-1970s, and came to the agenda mainly 1980s, with radical policies of conservative states (Black 1995).

2.1. Evolution of Transportation Planning

Public/private division was the tendency of the theorists in transportation planning for many years. Pluralists who were defensive interest groups protected existing situation, that is, public-supported transportation. Urban road investments programs and public inquiry process in 1970s allowed them to articulate their concerns. They were against elitist road construction companies and motorizing organizations, that is, private sector in transportation. Elitists represented corporatists and interested in exchange value rather than use value. Marxist sociologists asserted that fundamental conflict was between the advocates of capitalist economy and the group that gave importance to social priorities in urban development (Banister 1994).

Table 2. 1. The Evolution of the debates in planning theory.
(Source: Yiftachel 1989; Banister 1994)

Decade	*Theory*	*Planning and City Development*	*Transport*	*Procedures*
1970	Weberian analysis Corporatism Marxist analysis Pluralism	Natural expansion Containment Corridor development	Highway construction Management Public transport and subsidy	Systems analysis Incrementalism Mixed scanning
1980	Managerialism Reformist Marxism Neo-classicalism	Decentralization Renewal Consolidation Sustainability	Market dominance Gridlock	Advocacy Positive discrimination Pragmatism
1990	Company state	Dispersed cities Technological cities	Highway and rail construction	Quick response methods

In the period after 1960s, planning criticized and reassessed itself. The gasoline shortages became an essential determinant of transportation planning methodology. However theorists did not deal with such a political economy. In 1970s, transport theory was attacked of not being interested in social political issues such as globalization, geopolitics of oil and industrial restructuring. The system approach was reviewed.

Rationality and comprehensiveness became impossible in the politicized decision-making environment (Meyer and Miller 1984).

In 1980s neo-classical economy became dominant and welfare state notions replaced with market operations. This stimulated theoretical debates (that transportation avoided in the past) in all public sectors including transportation. First debates were about whether the subventions would be given to the user or the operator; there was no debate whether the organizations would be in public or private sector. Even there was an agreement in regulation issues; pluralists interpreted regulation as an intervention willingness of the state to the vested interest of elitists. Similarly, elitists asserted that regulation caused intervention. These theories are being tested in practice with regulation reforms and privatization in transportation. (Banister 1994)

In 1990s policies of transportation and urban planning were defined with growth, expansion and concentration. Technology, environment and sustainability were the major issues of 1990s. This period also presents the dilemma between increasing mobility in transportation and stabilizing pollution emissions.

Due to the recent literature of the subject, the last decade (2000's) can be added to the table of Yiftachel and Banister as;

Table 2. 2. Addition of the last decade 2000's to the table of Yiftachel and Banister.

Decade	*Theory*	*Planning and City Development*	*Transport*	*Procedures*
2000	Globalization	Global cities Urban region Polycentric cities	Land use effect Regional urban transit Induced demand	ITS Real time planning Demand control

Real time data processing using high capacity computers encouraged the transport planners to deal with the prediction of traffic accidents which seem more chaotic to estimate in early decades. Real time data gathered during these procedures can be used as the estimation variables of the accident prediction models by the researchers.

The graphics below demonstrate the poor condition of Turkey in terms of traffic accidents. Although there are some countries with comparable number of accidents to that in Turkey, when number of trips with accidents is rated, it is observed that Turkey comes first, which is a four times more risky country than its immediate follower, Georgia (See Figure 2.1).

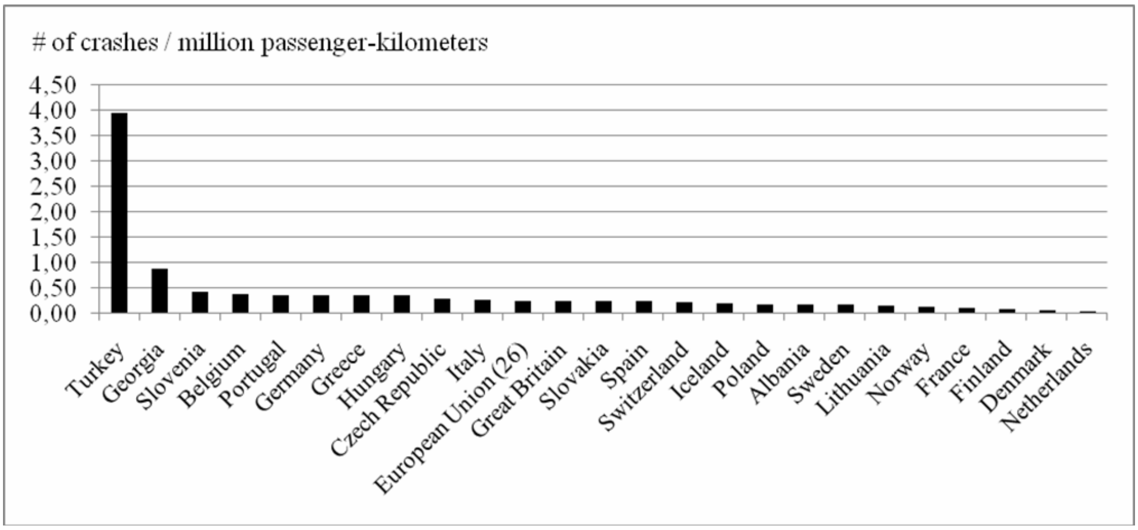

Figure 2. 1. Comparison of the several countries due to #of crashes per pass.-km
(Source: International Transport Forum 2008)

Figure 2.2 shows the ratio of total number of trips to the people who died in accidents in 2008 for each country. In this comparison, Turkey is the fourth among 24 countries. These indicators reveal the necessity of conducting research on road safety in Turkey.

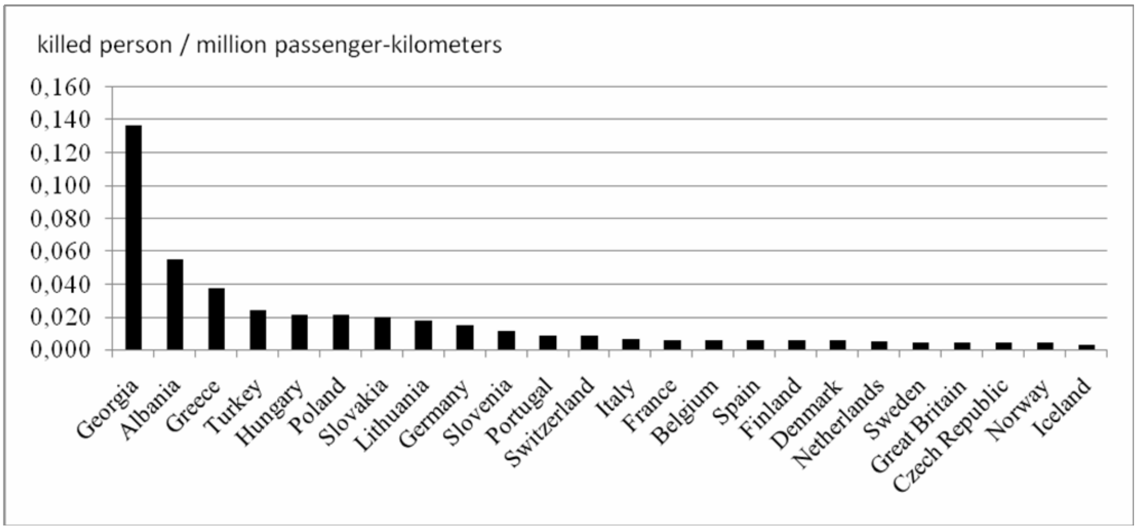

Figure 2. 2. Comparison of the several countries due to killed person per pass.-km
(Source: International Transport Forum 2008)

2.2. Road Safety Studies

Prediction of traffic accidents by using real-time data is relatively a recent issue in the literature. Transport planners, traffic engineers dealt with the issue of accident predictions using the statistical data for several decades. Development of telematics technologies (data sensoring, data communications, and real time database) has supported the development of uncertainty modeling point of view in the area of traffic management.

Generally, traffic accident statistics are taken as assessment indicators to estimate the quantity of the probable incidents on roads in the future. Recent studies indicate considerable efforts in this field. Serrano and Cuena (1999) searched the possible approaches from the uncertainty modeling point of view in the area of traffic management. They reached 428 papers about this issue and 403 of these studies were about Road transport, 25 of which were related to road safety concept. The table below gives the classification of these papers according to the problems and techniques of uncertainty modeling.

Table 2. 3. Road problems & technique relationship
(Source: Serrano and Cuena 1999)

Problem/Technique	*Fuzzy*	*Probabilistic*	*Fuzzy-mixed*	*Evidence Theory*	*Non-monotonic*	*Case-based*	*Other*	*Total sample*
Traffic classification	39	10	8	1	0	1	9	**67**
Traffic control	64	3	10	0	4	4	19	**104**
Traffic prediction	9	9	2	0	0	1	4	**25**
Vehicle classification	7	5	2	0	0	1	0	**15**
Vehicle control	63	9	16	0	0	3	7	**98**
Vehicle simulation	28	5	5	0	0	0	1	**39**
Vehicle design	27	0	5	0	0	0	0	**32**
Network management	33	1	5	0	0	0	1	**40**
Safety	9	15	0	1	0	0	0	**25**
Other problems	4	0	2	0	0	0	0	**6**
	262	**50**	**48**	**2**	**4**	**8**	**30**	**403**

* Several papers deal with more than one problem and/or technique.

As seen in Table 2.3 the use of probabilistic techniques was higher than the use of fuzzy techniques for safety issues.

Peled et al. (1996) described a GIS based road safety analysis system in their study. They analyzed the different traffic events from the location perspective. They pretended that Arc-Info GIS software offer an advanced engine to drive, both area-wide and location-oriented investigations. Road safety phenomenon involves the road infrastructure and its associated activities and land-uses. There are also other fields of activity, such as education, driver training, publicity campaigns, police enforcement, the court system, public health, and vehicle engineering. They considered that a spatial approach to the road safety issue was more suitable to apply to a geographic area rather than socio-economic, demographic or an epidemiological approach. That is, the issue involves a significant "space" ingredient. The pilot project area of the study was the Haifa Municipality in Israel. They tested the software with the three year accident data and adopted it as the basic tool for road safety management, analyses and improvement.

Mountain et al. (1998) examined "*the influence of trend on estimates of accidents at junctions*". They focused on traffic flow as an invariably explanatory variable of accident models in their research. The effects of flow changes were dealt with for non-linear relationship between accidents and exposure. Generalized Linear Modeling (GLM) was used to develop regression estimates of expected junction accidents. They determined the causing factors of the model as junction control, speed limit and traffic flow and site characteristics. Models were presented for total accidents and accidents disaggregated by severity, road surface condition and lighting condition.

The form of the linear model used to estimate the expected number of accidents was;

$$\mu = \alpha_0 \cdot \gamma^t \cdot Q_t^\beta \tag{2.1}$$

Where;

α_0 is the risk in year 0,
γ is the risk changes from year to year treatment effectiveness,
Q_t is the flow in year t, and
β is the parameter to be estimated.

They used the statistical package GLIM to apply the model. As a result the model indicated about 33% decline in the accident risk between 1975 and 1995 in UK. (Mountain, et al. 1998).

For the factors of the proportions of accidents, database became details of highway and junction characteristics, personal injury accidents and traffic flows on networks of A and B-roads in six United Kingdom counties for periods of 1980 and 1994. Junctions between A and B-roads were defined as major junctions, and roads of the junctions were determined as major roads and minor roads depending on their traffic volume. Junction accidents within 20 m of extended kerblines of a junction were classified. Different types of junctions, such as priority, traffic signals and roundabouts, were examined through traffic volume; major road having traffic inflow 6,000-12,000 and minor road having traffic inflow above 4,000, 4,000-2,000 and below 2,000. Each data for appropriate factor was converted to annual average daily traffic (AADT) flows. (Mountain, et al. 1998)

As aggregate junction model without trend, the form of the following function was used;

$$\mu = \alpha \cdot Q^{\beta_1} \cdot Q^{\beta_2} \qquad (2.2)$$

Where;

μ is the expected number of accidents per year,
Q is the major road inflow,
q is the minor road inflow and,
β_1 and β_2 are parameters to be estimated.

Factors described as carriageway type, number of arms, speed limit, method of junction control, method of junction control (two levels only) were tested. The study revealed that doubling the minor road entry flow would increase accidents by 13% at priority junctions and by 33% at signals and roundabouts. If major road inflows also doubled the increase would be 65% at priority junctions and 92% at signals and roundabouts.

Transport Road Safety Group in their DUMAS (Developing Urban Management and Safety) program emphasizes on the safety for pedestrians and two wheelers. They developed regression equations to estimate the approximate annual number of accidents per km road involving both the pedestrians and the two wheeler riders. One of the equations is given below (Busi 1998).

$$U = 1.15 \cdot 10^{-3} \cdot C^{0.87} \tag{2.3}$$

Where;

U is the annual number of accidents per km road involving cyclists/moped riders,
C is the bicycle/moped traffic flow along roads (AADT).

Martin (2002) observed 2,000 km of interurban motorways over two years and tried to describe the relationship between crash incidence rates and hourly traffic volume. He modeled the crash severity by an equation of negative-binomial regression. Some of his findings are as follows;

- Incidence rates involving property damage-only crashes and injury-crashes are highest when traffic is lightest (under 400 vehicles/h).
- For an equivalent light traffic level, the number of crashes is higher on three-lane than on 2-lane motorways and higher at weekends (when truck traffic is restricted) than on weekdays.

Ceder and Eldar (2002) examined the possibility of splitting an uncontrolled ‘‘X’’ intersection into two adjacent uncontrolled ‘‘T’’ intersections in terms of improving both the movement and safety of traffic. They tried to determine the optimal distance between the two adjacent T intersections, by applying operation research methods.

Main findings they stated are as follows;

- Under a medium level of traffic volume, the lengths of blocking queues are of the order of a few hundred meters and they are very sensitive to an increase of volume toward and beyond saturation flow.
- The passing probability function along the road segment between the two adjacent "T" intersections increases with the length of the segment and stabilizes at a length of a few hundred meters.
- There is a relationship between accident frequency (accident rate and density) and the distance between the split intersections. An example of this relationship is introduced.
- The optimal distance between the two adjacent T intersections is found not only theoretically, but also practically for possible implementations.
- Splitting an "X" intersection into two "T" intersections decreases the number of accidents almost by 50%.
- When the distance between two T intersections gets higher, the accident density decreases.

They derived the safety level point for a proper splitting length of intersections as seen in Figure 2.3.

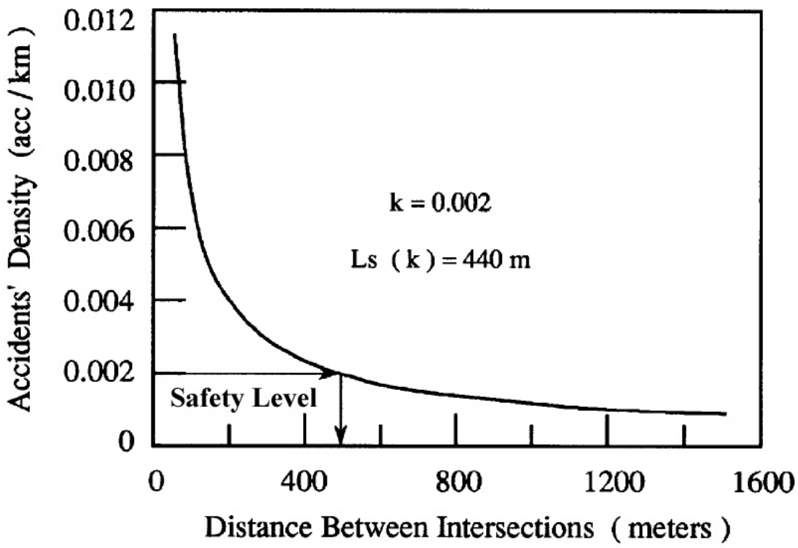

Figure 2. 3. Locating the proper splitting length for an expected accident density.
(Source: Ceder and Eldar 2002)

Ng et al. (2002) developed an algorithm to estimate the number of traffic accidents and assess the risk of traffic accidents in Hong Kong. They combined the Geographical Information Systems (GIS) mapping techniques and statistical methods in their estimation algorithm. They used negative binomial regression model to catch the relation between the number of accidents and the potential casual factors. According to their findings the algorithm proposed seems more efficient in the case of fatal and pedestrian-related accidents. The flow diagram of the algorithm can be seen in Figure 2.4.

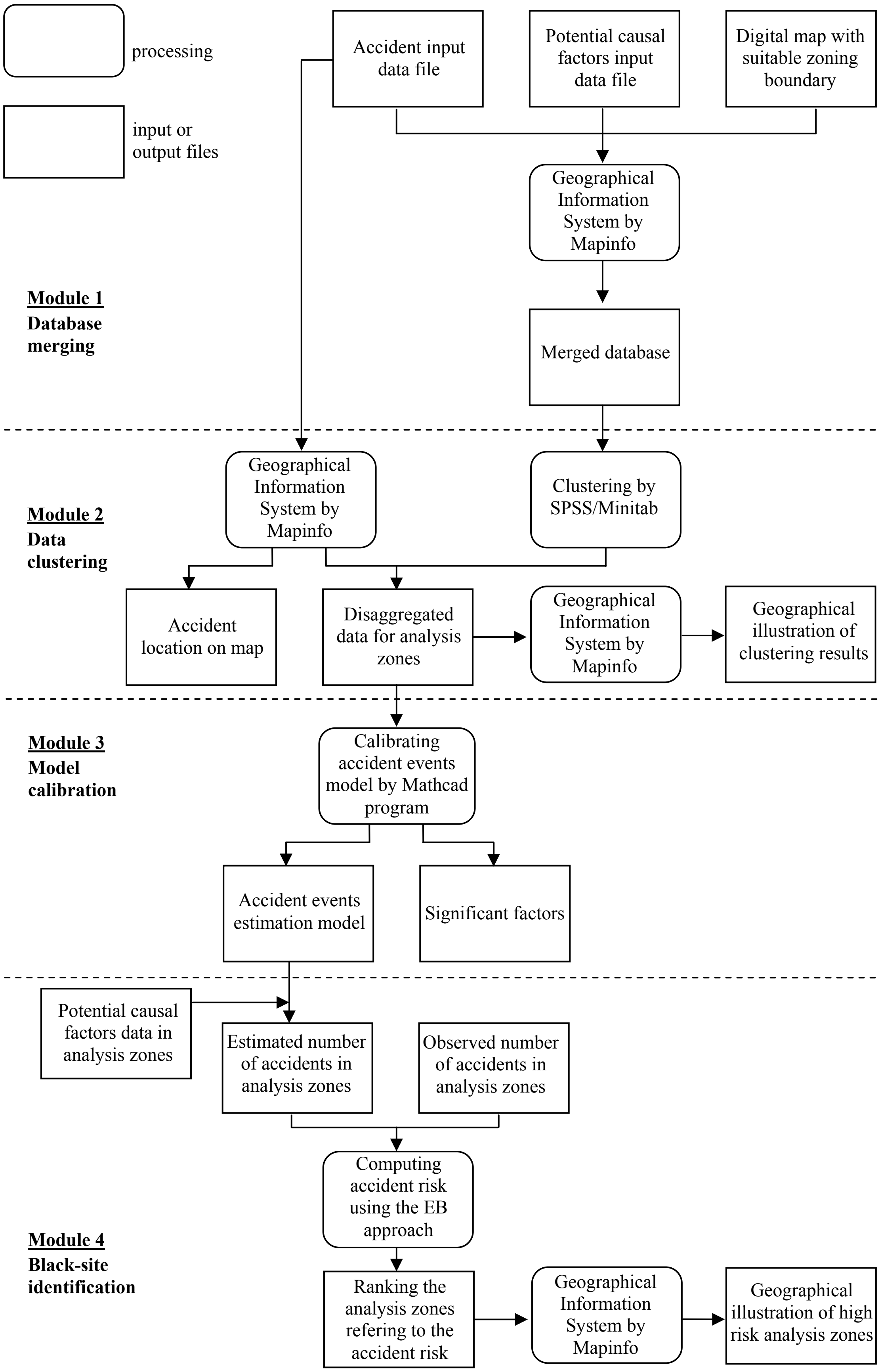

Figure 2. 4. Accident risk assessment algorithm flow diagram
(Source: Ng, et al. 2002)

Karlaftis and Golias (2002) overviewed the literature of accident rate estimation, which mostly based on Multiple Linear, Poisson or Negative Binomial regression models. These models suggest a variety of traffic and design elements such as AADT, cross-section design, horizontal alignment, roadside features, access control, pavement conditions, speed limit, lane width, and median width, affect accident rates. Karlaftis and Golias used these variables in non-parametric statistical methodology known as Hierarchical Tree Based Regression (HTBR) to reveal the effects of rural road geometry and traffic volumes on accident rates. Their remarkable finding is the importance of AADT for both rural two-lane and multilane roadways.

Hu et al. (2003) proposed a probabilistic model for prediction of traffic accidents by using 3D model based vehicle tracking method. Initially they obtained sample data including motion trajectories by 3D model based vehicle tracking and then they developed a fuzzy self-organizing neural network algorithm to learn the activity patterns from the sample trajectories. Finally they determined the occurrence probability of a traffic accident through the activity patterns of the observed trajectories. Flow diagram of the proposed scheme is illustrated in Figure 2.5.

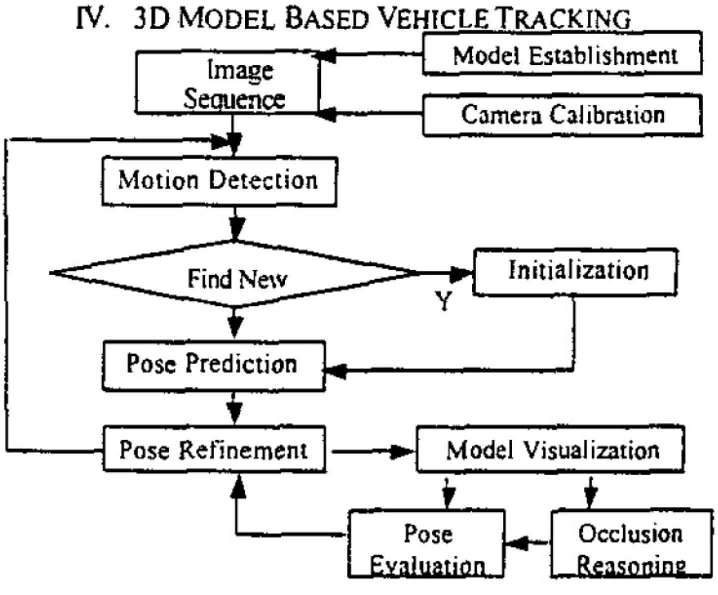

Figure 2. 5. Overview of 3D model based vehicle tracking (Source: Hu, et al. 2003)

Flannery and Maccubbin (2003) tried to evaluate the effect of automated enforcement cameras on reducing crashes and violations at signalized intersections by using meta-analysis techniques. They investigated the impact of an ITS application on safety at signalized intersections.

Greibe (2003), from Danish Transport Research Institute, tried to describe some of the main findings from two separate studies on accident prediction models for urban junctions and urban road links. The main goal of his study was to establish simple, *"practicable accident models"* that can predict the expected number of accidents at urban junctions and road links as accurately as possible. He examined 1,036 junctions and 142 km road links in urban areas. He used GLM techniques to relate accident frequencies to explanatory variables. His remarkable finding is;

- modeling accidents for road links is less complicated than for junctions and
- the most powerful variable for all models was motor vehicle traffic flow

He determined the following variables for the urban roads;

–traffic flow (motor vehicles, heavy vehicles and vulnerable road users)
–length of road section
–speed limit
–one/two-way traffic
–number of lanes
–road width
–speed reducing measures
–number of minor crossings/exits/side roads
–cyclist facilities
–footway
–central island
–parking facilities
–bus stop
–land use

and the following variables for the urban junctions;

–traffic flow (motor vehicles, heavy vehicles and vulnerable road users)
–number of lanes
–traffic island
–turning lane
–bicycle facilities
–signalised/non-signalised
–number of arms

Greibe also examined the correlations among variables. The Figure 2.6 shows the weak or strong correlations among variables schematically. Thick lines indicate ‘strong’ correlation (ρ > 0.6) and thin or no lines indicate ‘weaker’ correlation among variables. As seen there is a strong correlation between the number of lanes and the presence of a central island.

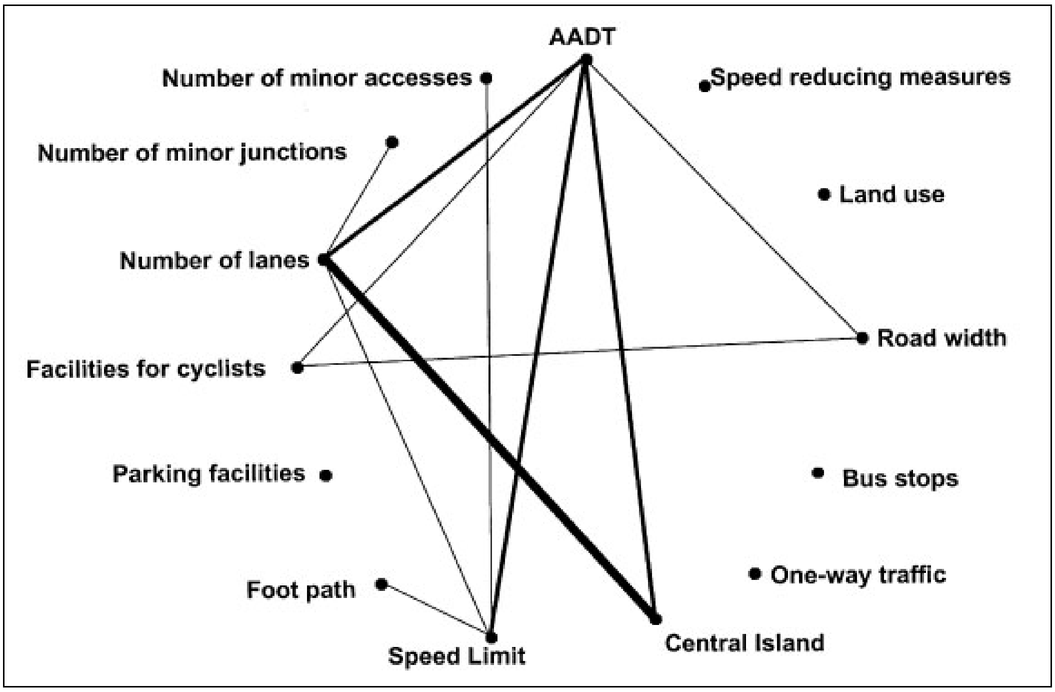

Figure 2. 6. Illustration of correlation matrix for road link data. (Source: Greibe 2003)

Chin and Quddus (2003) applied a Random Effect Negative Binomial (RENB) model as an alternative to the Poisson and Negative Binomial (NB) models, to examine traffic accident occurrence at signalized intersections of Singapore. They pretended that those models seem to be inappropriate due to unobserved heterogeneity and serial correlation in the accident data. They exposed that 11 variables significantly affected the safety at the intersections. The total approach volumes, the numbers of phases per cycle, the uncontrolled left-turn lane and the presence of a surveillance camera are among the variables that are the highly significant. Table 2.5 shows the explanatory variables and the regression coefficients of the Chin and Quddus study.

Table 2. 4. Variables of RENB model for total annual accident frequencies
(Source: Chin & Quddus 2003)

Explanatory variable	***Estimated coefficient (IRR*)***	***t-Statistic (P-value)***
Total approach volume in thousand (ADT)	0.0071 (1.01)	2.712 (0.0067)
Right-turn volume in thousand (ADT)	0.0101 (1.01)	1.516 (0.1296)
Uncontrolled left-turn lane (yes 1, otherwise 0)	0.3052 (1.36)	3.520 (0.0004)
Acceleration section on left-turn lane (yes 1, otherwise 0)	−0.2783 (0.76)	−2.113 (0.0346)
Intersection sight distance (m)	0.0006 (1.00)	3.141 (0.0017)
Median width greater than 2 m (yes 1, otherwise 0)	0.1947 (1.21)	2.462 (0.0138)
Number of bus stops	0.0556 (1.06)	1.592 (0.1114)
Number of bus bays	−0.0492 (0.95)	−1.738 (0.082)
Number of phases per cycle	0.1108 (1.12)	3.073 (0.0021)
Existence of surveillance camera (yes 1, otherwise 0)	0.2438 (1.28)	3.858 (0.0001)
Signal control type (adaptive 1, pre-timed 0)	−0.0522 (0.95)	−0.767 (0.4428)
Parameter, a	159.82	
Parameter, b	204.89	
Total number of observations	832	

* *IRR* : Incidence Rate Ratios

Kononov and Allery's (2003) contribution to the literature is the concept of Level of Service of Safety (LOSS) in the framework of Safety Performance Function (SPF). LOSS indicates the performance of the roadway due to the expected accident frequency. They normalized the certain amount of accident over a unit of time by using SPF. If the safety problem is present LOSS describes the magnitude of the problem. They also discussed the direct diagnostics and pattern recognition techniques in their study. One of the LOSS/SPF graphs of their study is given in Figure 2.7.

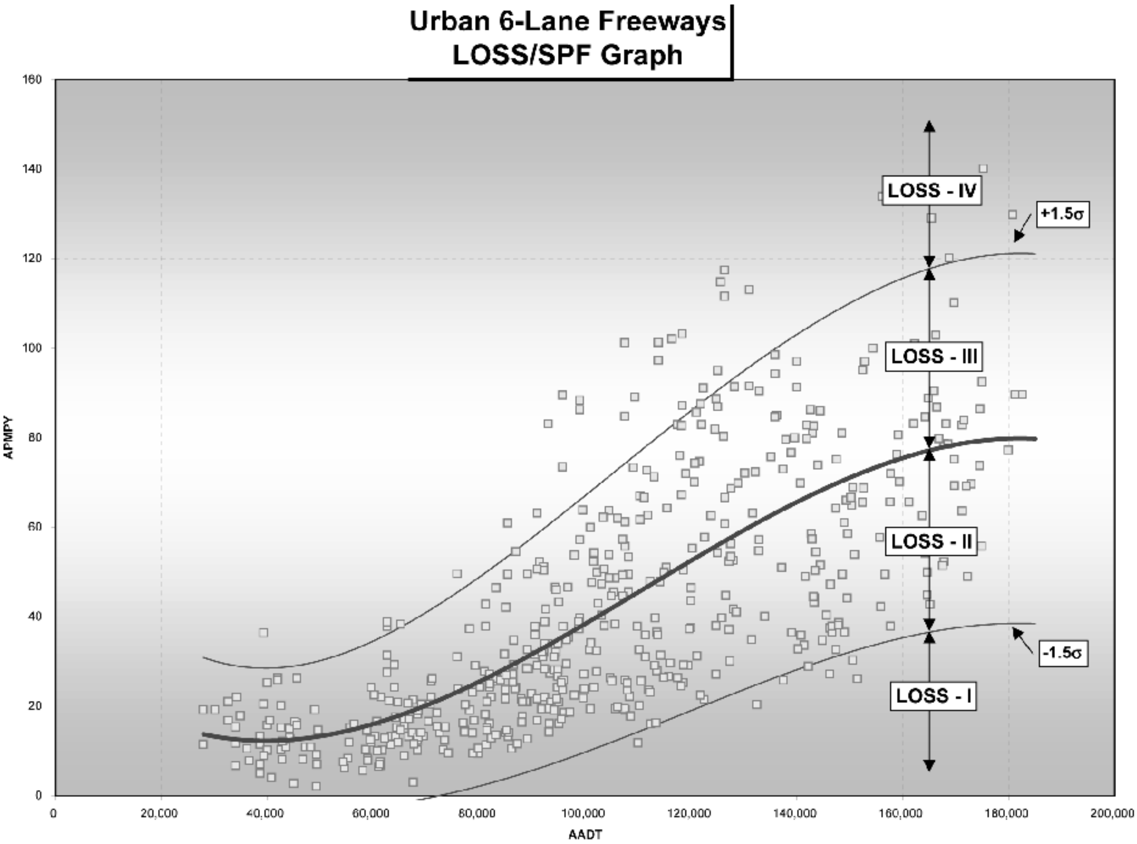

Figure 2. 7. Urban 6-Lane Freeway LOSS/SPF Graph (Total Accidents)
(Source: Kononov and Allery 2003)

They defined four Levels of Service of Safety (LOSS):

–LOSS-I Indicates low potential for accident reduction
–LOSS-II Indicates better than expected safety performance
–LOSS-III Indicates less than expected safety performance
–LOSS-IV Indicates high potential for accident reduction

Kweon and Kockelman (2004) examined the effects of speed limit changes on crash frequency and severity. They focused on over 6,000 highway segments of Washington State, with average lengths under 700 feet. Data was obtained from the U.S. Highway Safety Information System (HSIS). In their study, they used ordered logistic regression to examine the impacts of the 1996 speed limit changes statistically. The numbers of fatalities, injuries, crashes, fatal crashes, injury crashes, and property-damage-only (PDO) crashes were the units of the measurement of the model. The design variables of the research were as follows;

–horizontal and vertical curve lengths,
–degree of (horizontal) curve, grade, median width,
–number of lanes,
–indicators for mountainous and rolling terrains,
–AADT (Average Annual Daily Traffic) per lane
–VMT (Vehicle Miles Travelled) and
–pavement wetness.

They had remarkable findings. For example, 1,000 more AADT per lane is predicted to result in 6 % fewer fatalities and 8 % fewer fatal crashes. Interestingly driving in hilly or mountainous terrain reduces fatalities and fatal crashes. Median width is estimated as the reason for the increase of the injury crashes, PDO crashes, and total crashes. One of the most precious findings of the study is the prediction of the optimal speed limit -70 mi/h- for an average roadway segment (Kweon and Kockelman 2004).

Steenberghen and Dufays (2004) studied intra-urban location and clustering of road accidents in Mechelen, Belgium. They also based their work on geographic information systems to define road-accident concentrated areas (black zones). Two dimensional and linear clustering techniques were used to identify black zones. Dynamic segmentation was employed to indicate geocoding and intersection identification for the location of road accidents. One-dimensional and two dimensional clustering techniques were compared, and it was seen that accident-prone areas were identified through two-dimensional clustering techniques.

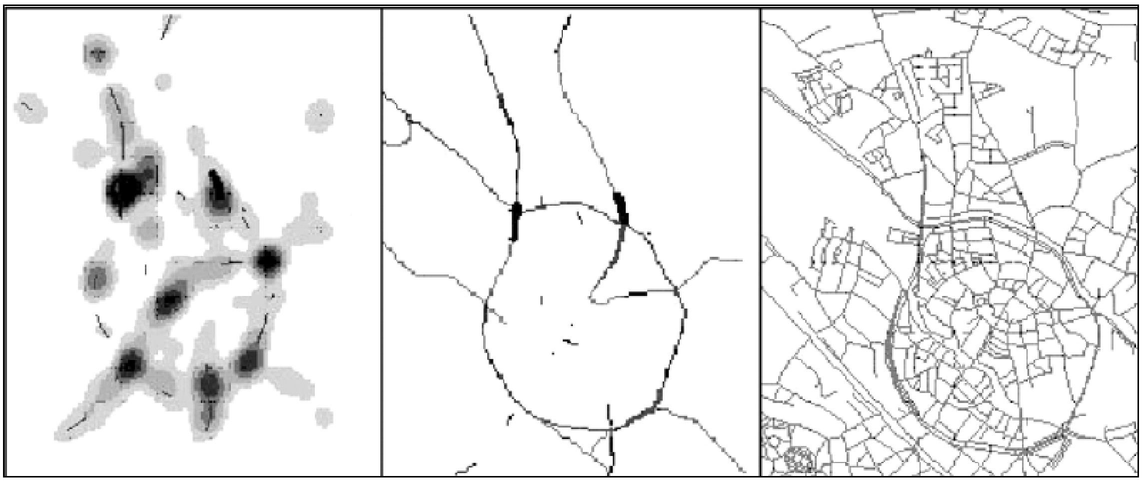

Figure 2. 8. Two-dimensional accident concentrations (left) versus linear concentrations (middle) in a street network (right) (Source: Steenberghen and Dufays 2004)

The impact of traffic-calming measures on the location and type of accidents were illustrated in Mechelen. Traffic safety was related to the balance between type of traffic and the road and neighborhood characteristics (Steenberghen and Dufays 2004).

Noland and Quddus (2004) analyzed the traffic accidents and land use types, road characteristics and demographic data of London's 8,414 wards (districts of UK) by using GIS tools. They used negative binomial model to expose the relation between these factors and the accident types such as fatalities, serious injuries and slight injuries. Their findings are as follows;

- urbanized more densely populated areas will tend to have fewer traffic casualties while areas with higher employment density have more traffic casualties.
- increasing speeds in urbanized areas by reducing congestion may have adverse safety consequences.

Berhanu (2004) in his study dealt with the models relating traffic safety and traffic flows for Addis Ababa. He mentioned the probabilistic nature of accidents, thus unpredictability of the accidents through statistical models at micro level. The models predict accidents by relating to explanatory measures; flow, site characteristics, and road geometry, at macro level. As studying on an unplanned city, he dealt with the models critically, as these prediction models were useful to identify and improve safety standards of new roads. He also criticized previous studies that typically used conventional multiple linear regression technique, which is insufficient to describe random, discrete, and non-negative events such as traffic accidents.

Berhanu (2004) used Poisson and Negative Binomial regression method in his study. The study indicated that improvements in roadway width, pedestrian facilities, and access management were effective in reducing road traffic accidents. Locations of accidents were determined on the map of the city with x and y coordinates. Explanatory variables of the regression model were vehicle-kilometer, lane width, number of lanes, median width, U-turn median openings, sidewalk width and surfacing, presence of raised kerb, number of minor junctions, curviness of road, grade, pedestrian traffic, parking, traffic density, and average speed of the traffic.

As a result, significant relationship was found between lane width and the total number of accidents on undivided roads. He also highlighted the importance of traffic engineering to reduce the accident risk. He suggested the increase in road curvature to prevent the drivers' tendency to travel at higher speeds (Berhanu 2004).

One of the probabilistic studies was about the modeling the effects of road safety measures dependent to the traffic accident statistics (Lu 2005). The statistical data was aggregated into different types or characters of accidents in this study. Accident frequency, accident severity, number of fatalities, number of injuries and amount of material damage were used as the parameters of the model. Traffic safety was described as the resultant of accident risk and accident consequence, which were defined as stochastic variables in the model.

$$TSP = f \cdot P(R, C) \tag{2.4}$$

TSP: Traffic safety in terms of probability
C : Accident Consequence
R : Accident Risk

Brabander et al. (2005) analyzed the road safety effects of 95 roundabouts built in Flanders between 1994 and 1999. They classified the intersections according to the speed limit of the arms. Summary of their research is that Flemish roundabouts reduced the injury accidents ranges from 15% to 59% with an average of 34%. The most effective reduction is seen at 90x70 km/h and 90x50 km/h roads with 59% and 55%, respectively. Table 2.3 shows the summary results of the research.

Table 2. 5. Reduction in the # of accidents due to roundabouts for all injury accidents from the first year after construction until 2000. (Source: Brabander 2005)

Speed limit (km/h) major road × adjacent road	*Reduction in the # of accidents* [a]	*Reduction in the # of light injury accidents* [a]	*Reduction in the # of serious injury accidents* [a]
50 × 50	39% (24%, 50%)*	37% (19%, 51%)*	28% (-29%, 60%)
70 × 50	15% (-5%, 30%)	14% (-12%, 33%)	36% (-4%, 60%)
70 × 70	42% (17%, 59%)*	42% (14%, 61%)*	50% (-13%, 78%)
90 × 50	55% (18%, 76%)*	45% (-7%, 72%)	54% (17%, 82%)
90 × 70	59% (44%, 71%)*	40% (8%, 61%)*	72% (42%, 86%)*
90 × 90	18% (-24%, 46%)	7% (48%, 42%)	27% (-77%, 70%)
All locations	34% (43%, 28%)*	30% (19%, 39%)*	38% (15%, 54%)*

A negative number means an increase in the # of accidents.
[a] 95% confidence interval between parentheses.
* Statistically significant at 5% level.

Jianming and Kara (2005) used clustered data from homogenous high-speed roadways of Washington State to investigate the relationship between crash frequencies and roadway design. They used linear regression models for the total number of crashes per million vehicle miles traveled (VMT). They also estimated a crash severity model by using an ordered logistic regression. The most valuable finding of their study is the speed limit information that was exposed from the regression equations. The models can give the optimal speed limits in order to minimize the crash rates. Their speed limits are also interesting; minimum expected crash cost is achieved at a speed limit of 70 miles/hour, while the maximum crash rate occurs at a speed limit of 43.5 miles/hour.

Chang (2005), in his comparative study, used Negative Binomial regression versus Artificial Neural Networks (ANN) to analyze the accident frequencies of the freeways in Taiwan. He contributed ANN as a *"consistent alternative method"* in analyzing freeway accident frequencies. He underlined the erroneous estimation risk of Negative Binomial Regression model, when its assumptions were violated. However ANN is more powerful since this method do not need any predefined underlying relationship between dependent and independent variables. The study analyzes 1997-1998 accident data for National Freeway-1 in Taiwan with both NB and ANN. He explains the commonly use of linear models in previous studies as *"accidents on a highway section can be regarded as a random event"*. He used the same variables which are highway geometry, traffic characteristics and weather conditions in both models.

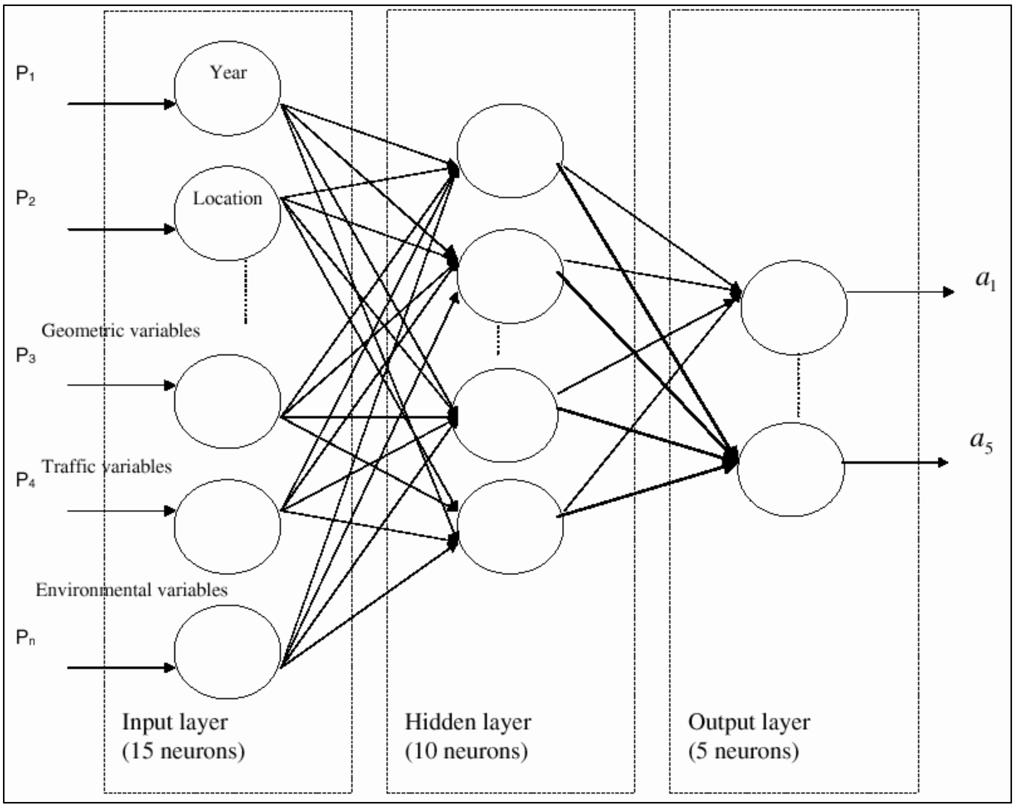

Figure 2. 9. The structure of the ANN model (Source: Chang 2005)

Chang discussed that ANN has advantage because an accident was the outcome of a series of factors. Besides a correlation problem between the explanatory variables does not affect the suitability of ANN model (Chang 2005).

Delen et al. (2006) also used ANN to identify the relationships between the injury severity levels and crash-related factors. They defended their reason for using ANN because of the potentially non-linear relationships between the injury severity and the factors of traffic accidents. They used Multi Layer Perceptron (MLP) with back-propagation gradient-descent supervised learning algorithm and sigmoid activation functions for the processing elements. They tried to enter the model almost all factors commonly accepted by the researchers as the cause of traffic accidents. Surprising result as they stated is;

- the weather conditions or the time of the accident did not seem to affect the severity risk of injury.

The graphical representation of the model with its independent (input layer) and dependent (output layer) variables are seen in Figure 2.10.

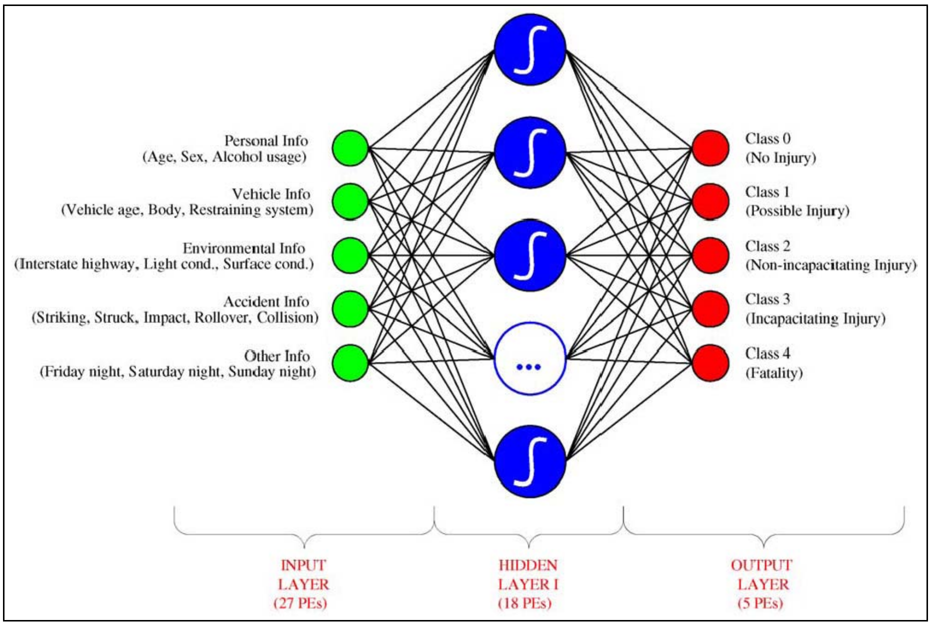

Figure 2. 10. Graphical Representation of MLP Neural Network Model
(Source: Delen, et al. 2006)

Geirt and Nuyts (2006) studied on cross-sectional accident models on Flemish motorways based on infrastructural design. They created a database of motorway accidents between 1996 and 2001, and infrastructure measurements between 1996 and 2003 for negative binomial regression modeling. Road characteristics such as; traffic density, number of lanes, lane width, shoulder width, barrier type, number of objects, speed limit and lane presence were the variables to apply the model. The results supported the previous studies, which revealed the importance of traffic volumes to predict the accidents. As a result, motorways split in three major zones: link zones, entry zones and exit zones. It was seen that the accident frequency changed significantly, beyond one kilometer upstream and downstream for both the entry and exit zones.

Tjahjono (2007) used the negative binomial modeling technique to model the frequency of accidents of toll roads in the Greater Jakarta Area. He described the relationship between accidents and traffic flow by "U" shaped curves according to the results of the models. Table 2.4 shows the minimum expected results of the models in terms of number of accidents per year per km and also per year per km per lane, for selected segment lengths. He summarized his study as the following statements;

- The relationship between total number of accidents and traffic flow in terms of AADT can be described by a U-shaped curve. For dual-2 and dual-3 toll roads, the U-shape is skewed to the right. The highest number of accidents occurs in heavy traffic conditions. On dual-4 toll roads, the U-shape is skewed to the left. The highest number of accidents occurs in light traffic conditions.
- Distance between junctions and number of lanes was found to have a significant impact on accident frequencies.

Table 2. 6. Minimum values of total number of predicted accidents
(Source: Tjahjono 2007)

Lanes & Segment Length	*Traffic Flow (Vehciles/day)*	*Predicted Accidents per year*	*Predicted Accidents per km per year*	*Predicted Accidents per km per lane per year*
Dual-2				
2 km	17,500	15	8	4
5 km	20,000	17	3	2
10 km	22,500	18	2	1
Dual-3				
2 km	22,500	11	8	4
5 km	35,000	13	3	2
10 km	40,000	15	2	1
Dual-4				
2 km	112,500	46	23	6
5 km	130,000	64	13	3

Erdogan et al. (2007) developed a system of transforming textual accident data into spatial visualisation by using the Geographical Information Systems (GIS) tools. They used the GIS tools of Kernel Density analysis and repeatability analysis to determine the hot spots of the highways in Afyonkarahisar. Finally they suggest using GIS as a management system for accident analysis and determination of hot spots in Turkey with statistical analysis methods in their study.

2.3. Evaluation of the Literature and Need for Fuzzy Logic Modeling

Literature review showed that researchers used commonly Poisson or NB Regression and GLM techniques for analyzing or estimating the severity of the traffic accidents in their studies (Mountain, et al. 1998, Busi 1998, Martin 2002, Ng, et al. 2002, Karlaftis and Golias 2002, Greibe 2003, Chin and Quddus 2003, Kononov and

Allery 2003, Kweon and Kockelman 2004, Noland and Quddus 2004, Berhanu 2004, Lu 2005, Jianming and Kara 2005, Tjahjono 2007).

Wang et al. (2007) relate this preference to the 350-year-old hegemony of probability and statistics methodology. However, these models refer *pre-defined* relationship between dependent and independent variables and neglecting this relation could cause an erroneous estimation of an accident possibility (Chang 2005).

Many studies on accident analysis and prevention, road safety, etc. proved that traffic accidents are affected by lots of factors which are not always linear or have purely defined information. Traffic accidents include uncertainty, and the studies in that field cannot process pure explicit data. Hence the prediction model could be nonlinear and to have a sub-solution is better than a false or no-solution (Wang, et al. 2007).

Another problem is excluding expert knowledge in the models. It is common that practices of many studies operate separately from the theory. Most of the findings of the researches have locality in practice. This indicates that any theory should include and the expert knowledge and intuitions as its own rules. Besides, the complexity of the real world also complicates obtaining precise information.

The fuzzy logic approach seems very suitable for dealing with uncertainty phenomena; although the use of probabilistic techniques was higher than the use of fuzzy techniques for safety issues (Serrano, et al. 1999). Serrano et al. also recommend to the researchers to use the fuzzy set technologies if the study must deal with vague knowledge or needs to communicate with the user in a more humanlike way.

Jang and Gulley (1995) stated the advantages of Fuzzy Logic as follows:

- Fuzzy Logic is a conceptually easy to understand. The mathematical concepts behind fuzzy reasoning are very simple. Naturalness of the approach makes it preferable to the other techniques.
- Fuzzy logic is flexible, tolerant of imprecise data, and it can model nonlinear functions of arbitrary complexity.
- Fuzzy logic can be blended with conventional control techniques. In many cases fuzzy systems expends the concept of the conventional control techniques 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.

Salmani and Akbari (2008) evaluated the contribution of Fuzzy Logic to the change of a scientific world view in handling the issue of reality. As seen in the table below, fuzzy thinking appeared with the recognition of the complexity of the reality. While fuzzification is not necessary in positivism, the most complicated fuzzy thinking required to understand reality in post-structuralism.

Table 2. 7. Cross tabulation of research paradigms, common research methods and fuzzy logic (Source: Salmani and Akbari, 2008)

Research paradigms	***Ontology***	***Epistemology***	***Methodology***	***Common Research method***	***Fuzzy***
Empirical analytical positivism	Reality is out there	Knowledge can be objective	Experts formulate research questions then test them empirically	Experiments, controlled surveys	No use of fuzzy
Imperativisim / Constructivism	Reality is not out there, it is conditional upon human experience	Knowledge is not objective and constructed	Identification of varied interpretations of reality and attempt to recognize the pattern	Ethnographic, Case study, phenomenology …	Fuzzy starts as a philosophy and a tool
Critical theory	Reality is not out there, it is material , never fully understood	Knowledge is not objective, values and power play pivotal role.	Research seeks to understand the effect of power, then empower people to…	Particularly action research …	More complicated
Post structuralism	Multiple representation of reality	Events are understood in theme of powerful and subordinated discourses	Research seeks to expose how dominant interests preserve social inequalities	Discourse analysis	The most complicated as we have multiple representation of the reality

Using fuzzy logic is convenient in explaining traffic accidents, in which uncertainty is very dominant. In the literature, statistical predictions were made generally with limited parameters. Models established on predictions were commonly based on one or two parameters such as traffic flow and traffic density.

Traffic accidents have uncertain reasons such as the road factors, features of the traffic, whether conditions, etc. Some of these factors as geometry of the road may be static and some may be dynamic like traffic density. The nature of the traffic accidents needs a flexible model that can tolerate imprecise data.

This study aims to contribute all related numeric or linguistic parameters of traffic accidents to the prediction model. Hence, for all the stated reasons Fuzzy Logic Modeling approach is chosen for modeling the accident risk on urban roads.

CHAPTER 3

FUZZY LOGIC MODELING

"Aristotle Logic" in other words "bi-valued logic" approach has been dominated the later mathematicians for many years, until a man Lütfi Askerzade (Lotfi Asker Zadeh) from eastern world challenged the arena of science by his *fuzzy sets*.

Around the years 400 B.C. Aristotle posited the "Law of the Excluded Middle" in one of his famous "Law of Thought". This rule states that "every proposition must either be *True* or *False*. Even in those years Heraclitus proposed that things could be simultaneously *True* and *not True* (Brule 1985, Salmani and Akbari 2008).

Lukasiewicz in 1920's described a systematic alternative to the bi-valued logic of Aristotle. He proposed a three-valued logic which has the terms *true, false* and *possible*. He assigned a numeric value between true and false to the term possible. He proposed entire notation and axiomatic system from which he hoped to derive modern mathematics. Later he developed the four-valued logics and at last he declared the derivation of an infinite valued logic (Kulkarni 2001, Salmani and Akbari 2008).

Donald Ervin Knuth from Stanford University has also proposed a three-valued logic in his balanced ternary theory, similar to Lukasiewicz's, which uses the three digits [-1, 0, +1] (Brule, 1985).

Eventually Lotfi A. Zadeh from the Department of Electrical Engineering and Electronics Research Laboratory of University of California introduced the mathematically expression of an infinite-valued logic by his *Fuzzy Sets.* Zadeh (1965) defined the concept of Fuzzy Sets in the following way:

> A fuzzy set is a class of objects with a continuum of grades of membership. Such a set is characterized by a membership function which assigns to each object a grade of membership ranging between zero and one. The notions of inclusion, union, intersection, complement, relation, convexity, etc., are extended to such sets, and various properties of these notions in the context of fuzzy sets are established. In particular, a separation theorem for convex fuzzy sets is proved without requiring that fuzzy sets to be disjoint. (Zadeh, 1965)

3.1. Introduction to the Concept of Fuzzy Logic

A fuzzy set is defined as the extension of a crisp (classical) set which allows only full membership or no membership to its elements (Zadeh, 1965).

In a crisp set;

If x is an element of set A then $\mu_A(x) = 1$,

x is not an element of set A then $\mu_A(x) = 0$

$\mu_A(x_1)=1$, $\mu_A(x_2)=1$, $\mu_A(x_3)=1$,

$\mu_A(x_4)=0$, $\mu_A(x_5)=0$,

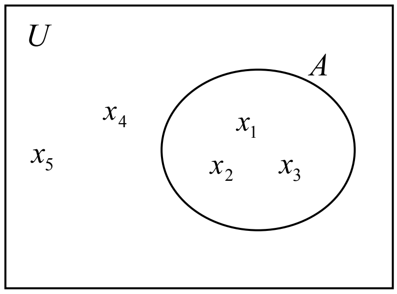

Figure 3. 1. Representation of a crisp (classical) set

Fuzzy set theory extends this concept by defining partial membership. A fuzzy set A on a universe of discourse U is characterized by a membership $\mu_A(x)$ that takes values in the interval [0, 1].

In a fuzzy set;

$\mu_A(x_1)=1.0$

$\mu_A(x_2)=0.9$

$\mu_A(x_3)=0.6$

$\mu_A(x_4)=0.1$

$\mu_A(x_5)=0.0$

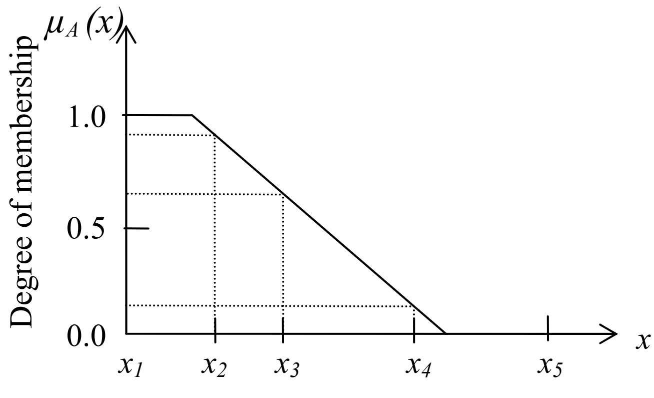

Figure 3. 2. Representation of a fuzzy set

The main challenge of the fuzzy logic theory is the rejection of any object belonging to a single set. Instead, this approach suggests partial belongings of any object to different subsets of a universal set. Fuzzy membership functions may take on many forms according to the experts. However, in practical applications triangular and trapezoidal functions are preferred as simple linear functions (Tayfur, 2003).

Examples of fuzzy sets are given in Figure 3.3:

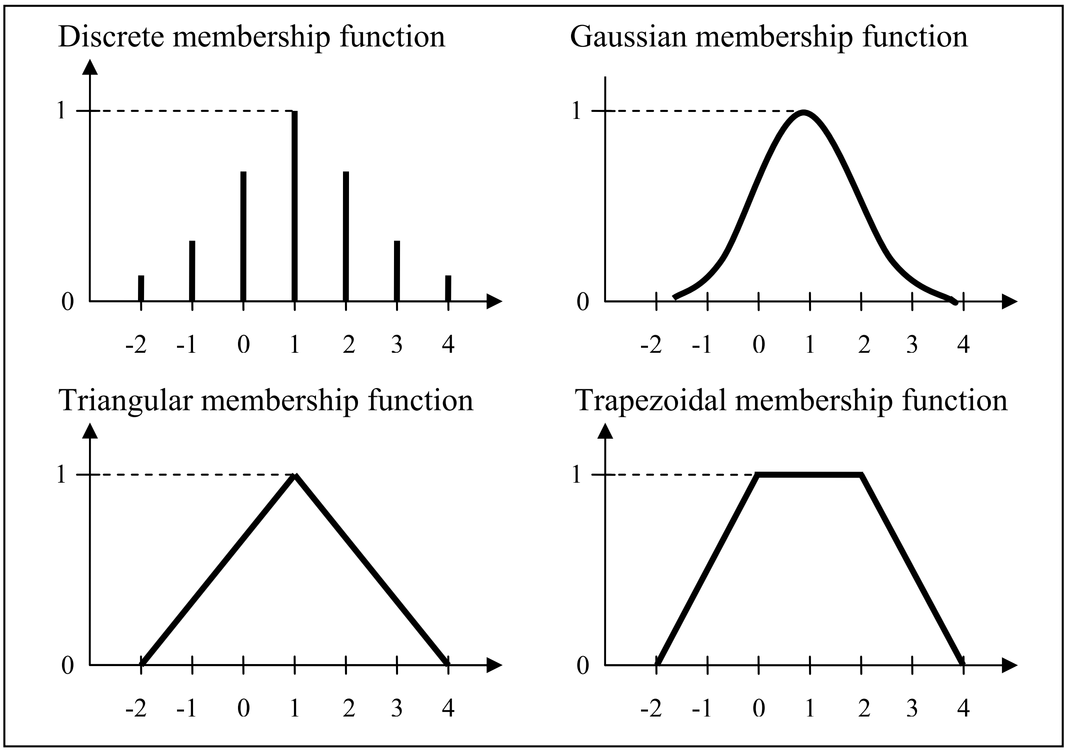

Figure 3. 3. Membership functions for “x is close to 1”

All contradictory phenomenons can be fuzzified in terms of their membership degrees. Fuzzy state of the opposite colors white and black is illustrated in Figure 3.4.

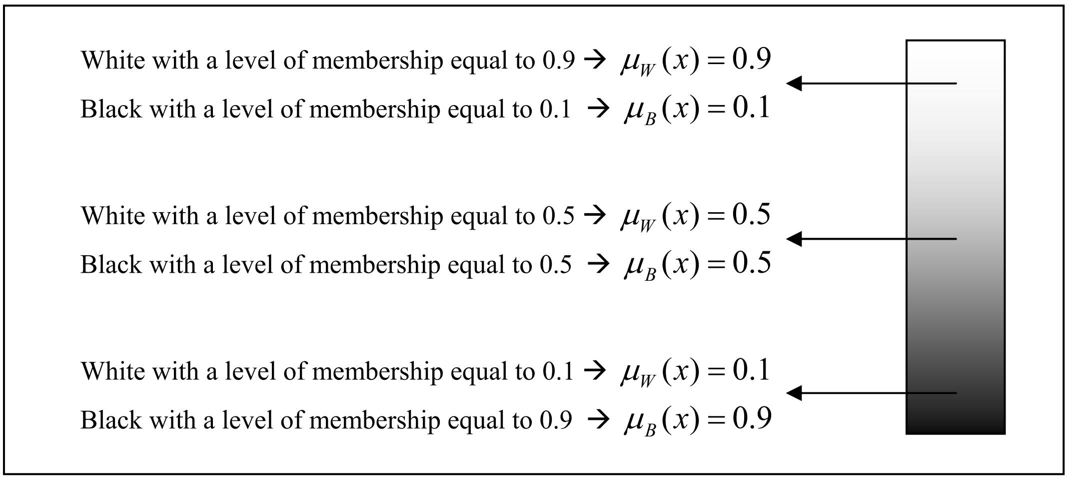

Figure 3. 4. Schematic illustration of “Fuzzy” white and black

Some of the essential characteristics of fuzzy logic are on follows (Zadeh, 1989):

- In fuzzy logic, exact reasoning is viewed as a limiting case of approximate reasoning.
- In fuzzy logic, everything is a matter of degree.
- Any logical system can be fuzzified.
- In fuzzy logic, knowledge is interpreted a collection of elastic or, equivalently, fuzzy constraint on a collection of variables.
- Inference is viewed as a process of propagation of elastic constraints.

3.2. Fuzzy Sets and Membership Functions

Fuzzy sets represent commonsense linguistic labels like cold-warm-hot, heavy-light, low-medium-high, etc. A given element can be a member of more than one fuzzy set at the same time. Following sample of crisp set and its fuzzy implementation is developed from the city planning area of science.

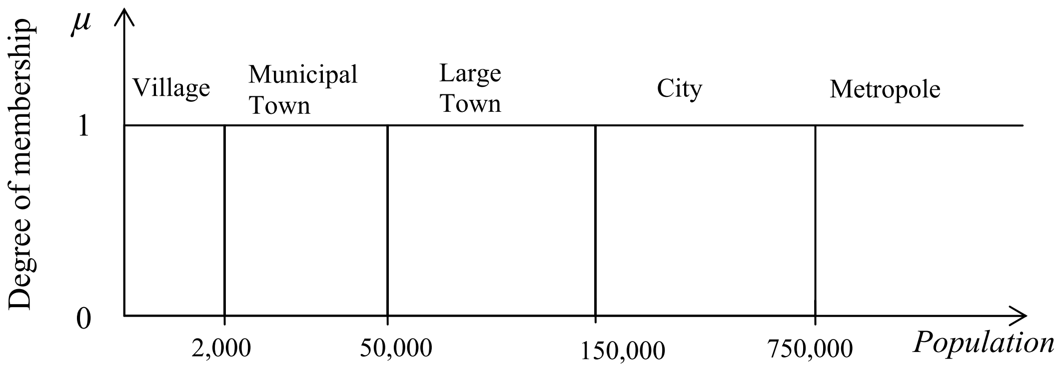

Figure 3. 5. Crisp set of a settlement hierarchy due to population

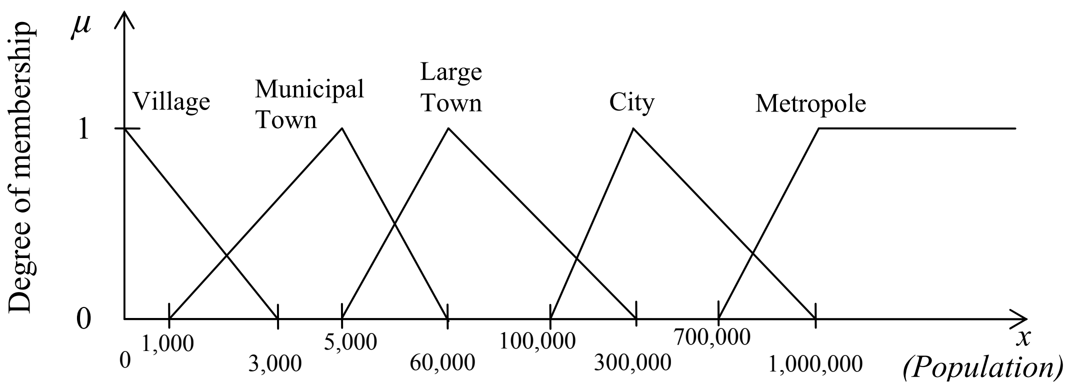

Figure 3. 6. Fuzzy set of a settlement hierarchy due to population

Any graduated phenomenon can be expressed by a fuzzy classification technique. One of the argumentative classifications of city planning discipline is tried to be expressed as a fuzzy set in Figure 3.6. It is obvious that two settlements with the population of 1,999 and 2,001 respectively have no different demographic characteristics from each other to be a municipality or not. However with the last municipality regulation in Turkey, some of the settlements lost their municipal status because of this small difference.

Let x be an element of a non empty set and indicates the population of a settlement. Then mathematical expression of the membership functions of any settlement according to the former Fuzzy Set is;

$$\mu_{VIL}(x) = \left\{ \frac{3{,}000 - x}{3{,}000 - 1{,}000} \ , \ If \quad 1{,}000 < x \leq 3{,}000 \right\} \tag{3.1}$$

$$\mu_{MUN}(x) = \begin{cases} \dfrac{x - 1{,}000}{5{,}000 - 1{,}000} \ , & If \quad 1{,}000 < x \leq 5{,}000 \\ \dfrac{60{,}000 - x}{60{,}000 - 5{,}000} \ , & If \quad 5{,}000 < x \leq 60{,}000 \end{cases} \tag{3.2}$$

$$\mu_{TOW}(x) = \begin{cases} \dfrac{x - 20{,}000}{60{,}000 - 20{,}000} \ , & If \quad 20{,}000 < x \leq 60{,}000 \\ \dfrac{300{,}000 - x}{300{,}000 - 60{,}000} \ , & If \quad 60{,}000 < x \leq 300{,}000 \end{cases} \tag{3.3}$$

$$\mu_{CITY}(x) = \begin{cases} \dfrac{x - 100{,}000}{300{,}000 - 100{,}000} \ , & If \quad 100{,}000 < x \leq 300{,}000 \\ \dfrac{1{,}000{,}000 - x}{1{,}000{,}000 - 300{,}000} \ , & If \quad 300{,}000 < x \leq 1{,}000{,}000 \end{cases} \tag{3.4}$$

$$\mu_{MET}(x) = \begin{cases} \dfrac{x - 700{,}000}{1{,}000{,}000 - 700{,}000} \ , & If \quad 700{,}000 < x \leq 1{,}000{,}000 \\ 1 \ , & If \quad 1{,}000{,}000 < x \end{cases} \tag{3.5}$$

According to the membership functions given above if a settlement has the population of 3,800 then;

- It is a *village* with the membership of 0.3 $\mu_{VIL}(3{,}800) = 0.3$ and,
- It is a *municipal town* with the membership of 0.7 $\mu_{MUN}(3{,}800) = 0.7$

3.3. Constructing a Fuzzy Model (Fuzzy System)

Fuzzification is the initial process of a fuzzy model where fuzzy subsets of universal set of fuzzy variable are constructed. If there is no data, intuition and experience can be used in fuzzification process. By simply looking at the distribution of data of each variable the obvious clusters can be seen and fuzzified. The figure below shows an example of a clustering fuzzification method.

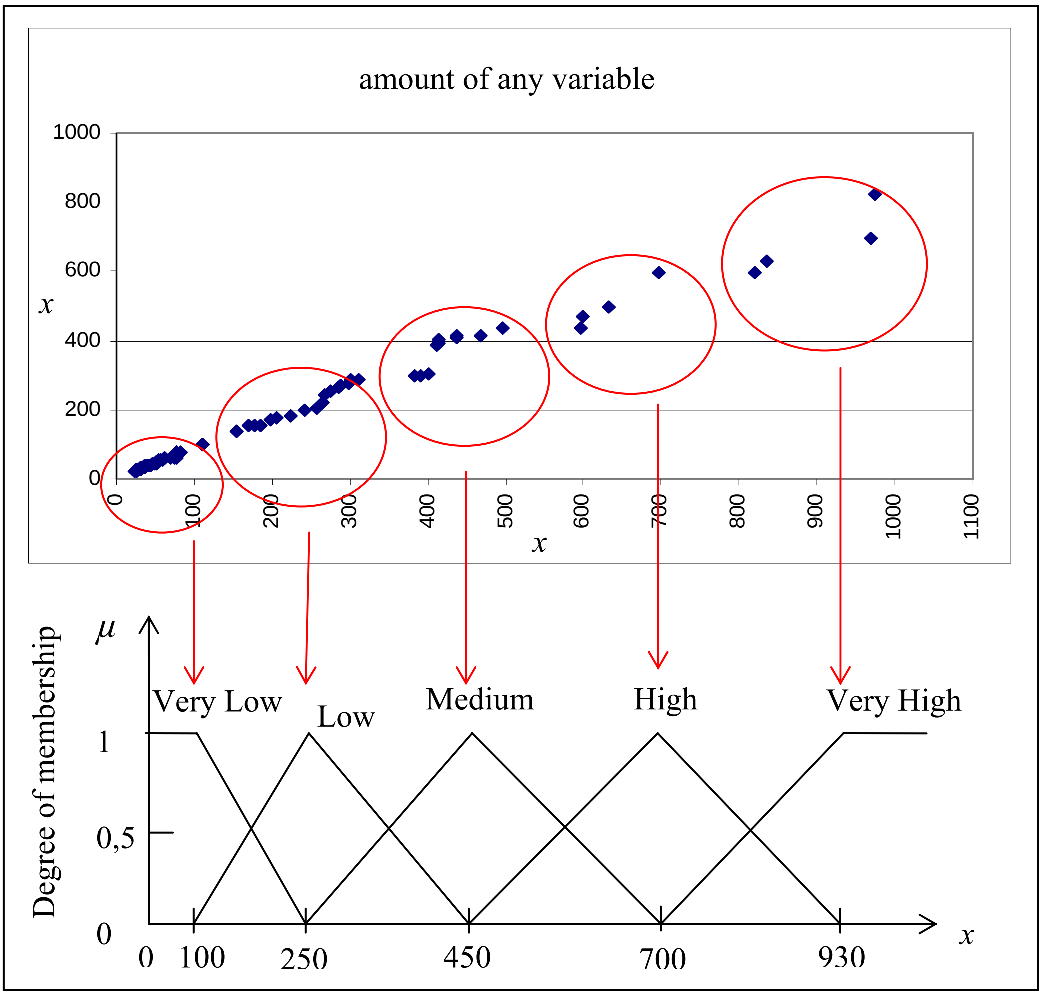

Figure 3. 7. Example of a fuzzification process by clustering

If there is available data initially the dataset is portioned into two sets; calibration (training) and verification (testing). Calibration set is used for fuzzification and constructing the fuzzy rules. Verification set is used for testing the accuracy of the model set.

3.4. Fuzzy Inference System (FIS)

It takes into account all the fuzzy rules in the rule base and learns how to transform a set of inputs to corresponding outputs. There are four sub-processes:

– Fuzzification
– Rule Production
– Composition or aggregation
– Defuzzification

Figure 3.8 shows the schematic diagram of a fuzzy inference system.

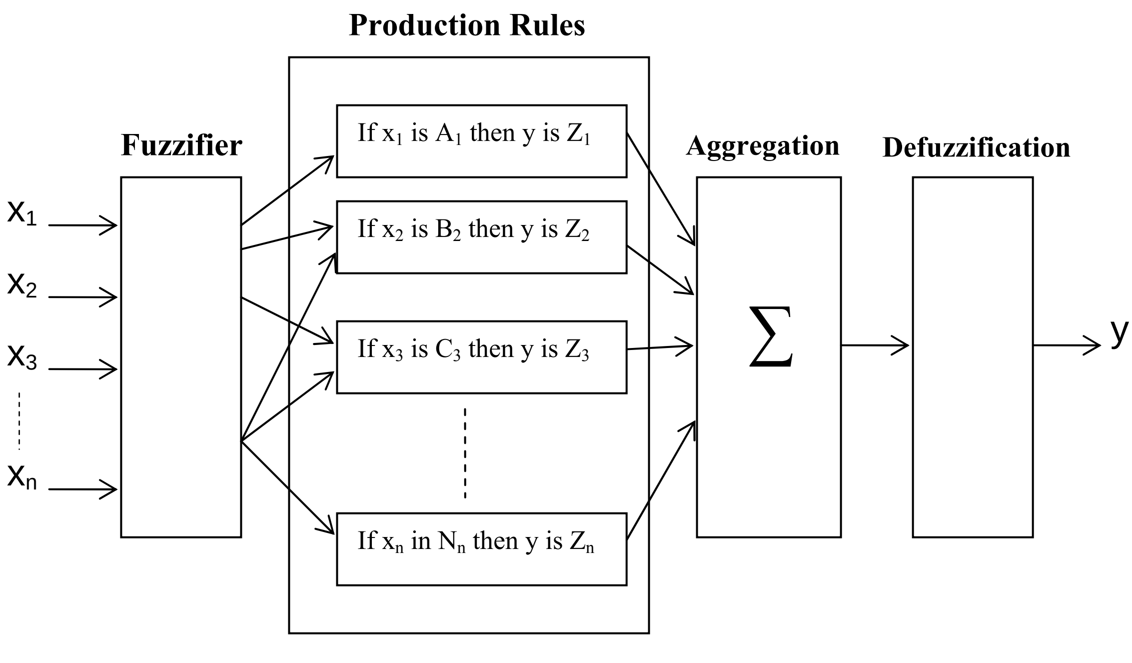

Figure 3. 8. Schematic diagram of a fuzzy inference system

A basic example is established for better understanding the Fuzzy Inference System. Let's narrow the settlement hierarchy problem into a decision of a settlement being *Village* or *Municipal Town* with considering two input variables; *population* and *the distance to the closest municipal town*.

Fuzzification of input and output variables:

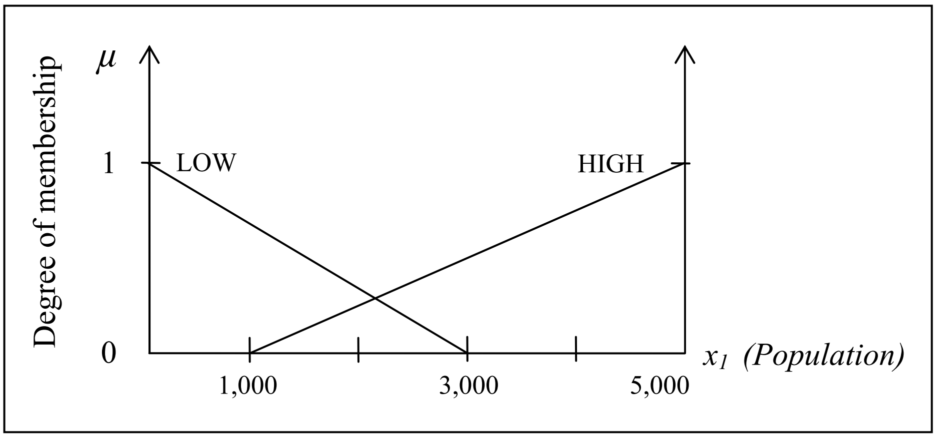

Figure 3. 9. Fuzzy set of input x_1

$$\mu_{LOW}(x_1) = \frac{3{,}000 - x_1}{3{,}000} \quad , \quad If \quad 0 < x_1 \leq 3{,}000 \tag{3.6}$$

$$\mu_{HIGH}(x_1) = \frac{x_1 - 1{,}000}{5{,}000 - 1{,}000} \quad , \quad If \quad 1{,}000 < x_1 \leq 5{,}000 \tag{3.7}$$

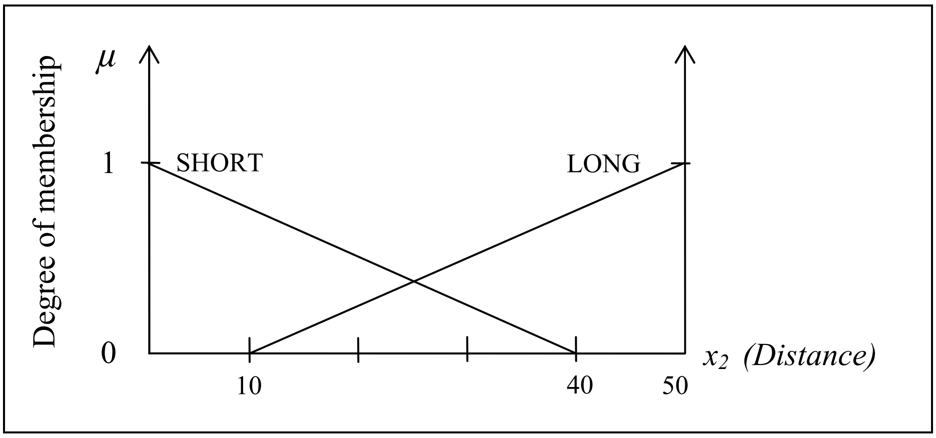

Figure 3. 10. Fuzzy set of input x_2

$$\mu_{SHORT}(x_2) = \frac{40 - x_2}{40} \quad , \quad If \quad 0 < x_2 \le 40 \tag{3.8}$$

$$\mu_{LONG}(x_2) = \frac{x_2 - 10}{50 - 10} \quad , \quad If \quad 10 < x_2 \le 50 \tag{3.9}$$

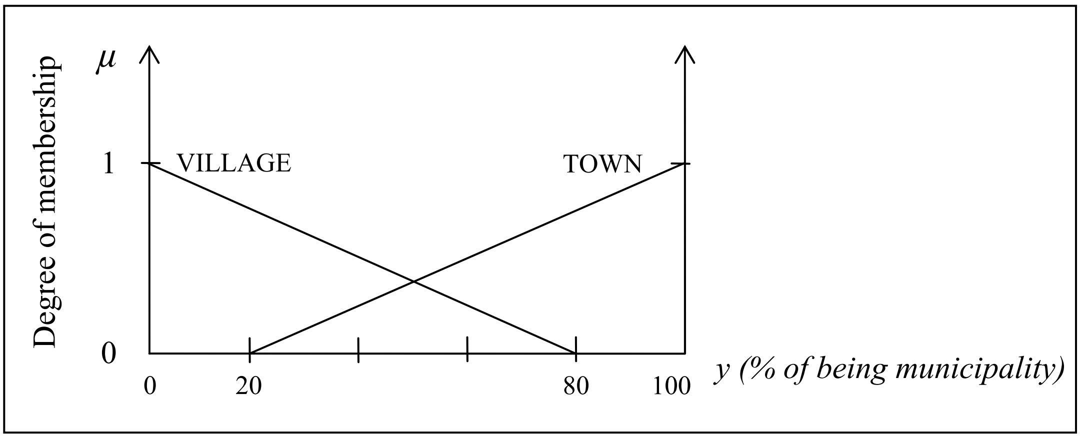

Figure 3. 11. Fuzzy set of output *y*

$$\mu_{VILLAGE}(y) = \frac{100 - y}{100} \quad , \quad If \quad 0 < y \le 80 \tag{3.10}$$

$$\mu_{TOWN}(y) = \frac{y}{100 - 20} \quad , \quad If \quad 20 < y \le 100 \tag{3.11}$$

Production Rules:

At this stage the truth value of each rule is computed, and then applied to the corresponding part of each rule. *Fuzzy Rule Base* contains all the possible fuzzy relations between input variables and the output variable. If there is no data; intuition, inductive reasoning or experience can be tools for setting the rules.

Interpreting an *If-Then* rule production is a three part process (Kulkarni, 2001):

a- *Fuzzify inputs*: Resolve all fuzzy statements in the antecedent to a degree of membership between 0 and 1.

b- *Apply fuzzy operator to multiple part antecedents*: If there are multiple parts to the antecedent, apply fuzzy logic operators and resolve the antecedent to a single number between 0 and 1, is the degree of support for the rule.

c- *Apply the implication method*: Using the degree of support for the entire rule to shape the output fuzzy set. If the rule has more than one antecedent, the fuzzy operator is applied to obtain one number that represents the result of applying that rule.

Rules are produced by an intuitive approach for this example. Following rules are constituted for the example.

R_1 : If x_1 is LOW and x_2 is SHORT then y is VILLAGE
R_2 : If x_1 is LOW and x_2 is LONG then y is TOWN
R_3 : If x_1 is HIGH and x_2 is SHORT then y is TOWN
R_4 : If x_1 is HIGH and x_2 is LONG then y is TOWN

For the first rule; it is assumed as if the population of the settlement (x_1) is low and the distance to the closest municipality (x_2) is low then the rate of being municipality (y) is low.

Composition or Aggregation:

Each fuzzy rule gives a single number that represents the truth value of that rule. The input for the implication process is a single number given by the antecedent, and the output is a fuzzy set. Two methods are commonly used; the *minimum* and the *product operation* methods. In this example *minimum operation* method is used for aggregation. Figure 3.12 illustrates the aggregation process of the model.

As an example, the settlement with the population 1,900 and 18 km far from the closest municipal town enters the following FIS operator. As seen in Figure 3.12 minimum shaded area of the each rules output set is selected due to the *minimum operation* method. Then, these areas are summed geometrically to obtain the fuzzy output diagram for these dataset. Next stage is the defuzzification process to get crisp output from the aggregated fuzzy output.

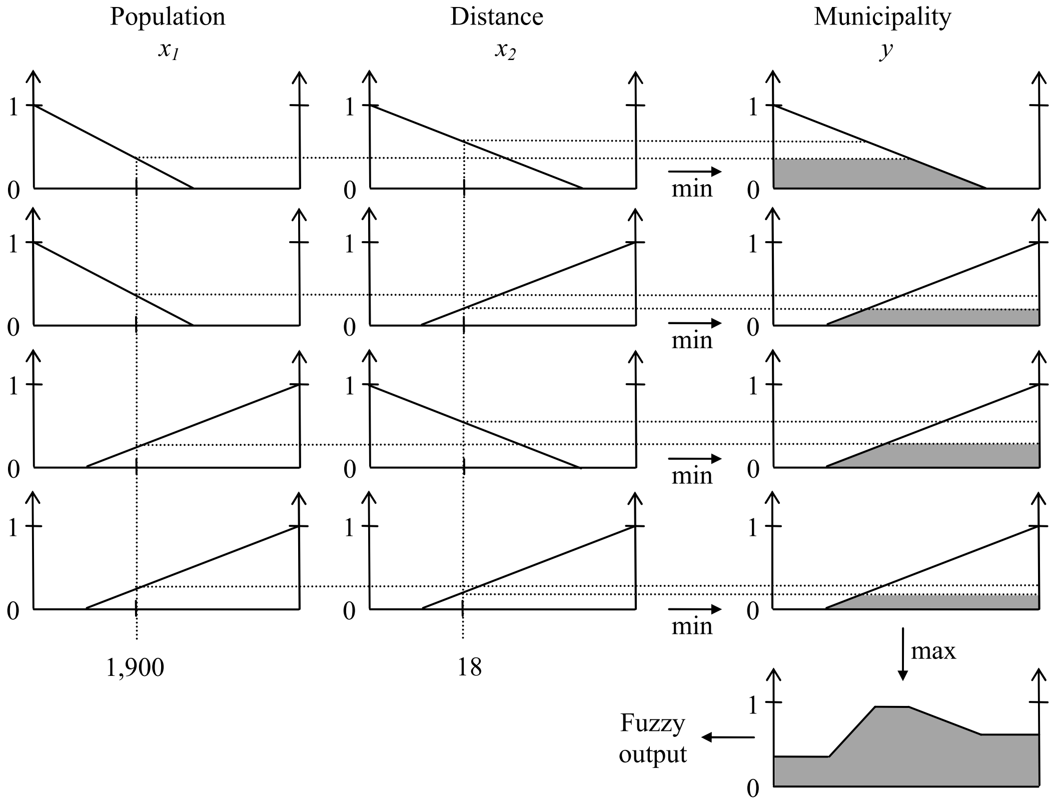

Figure 3. 12. Aggregation process of FIS (Mamdani type inference)

Defuzzification:

The procedure of converting each aggregated fuzzy output set into a single crisp value is called *defuzzification*. There are seven common defuzzification methods (Sivanandam 2007):

1. Centroid method (also called; Center of Area-CoA / Center of Gravity-CoG),
2. Max-membership principle,
3. Weighted Average method,
4. Mean–max membership,
5. Centre of Sums,
6. Centre of Largest Area
7. First of Maxima or Last of maxima

Centroid method which is the most widely used one is employed for our *Municipality Decision* problem. Centroid, (CoA/CoG) method determines the geometric gravity center of the shape of the fuzzy output set. Mathematical expression of the CoG method for continuous membership function is given in the Equation 3.12 and the geometric illustration of CoG defuzzification method is given in Figure 3.13.

$$y^* = \frac{\int U \cdot y \cdot \mu_U \cdot (y) \cdot dy}{\int U \cdot \mu_U \cdot (y) \cdot dy} \tag{3.12}$$

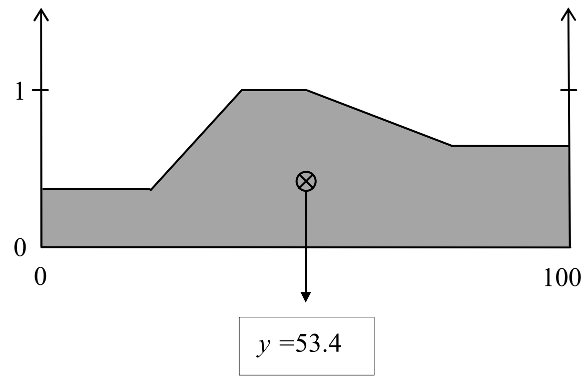

Figure 3. 13. Application of CoG defuzzification method to the fuzzy output result

This result means that a settlement with the population of 1,900 and 18 km far from the closest municipal town has the right for being municipality with the rate of 53.4%. Absolutely this is a very simple solution with two input variables and only four rules which are produced intuitionally. With the help of computer software as Matlab FL toolbox with more variables and more empiric rules, the problem can be solved more scientifically. Figure 3.14 illustrates the solution surface of the *municipality decision* problem.

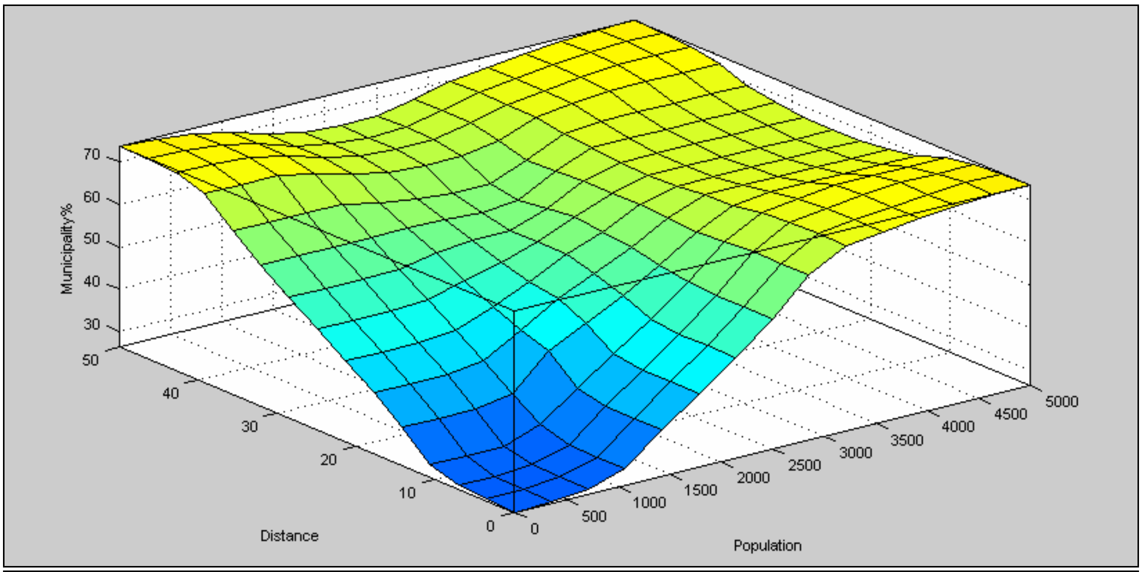

Figure 3. 14. Mapping surface of the model’s solution set (Matlab Fuzzy Logic Toolbox is used for illustration)

3.5. Fuzzy Logic Modeling Studies

Fuzzy logic is mostly used in studies, which have uncertain, vague, or missing input information. This provides the researchers to reach a definite conclusion from imprecise data.

Lee et al. (1998) developed a fuzzy-logic-based incident detection algorithm for signalized urban diamond interchanges. The model has the ability to detect lane-blocking incidents by observing abnormal traffic conditions similar to the incident induced conditions. They defined the reason for choosing fuzzy logic approach as;

- an effective solution for systems that must operate in real-time
- require approximate reasoning and exhibit uncertainty
- minimizes the impact of the boundary condition problems in conventional threshold-based algorithms
- captures system-wide incident effects utilizing multiple measures for more accurate and reliable detection

Performance measures of the model is presented in Table 3.1.

Table 3. 1. Performance of the proposed incident detection algorithm
(Source: Lee, et al. 1998)

Performance measures	Volume cases	Incident severity			Overall
		1 Lane Blocked	2 Lanes Blocked	3 Lanes Blocked	
Detection Rate (%)	Light	17	75	100	62
	Medium	50	92	90	77
	Heavy	58	92	90	79
	Overall	42	86	93	73
False alarm rate (%)	Light	0	0	0	0.00
	Medium	0.69	0.97	0.42	0.74
	Heavy	1.11	0.69	0.83	0.93
	Overall	0.60	0.56	0.50	0.56
Mean time to detect (min)	Light	6.5	4.4	4.3	4.6
	Medium	4.0	4.2	3.8	4.0
	Heavy	4.2	3.8	3.4	3.7
	Overall	4.4	4.1	3.9	4.1

Sanal (1999) proposed an intelligent traffic signal control system based on fuzzy logic approach to improve the traffic flow on a single intersection of two one-way streets. Schematic representation of the system is seen in Figure 3.15.

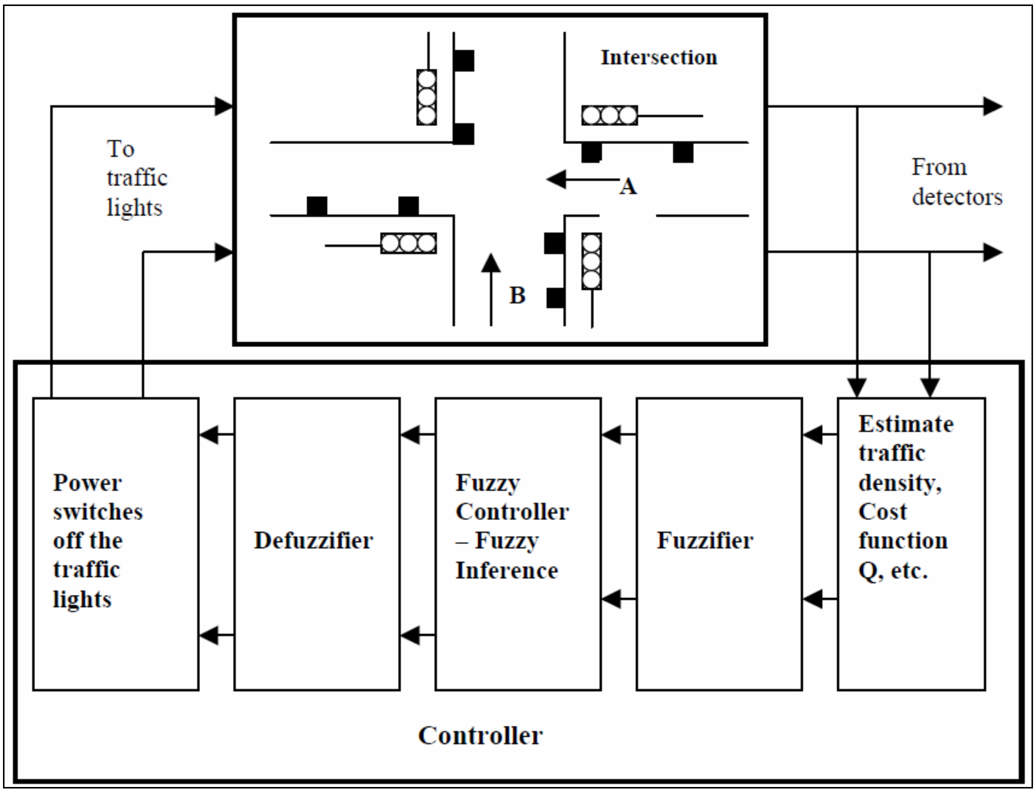

Figure 3. 15. Schematic diagram of the FL based traffic control system
(Source: Sanal 1999)

Yin et al. (2002) applied fuzzy-neural approach for urban traffic flow prediction. They underlined the commonly use of neural networks for such studies, since *"stochastic nature of traffic flow and the strongly nonlinear characteristics for short-term prediction".* Their fuzzy-neural model works over two modules; a gate network (GN) using fuzzy approach and an expert network (EN) of neural network approach. Gate network classifies traffic patterns of similar characteristics (input data) into clusters, and export network specifies the input-output relationship. Figure 3.16 shows the structure of the Fuzzy-Neural Model (FNM).

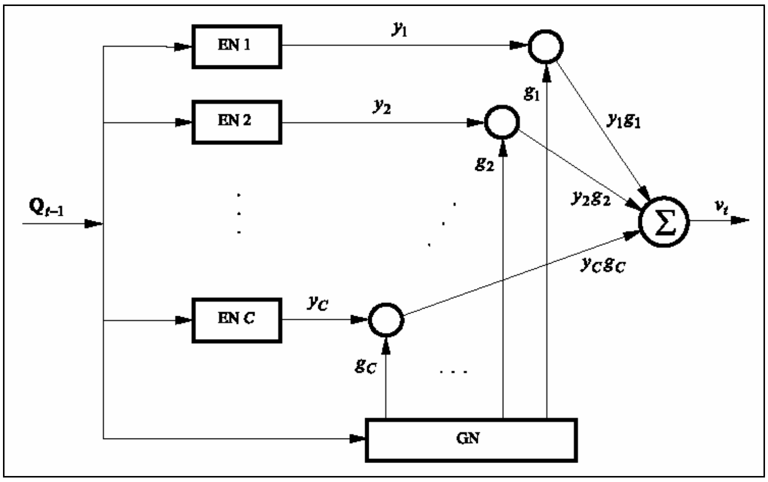

Figure 3. 16. The Structure of the FNM (Source: Yin, et al 2002)

Online rolling training procedure is proposed to enhance predictive power of the model in the real-time traffic conditions. Simulation and real observation data from five test sites in Hong Kong were used to assess the effectiveness of the method. Figure 3.17 shows the observed and the predicted results based on the models (Yin, et al. 2002).

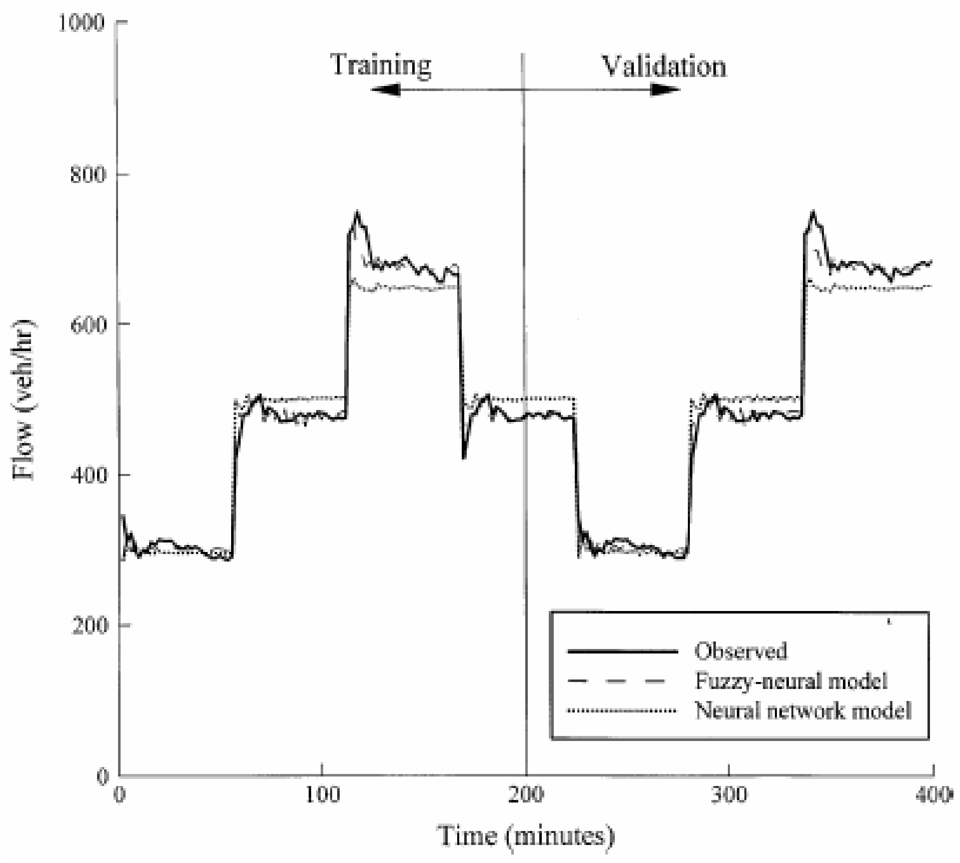

Figure 3. 17. Observed and predicted results based on the trained coefficients from first 100 dataset (Source: Yin, et al. 2002)

Tayfur et al. (2003) developed a fuzzy logic algorithm to estimate sediment loads from bare soil surfaces. Parameters of "slope" and "rainfall" are defined as the input variables of the model and weighted average method was employed for the defuzzification. They compared the fuzzy model with the ANN and Physic-based models and stated that the fuzzy model performed better under very high rainfall intensities over different slopes and over very steep slopes under different rainfall intensities. Table 3.2 shows the comparison of three models' results.

Table 3. 2. Prediction results of the measured mean loads by three models (g/m/s)
(Source: Tayfur, et al. 2003)

	5.7%	10%	15%	20%	30%	40%
32 mmth						
Observed	0.10	0.29	0.56	0.63	0.93	1.35
ANNs	0.35	0.46	0.66*	0.96*	2.18	5.27
Fuzzy	0.11*	0.13	1.03	1.08	1.09*	1.35*
Physics-based	0.06	0.23*	0.82	1.56	3.19	4.89
57 mmth						
Observed	0.30	1.50	2.81	5.71	10.17	13.08
ANNs	0.74	1.02	1.53	2.33	5.67	13.85*
Fuzzy	0.26*	1.19*	3.57*	5.95*	11.42*	15.00
Physics-based	0.50	1.97	3.89	5.89*	9.83*	13.68*
93 mmth						
Observed	0.65	3.68	7.11	14.95	23.10	37.96
ANNs	2.60	3.80*	5.96	9.37	21.80*	41.22*
Fuzzy	1.59*	4.68	7.81*	19.5	33.30	45.40
Physics-based	2.37	5.78	9.78	13.68*	22.07*	28.16
117 mmth						
Observed	1.48	5.97	12.89	26.55	37.53	65.11
ANNs	6.57	9.68	14.98*	22.42*	41.96*	58.85*
Fuzzy	2.11*	6.37*	10.61	23.60*	42.74*	60.14*
Physics-based	3.95	8.69	14.07*	19.25	28.96	38.19

* Good estimates of the related observed data

In many studies within the literature, fuzzy-logic is integrated with neural networks, and appears as neuro-fuzzy modeling. These studies benefited the advantages of both approaches; neural networks provide “learning from examples and optimization by taking advantage of desired input-output datasets”, and fuzzy systems provide “meaningful representations, encoding knowledge, fuzzy if-then rules, and fuzzy reasoning” (Samadzagedan, et al. 2004).

Samadzagedan et al. (2004) produced a work based on neuro-fuzzy modeling within the field of photogrammetry. They studied on automatic 3D object recognition and reconstruction of natural and man-made objects of cities. They defined the descriptors of the model as; structural descriptors (related to the geometry of a region), textural descriptors (related to the spatial variation of the image intensities), and spectral descriptors (related to the color of an image region). They defined six input and three output variables which are all linguistic variables (See Table 3.3).

Table 3. 3. Linguistic variables and labels for the fuzzy-based object recognition process (Source: Samadzagedan, et al. 2004)

	Type	*Linguistic variable*	*Linguistic labels*
Input	Structural	Height	*Very Low, Low, Medium, Tall, Very Tall*
		Area	*Very Small, Small, Medium, Large, Very Large*
		Relief	*Very Irregular, Irregular, Regular, Very Regular*
		Shape	*Not Stretched, Stretched, Very Stretched*
	Textural	Roughness	*Very Irregular, Irregular, Regular, Very Regular*
	Spectral	Colour	*Light Green, Medium Green, Deep Green*
Output	Object	Building	*False, Probably False, Probably True, True*
		Tree	*False, Probably False, Probably True, True*
		Car	*False, Probably False, Probably True, True*

The study recognized buildings, cars and tree as city objects through the *If-Then* fuzzy rules and each rule is modeled by a linear combination of the input variables. They integrated neural networks to the model to enable its adaptability in the real world. Learning based input-output dataset is introduced as a neural network to the fuzzy recognition process. As a result of the study, three reconstruction schemes related to the recognition process were determined; point-based, area-based and volume-based reconstruction. Investigation was realized to assess the efficiency of the proposed model in the town of Engen in Germany (Samadzagedan, et al. 2004).

Hatipkarasulu (2002) developed a fuzzy model to estimate the time lag of a car by using the following car datasets as explanatory variables in his study. He used, "*following vehicle speed, following vehicle acceleration, relative speed, and relative distance"* as the input data of the model.

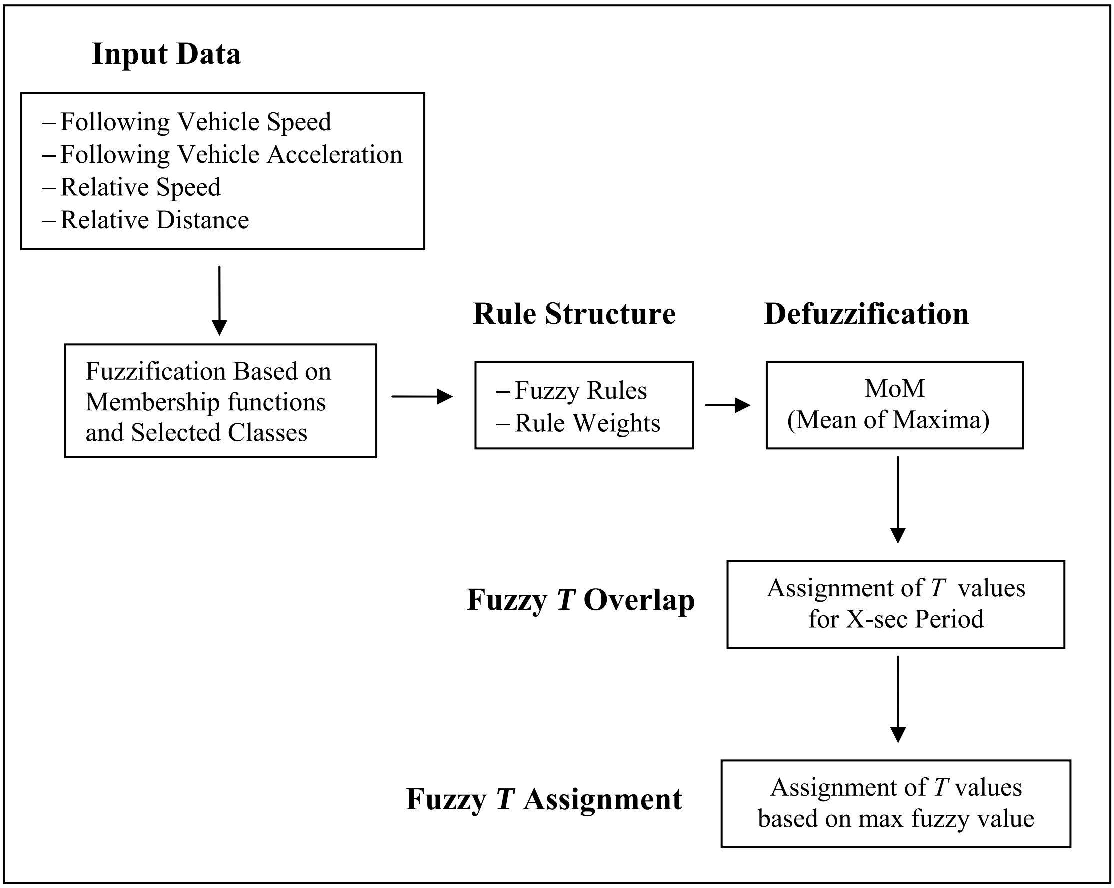

Figure 3. 18. Fuzzy time lag assignment algorithm for car following data sets (Source: Hatipkarasulu 2002)

Usenik and Bogataj (2005) developed an alternative fuzzy approach to the classical analytical approach of spatial interaction models. They tried to estimate the annuity streams of production with five input variables. They compared the results of analytical model and the fuzzy model and finally suggest using fuzzy modeling when the supply units are exposed to uncertain demand. The comparison of the models is seen in Table 3.4.

Table 3. 4. Numerical example results (Source: Usenik and Bogataj 2005)

Alpha	Costs	Demand	M	Price	Stream ‘fuzzy approach’	Annuity stream pρNV ‘analytical approach’	Relative difference (%)
0.70	100	387	1	100	17673	18735	-6
0.90	100	107	1	150	10282	10410	-1
0.99	100	255	1	100	10735	12222	-12
0.98	100	145	1	100	6480	6843	5
0.98	160	289	1	200	33598	34016	-1
0.99	200	127	1	200	12060	12222	-1
0.80	150	240	2	100	5936	5389	10
0.98	200	289	2	150	11813	13687	-13
0.99	100	255	2	150	25794	24954	3
0.99	100	255	2	200	36990	37688	-2
0.98	200	253	2	200	24874	24582	1
0.40	130	599	3	70	6399	5029	26
0.70	100	207	3	100	10295	9841	4
0.90	150	307	3	100	6739	6949	-3
0.98	100	130	3	70	2216	2232	-1
0.99	100	223	3	100	9916	10658	-7
0.98	100	145	3	100	6241	6839	-9
0.99	200	127	3	200	12060	12217	-1
0.98	200	289	3	200	29766	28143	6

Yıldırım and Bayramoğlu (2006) used adaptive neuro-fuzzy based modeling to monitor and forecast air quality. The model estimates daily SO_2 and TSP concentration levels that cause air pollution in city of Zonguldak. Meteorological parameters were used in adaptive neuro-fuzzy inference system (ANFIS) modeling approach. Input variables used in the model were temperature, pollutant (SO_2 and TSP) concentration of the previous day, wind speed, relative humidity, pressure, solar radiation, and precipitation. Model resulted in the performance between 75-90% and 69-80% respectively.

Quek et al. (2009) applied a specific class of self-organizing fuzzy rule-based system known as the Pseudo Outer-Product Fuzzy Neural Network (POPFNN) using the Truth-Value-Restriction method (TVR) as an alternative method to the feed-forward neural networks (FFNN) using conventional back-propagation learning (FFBP). They collected both vehicle classification counts and speed data from a five-lane section Pan Island Expressway in Singapore.

They collected the data at five minute intervals over a period of six days with the number of 660 traffic counter classifier. The result of the study is given on Table 3.5.

As seen R^2 values for speed prediction is not satisfactory, density prediction is much better and beside the worse prediction of speed, the general trend of the traffic flow is well captured.

Table 3. 5. R^2 of speed and density for each lane (Source: Quek, et al. 2009)

Lanes	***R^2 of speed***		***R^2 of density***	
	FFBP	POPFNN-TVR	FFBP	POPFNN-TVR
1	0.298021	0.282159	0.746806	0.675296
2	0.620210	0.592842	0.792190	0.768371
3	0.102240	0.010045	0.838725	0.796968

Literature review indicated that researchers mostly preferred hybrid methods such as neuro-fuzzy or fuzzy-neural methods to carry out their studies. They used fuzzy approach usually for clustering and neural network approach to expose the specific relationship within each cluster. There are also researchers (Lee, et al. 1998, Sanal 1999, Tayfur, et al. 2003, Hatipkarasulu 2002, Usenik and Bogataj 2005) who used pure FLM approach as a tool for their studies.

CHAPTER 4

İZMİR URBAN REGION AS A CASE STUDY AREA

The responsibility area of Traffic Inspection Department of İzmir (TIDI) is assigned as the case study area of the dissertation. Boundary of the study can be seen in the Figure 4.1 which is derived by the help of ArcGIS spatial analysis tools. Kernel density distribution is applied to the all geocoded accidents happened in 2005, to reveal the boundaries of the case study area. The brown spots represent the most dense accident spaces.

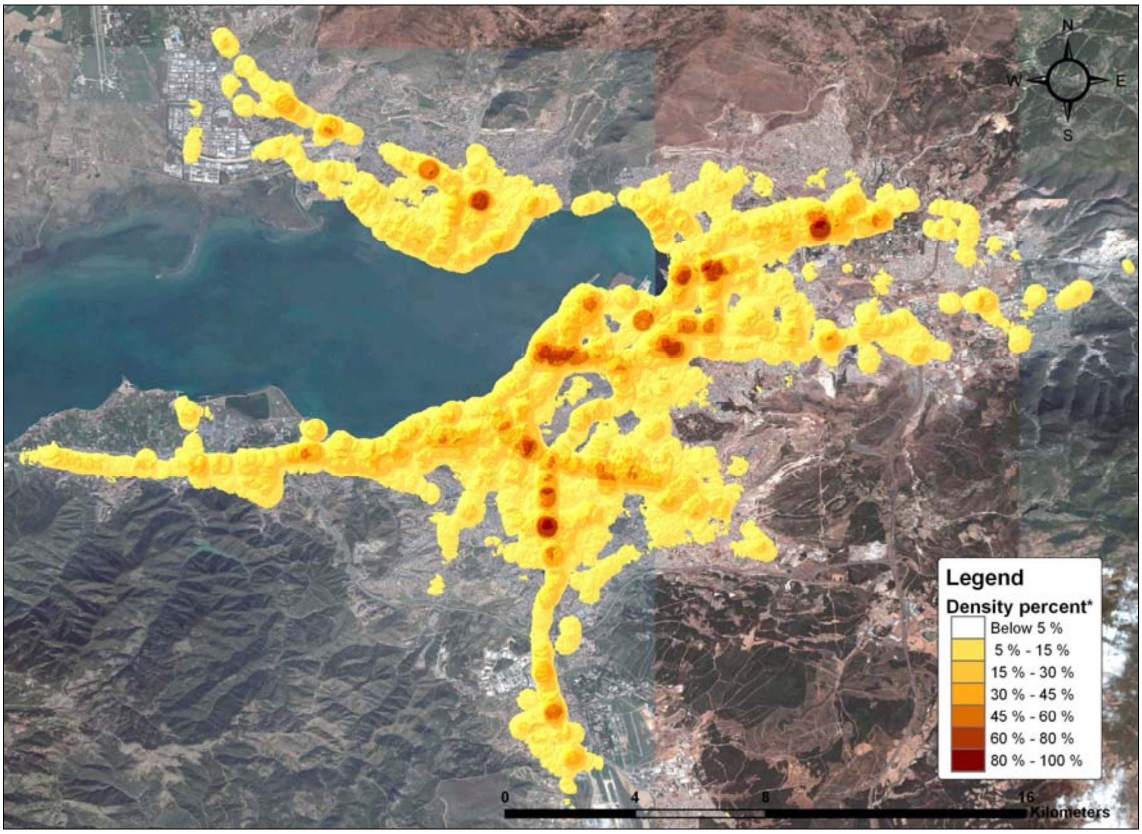

Figure 4. 1. Boundaries of the case study area, TIDI's zone of responsibility. Density distribution of all accidents in 2005. (Aerial photo from Google Earth)

* Point objects which drop to each cell

Data gathering has been a major problem as a constraint of the study. TIDI collected the most accurate accident data with their spatial coordinates in the year 2005. Therefore spatial analysis has pursued through the year 2005 dataset. However, the traffic counting data which has a big influence on the occurrence of the accidents could be obtained for the year 2007. For this reason Fuzzy Logic Modeling was carried on through the year 2007 dataset. Following part gives the profile of the accident data.

4.1. Descriptive Statistics of the Traffic Accidents in İzmir

In the year 2005, TIDI recorded 42,792 traffic accidents with their information such as; location, time, circumstance of the road and weather, and type of the accident, number of killed or injured people etc. 20% of these records have no geographic coordinates, so the spatial analysis could be performed on the rest of the records. Table 4.1 gives some descriptive statistics about the accidents recorded in 2005.

Table 4. 1. Descriptive Statistics of Raw Data (Accidents happened in 2005)

	Recorded Accidents		Recorded Accidents with Coordinates	
Total	42,792	100.00%	39,292	100.00%
Killed or injured	3,500	8.18%	3,416	8.69%
Property damaged	39,292	91.82%	35,876	91.31%
# of killed persons	39	0.82%	39	0.84%
# of injured persons	4,734	99.18%	4,638	99.17%
Rainy days	5,425	12.69%	4,610	13.17%
Cloudy days	3,150	7.37%	2,710	7.74%
Sunny days	34,172	79.94%	27,680	79.09%

It is seen on the Table 4.1 that the distribution rate of the coordinated accidents is as close as to be the sample of the whole accidents. However, as seen in Table 4.2 TIDI gave up collecting the coordinates of the damaged accidents in 2007 and this factor makes a big different between the whole population of the accidents and the coordinated ones. The coordinated accidents do not represent the whole population of the accidents as a sampling group. The rates of the killed-injured and damaged only accidents differ. Hence the year 2005's coordinated accidents were chosen for the spatial analysis and the year 2007's accidents were chosen for fuzzy modeling.

Table 4. 2. Descriptive Statistics of Raw Data (Accidents happened in 2007)

	Recorded Accidents		Recorded Accidents with Coordinates	
Total	56,376	100,00%	3,935	100,00%
Killed or injured	3,755	6,66%	3,239	82,31%
Property damaged	52,610	93,32%	695	17,66%
# of killed persons	46	0,89%	45	1,00%
# of injured persons	5,148	99,11%	4,455	99,00%
Rainy days	4,121	7,31%	231	5,87%
Cloudy days	3,695	6,56%	232	5,90%
Sunny days	48,545	86,13%	3,469	88,22%

4.2. Spatial Analysis of the Traffic Accidents in İzmir

The distribution of the accidents in the urban geography were assesses with ArcGIS 9.2 software's Spatial Analyst Tool. As an initial step, 39,292 accidents of the year 2005 were located on the coordinate system of İzmir, by GIS. By the help of the GIS tools geocoding of each accident is performed and after geocoding *spatial density analysis* maps were produced by kernel density distributions. Density analyses were conducted according to several categories based on the proximity of the accidents. Figure 4.2 illustrates the density distribution of killed-injured accidents and the Figure 4.3 illustrates the density distribution of damaged only accidents. Concentrated areas are the brown dense regions and yellow regions are the least dense spaces of the accidents. As seen on both two maps, accidents do not scatter homogeneously. This indicates that there must be some spatial reasons of the traffic accidents. Figure 4.4 illustrates the density distribution of peak hour accidents and the Figure 4.5 illustrates the density distribution of off-peak hour only accidents.

Detailed spatial analysis is accomplished in Appendix A. Concentration maps of the killed-injured and damaged only accidents according to the peak hour or off-peak hour are illustrated in Appendix A.

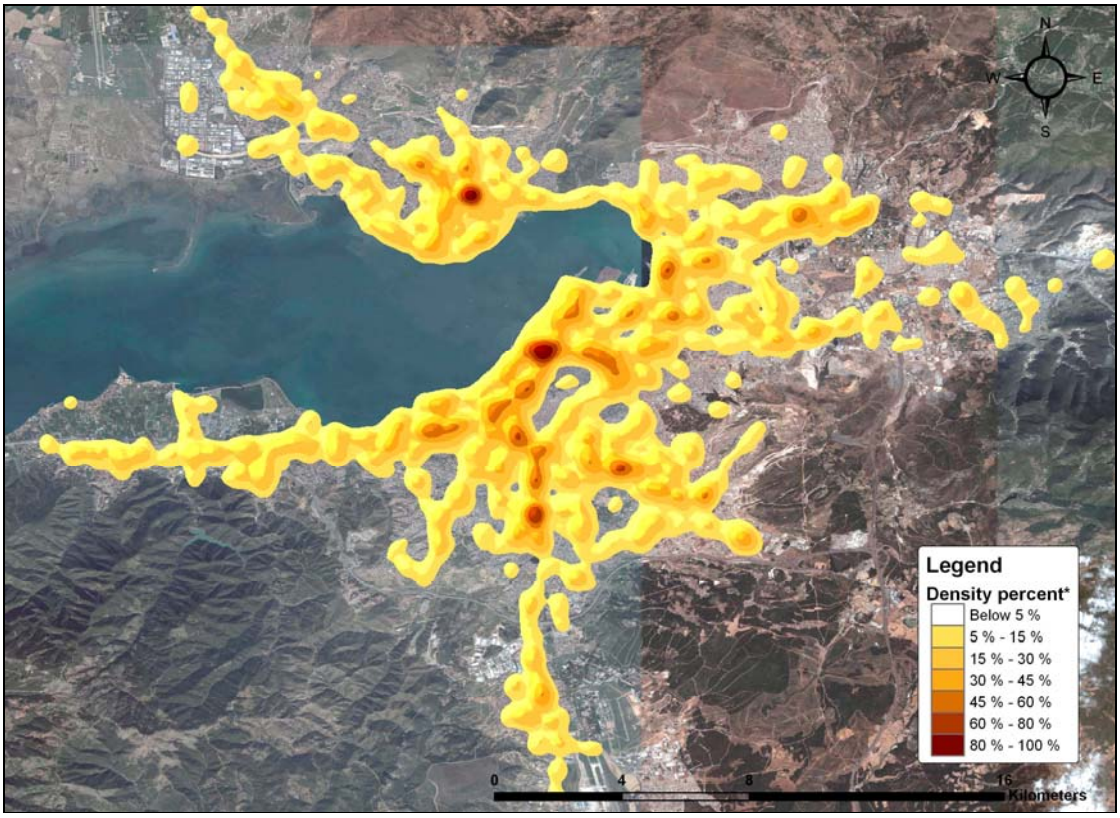

Figure 4. 2. Concentration of the killed-injured accidents occurred in İzmir in 2005.

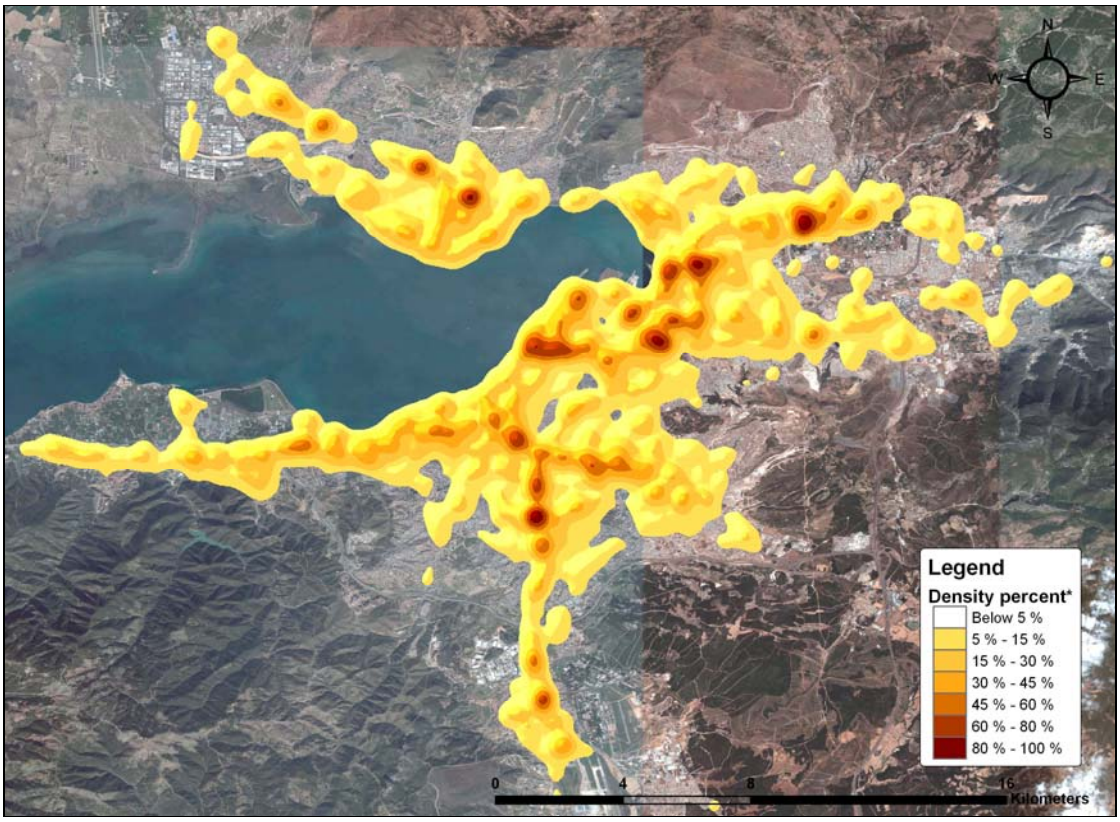

Figure 4. 3. Concentration of the damaged only accidents occurred in İzmir in 2005.

* Point objects which drop to each cell

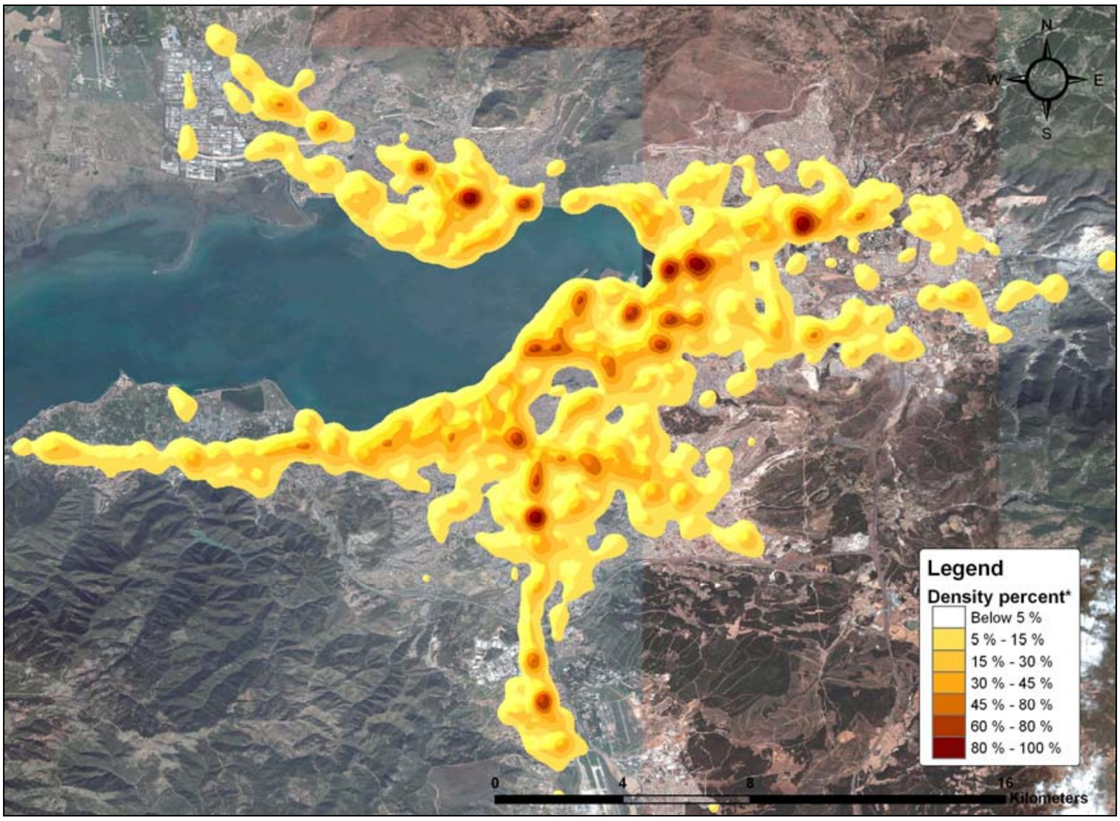

Figure 4. 4. Concentration of the peak hour accidents occurred in İzmir in 2005.

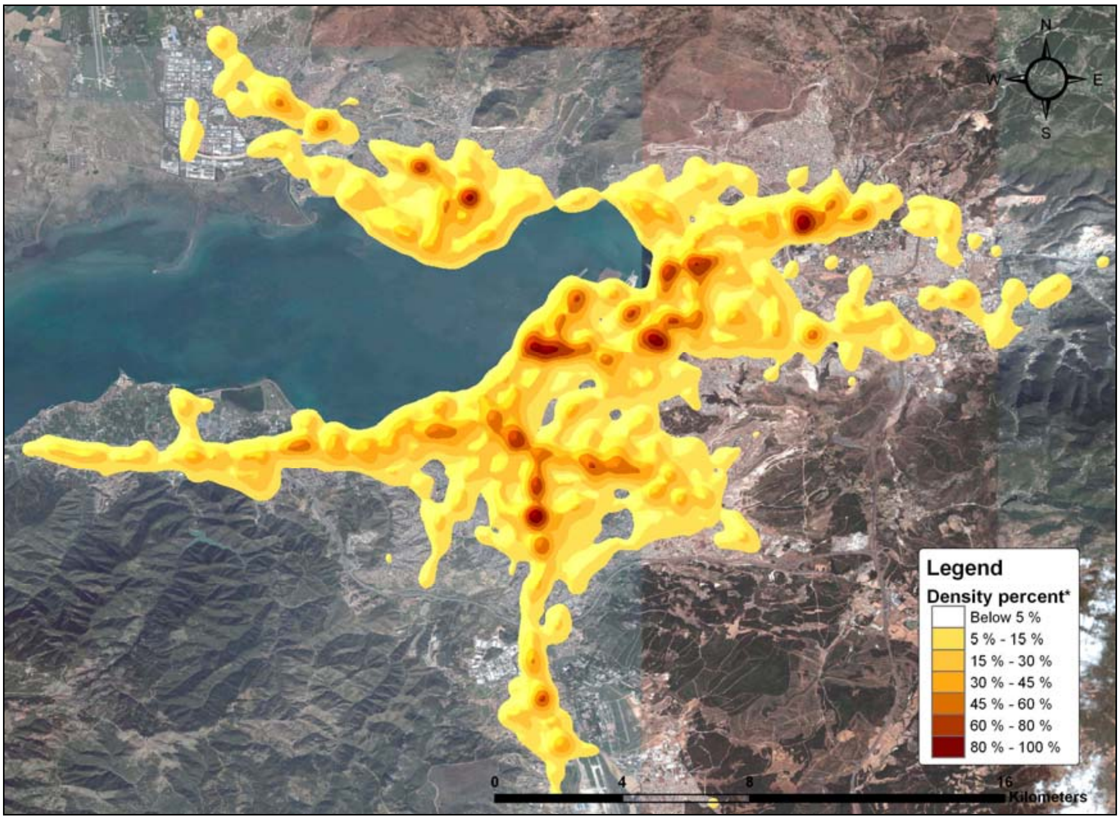

Figure 4. 5. Concentration of the off-peak hour accidents occurred in İzmir in 2005.

* Point objects which drop to each cell

4.3. Findings and Discussion of Spatial Analysis

When killed-injured accidents and damaged only accidents are compared, it was observed that killed or injured accidents concentrate on Fevzipaşa and Gazi Boulevard that traverse the city centre; on Soğukkuyu Intersection on the Anadolu Street in the north; and on the intersection of Yeşillik Street and Dostluk Boulevard in the south. When the distribution of the damaged only accidents were examined, alongside the abovementioned intersections, it is seen that the frequency of accidents increase on Ege Üniversitesi Intersection on Ankara Street, Egemak Intersections and Zafer Payzın Intersection, and on Serinkuyu Intersection on Anadolu Street.

Figure 4.4 shows the accidents during peak hours, whereas Figure 4.5 lists the distribution of the accidents during off-peak hours. The hourly traffic counts demonstrate that the peak hours in which congestion takes place for the city of İzmir is between 08:00 - 09:30 in the morning and 18:00 – 19:30 in the evening. 27% of the total accidents take place during peak hours. This indicates that the city centre is safer during the peak hours than off-peak hours. A less dense pattern was observed during the peak hours on Gazi Boulevard, which is the most accident generator street in general. Moreover, it was detected that the accidents have more point spread than off-peak hours. Furthermore, it was noticed that the accident density increased remarkably during peak hours upon the entry to another important point, Altınyol Karşıyaka.

A valuable finding in terms of transportation planning was discovered through spatial analysis; in peak-hour accidents are concentrated on rapid roads which give service to the sub-centers. On the contrary in off-peak hour the most accident dense streets are Fevzipaşa and Gazi Boulevard which pass through the city center.

Besides, it is possible to evaluate the relation between traffic accidents and traffic speed through this finding. Although the traffic speed could not be measured for the case study, it is known that because of the traffic jam the speed of the traffic decreases (below 30 km) in peak-hours within the city center, where as it is much more high (over 70 km) on roads to the sub-centers such as Anadolu and Ankara Streets. It is possible to make this inference through observations. As a recommendation, relation between traffic speed and traffic accidents should be studied in further studies, in detail.

Other significant relation was discovered between traffic accidents and intersection designs. It is observed that accidents concentrate at two intersections (Soğukkuyu and Serinkuyu) before and after cloverleaf intersection which separates the Girne Street and Anadolu Street. This indicates that by constructing only one safe intersection on an expressway, you just change the place of the accidents.

4.3. Aggregation of the Accident Data Based on the Streets

TIDI gathered each accident with the following information; occurrence time, district, street, type of the accident, number of killed or injured people and weather conditions. There is also inadequate information such as the faulty types of the drivers. This incomplete information damages the quantity distribution of the accidents, and thus it is not considered in the dissertation.

Accident data is aggregated into streets and following charts (Figure 4.6 and Figure 4.7) are derived to decide the most risky streets of İzmir.

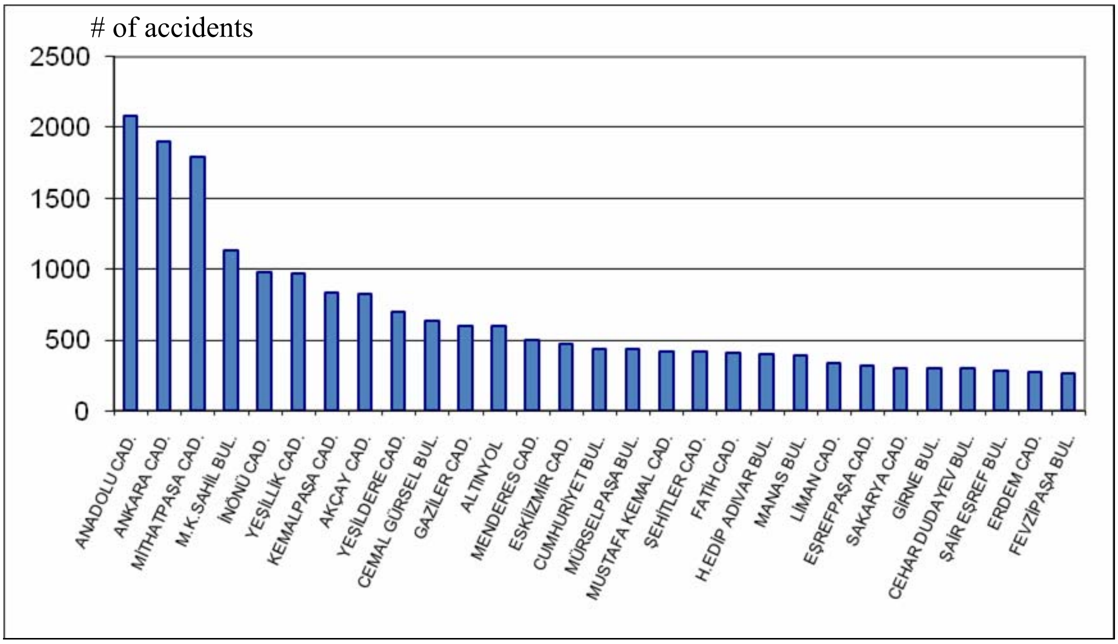

Figure 4. 6. Number of all accidents occurred in 2005, the first 30 streets of İzmir

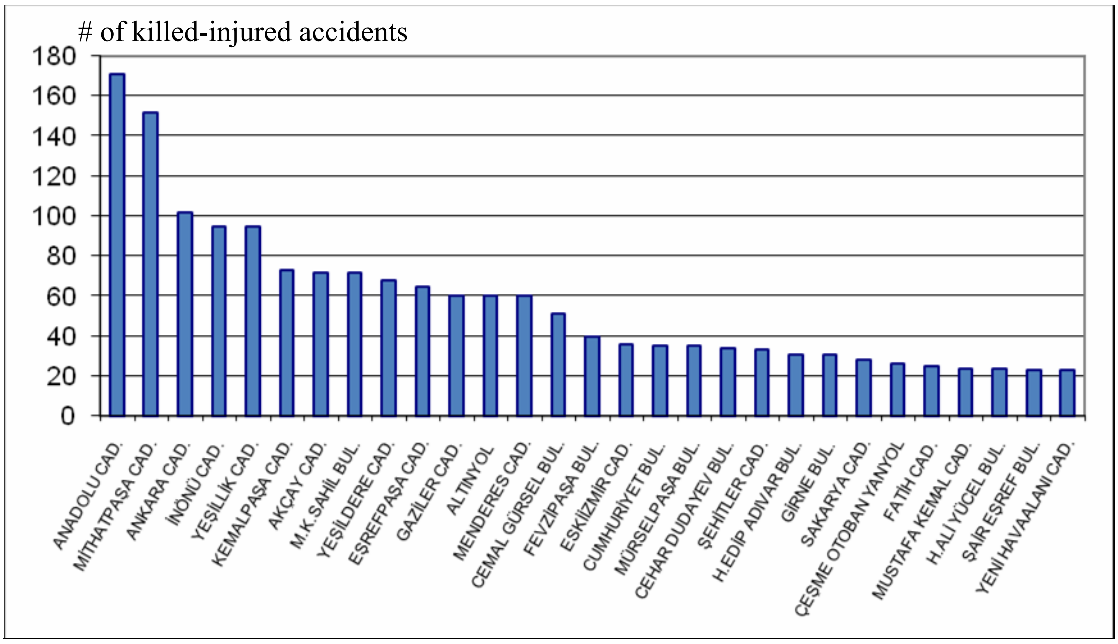

Figure 4. 7. Number of killed-injured accidents in 2005, the first 30 streets of İzmir

Anadolu Street seems as the most '*accident producer'* street of İzmir. However the length of the streets must also be considered to see the most accident producer streets in one kilometer. The length of the streets gathered mostly from the report of Oral et al. (2002) and the rest are computed by the help of GIS tools. In Oral et al.'s Highway Network Project, 14 types of technical problems were defined for the highways of İzmir. Both the junctions and the segments of the highways were coded systematically and a table of problem types of the segments was constituted in this project.

After the computations the amount of accidents on streets are normalized by their length attributes and a new risky road list was obtained. Figure 4.8 shows the number of all accidents and Figure 4.9 shows the number of killed or injured accidents occurred in one km in the year 2005.

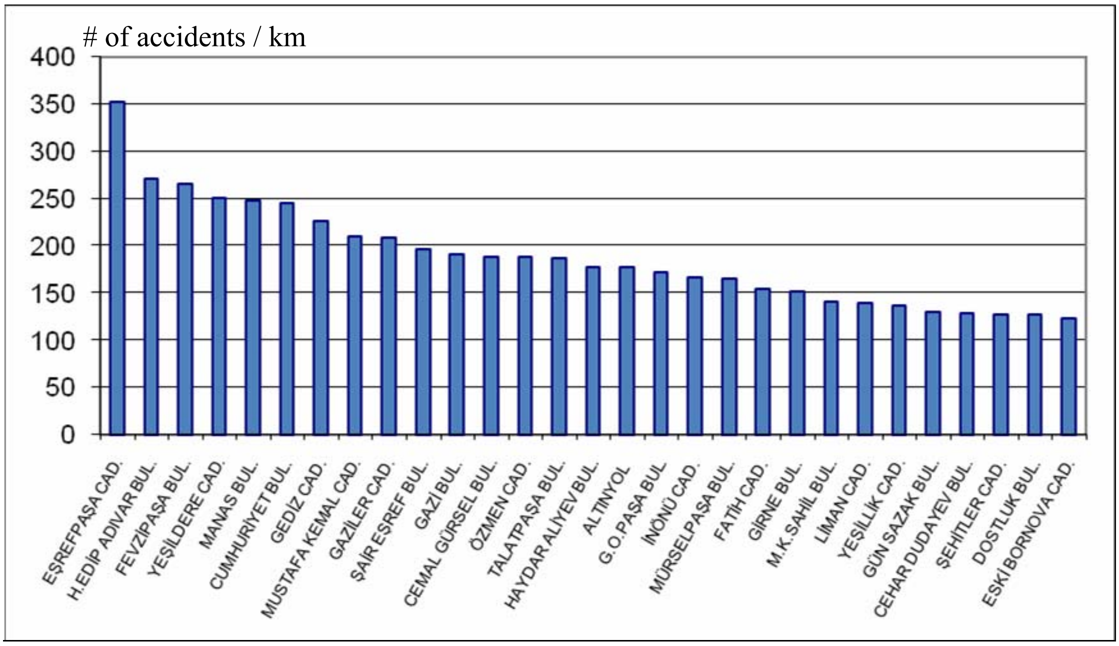

Figure 4. 8. Number of accidents occurred per km in 2005, the first 30 streets.

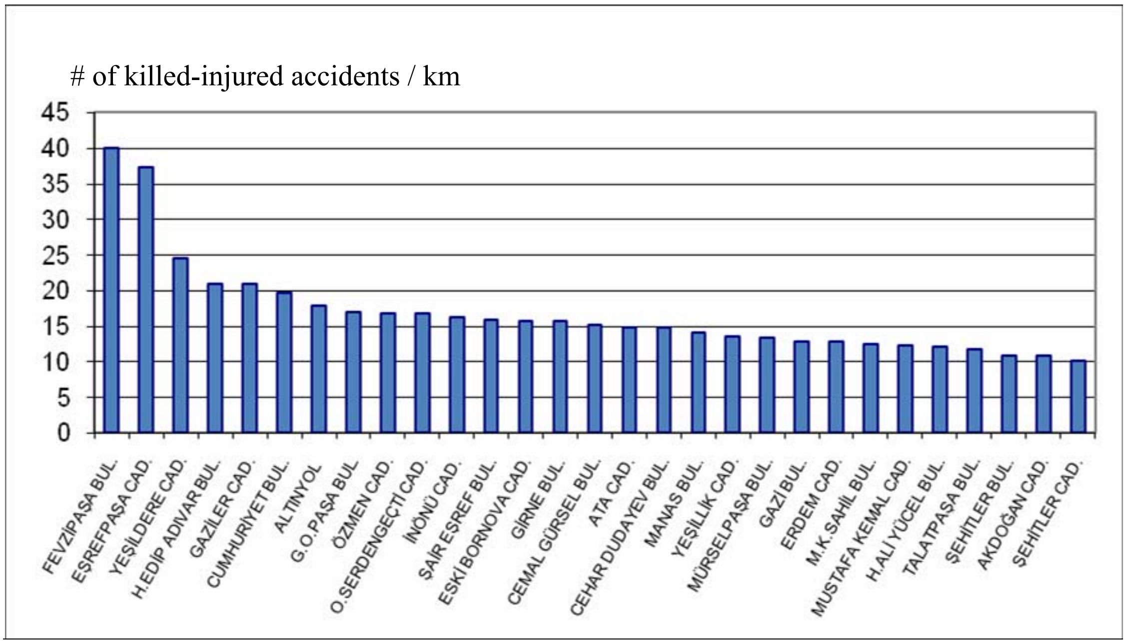

Figure 4. 9. Number of killed-injured accidents per km in 2005, the first 30 streets

Through the spatial and quantitative analysis the "real" black zones of İzmir is achieved. The next step is the organization of the factors causing or affecting the traffic accidents. As stated in many studies in the literature, following factors are determined as the "provisional" explanatory variables of the prediction model;

- Traffic variables (Planned to obtain by counting with the equipments of the IZTECH Transportation Laboratory.)
    - traffic flow
    - traffic density
    - average speed
    - average gap between vehicles
- Geometric variables (Planned to obtain by remote sensing.)
    - road width
    - number of lanes
    - number of minor accesses
    - percent of medians (refuge)
- Environmental variables (Planned to obtain from the foundations and surveys.)
    - number of bus stops
    - weather conditions

Geometric and environmental variables were obtained as planned. However, Metropolitan Municipality of İzmir (MMI) did not allow the undertaking of traffic counting; putting forward that it could hinder the traffic flow during installation and could impair road pavement. Instead, the traffic counting carried out in 2007 for a TÜBİTAK project, conducted under the supervision of Assoc. Prof Dr. Tolga Elbir, entitled "Determining Air Pollution Caused by Road Traffic in Metropolitan Centers". However, parameters such as traffic density, average speed and average gap between vehicles could not be included in the model since these counts consist of only traffic flow values. Moreover, instead of the first 20 streets in terms of frequency of accidents per km, the 19 streets determined in the same study were used for modeling.

In 2007, Elbir et al. counted 19 streets which are decided as the main arterials of İzmir for their ongoing project (TÜBİTAK project 106Y009). In this project, the traffic flow is counted for average one week both in the summer and the winter season of 2007. Table 4.3 shows the order of preference of the streets according to the number of accidents in one km and the streets decided by Elbir's TÜBİTAK study. The raw traffic count data obtained from this project is given in Appendix B.

Table 4. 3. Importance list of the streets according to the risky levels (due to the number of accidents per km) and the selected ones for modeling

Name of the streets	Risky level	Name of the streets	Risky level
Fevzipaşa Boulevard	1	M.K. Sahil Boulevard	23
Eşrefpaşa Street	2	Mustafa Kemal Street	24
Yeşildere Street	3	Hasan Ali Yücel Boulevard	25
H. Edip Adıvar Boulevard	4	Talatpaşa Boulevard	26
Gaziler Street	5	Şehitler Boulevard	27
Cumhuriyet Boulevard	6	Akdoğan Street	28
Altınyol Street	7	Şehitler Street	29
G.O. Paşa Boulevard	8	Haydar Aliyev Boulevard	30
Özmen Street	9	Anadolu Street	31
O. Serdengeçti Street	10	Polat Street	32
İnönü Street	11	Fatih Street	33
Şair Eşref Boulevard	12	Abdi İpekçi Street	34
Eski Bornova Street	13	Gediz Street	35
Girne Boulevard	14	Dr. Refik Saydam Boulevard	36
Cemal Gürsel Boulevard	15	İsmail Sivri Boulevard	37
Ata Street	16	Menderes Street	38
Cehar Dudayev Boulevard	17	Kamil Tunca Boulevard	39
Manas Boulevard	18	:	:
Yeşillik Street	19	:	:
Mürselpaşa Boulevard	20	Mehmet Akif Street	51
Gazi Boulevard	21	Mithatpaşa Street	52
Erdem Street	22	Ankara Street	53

* Gray cells are the streets decided by Elbir's study.

Elbir's traffic flow counts are classified according to 24 hours of a day. This classification provides to divide decided 19 streets into 24 time frames to increase and specify the data points. Therefore (19 × 24 =) 456 data points were obtained for modeling. Table 4.4 illustrates the final data points of the model. Following panel data is generated from the obtained raw data.

Table 4. 4. Data points and their representations

Data point	*Representation*
Altınyol Street between 00:00 – 01:00	ALT01
Altınyol Street between 01:00 – 02:00	ALT02
:	:
:	:
Anadolu Street between 07:00 – 08:00	AND08
:	:
Ankara Street between 14:00 – 15:00	ANK15
:	:
Cemal Gürsel Boulevard between 10:00 – 11:00	CEM11
:	:
Eşrefpaşa Street between 09:00 – 10:00	ESR10
:	:
Fevzipaşa Street between 05:00 – 06:00	FEV06
:	:
Gazi Boulevard between 03:00 – 04:00	GAZ04
:	:
Girne Boulevard between 18:00 – 19:00	GIR19
:	:
Halide Edip Adıvar Boulevard between 16:00 – 17:00	HEA17
:	:
İnönü Street between 12:00 – 13:00	INO13
:	:
Kamil Tunca Boulevard between 10:00 – 11:00	KAM11
:	:
Mehmet Akif Street between 13:00 – 14:00	MAC14
:	:
Mithatpaşa Street between 21:00 – 22:00	MIT22
:	:
Mustafa Kemal Street between 19:00 – 20:00	MKC20
:	:
Mustafa Kemal Sahil Boulevard between 02:00 – 03:00	MKS03
:	:
Şair Eşref Boulevard between 04:00 – 05:00	SAI05
:	:
Talatpaşa Boulevard between 06:00 – 07:00	TAL07
:	:
Yeşildere Street between 20:00 – 21:00	YED21
:	:
:	:
Yeşillik Street between 22:00 – 23:00	YEL23
Yeşillik Street between 23:00 – 24:00	YEL24

4.4. Constructing the Fuzzy Logic Model

The data were separated randomly into two parts: the data points are alphabetically ordered and enumerated 1 to 456. The data points fit to the odd numbers are selected for the construction and the rest of them are selected for testing the model. Hence first group contained 228 data points to be used in construction and the second group had 228 data points to be used in testing stages of the model.

Final parameters affecting the amount of traffic accidents are defined as follows;

- Traffic variables (is obtained from a recent study of MMI; Elbir's project)
    - traffic flow
- Geometric variables (is obtained by remote sensing)
    - road width
    - number of lanes
    - number of minor accesses
    - percent of medians
- Environmental variables (is obtained from the foundations and surveys)
    - number of bus stops
    - weather conditions

Finally following dataset is obtained through the all aggregated data. Seven input variables and one output variable are considered for the fuzzy modeling study.

<u>Input variables:</u>

AAHTL: Annual Average Hourly Traffic per Lane, defined as the number of passing vehicles per hour per lane for each street.

AHRT: Annual Hourly Rain Total, defined as the total duration time of rain in defined time interval.

RW: Road Width, defined as the distance of vehicle track of the street.

PM: Percent of Median, defined as the refuge percent along the street.

BS: Number of Bus Stops, defined as the number of bus stops along the street over the length of the street in kilometers.

SJ: Number of Signalized Junctions along the street over the length of the street in kilometers.

MA: Number of Minor Access along the street over the length of the street in kilometers.

Output variable:

AAA: Annual All Accidents, defined as the number of all accidents happened in the streets in defined time interval of a day.

Table 4.5 gives the descriptive statistics of the variables of the calibration set of data and Table 4.6 gives the descriptive statistics of the variables of the testing set of data.

Table 4. 5. Descriptive statistics of the variables of the calibration set of data

		Average	*Min*	*Median*	*Max*	*St. Dev.*
Input	AAHTL	404.33	14.61	372.35	1,323.94	291.93
	AHRT	12.37	8.25	12.39	15.97	1.96
	RW	18.95	13.00	18.00	28.00	4.13
	PM	0.80	0.19	0.93	1.00	0.24
	BS	3.37	0.00	3.79	7.36	1.97
	SJ	3.51	0.00	2.84	11.59	2.80
	MA	16.17	3.02	18.40	28.69	7.42
Output	AAA	8.46	0.00	6.40	32.65	7.19

Table 4. 6. Descriptive statistics of the variables of the testing set of data

		Average	*Min*	*Median*	*Max*	*St. Dev.*
Input	AAHTL	401.10	13.79	366.55	1,303.85	290.14
	AHRT	12.36	8.25	12.39	15.97	1.98
	RW	18.95	13.00	18.00	28.00	4.13
	PM	0.80	0.19	0.93	1.00	0.24
	BS	3.37	0.00	3.79	7.36	1.97
	SJ	3.51	0.00	2.84	11.59	2.80
	MA	16.17	3.02	18.40	28.69	7.42
Output	AAA	8.41	0.00	6.94	31.90	6.78

The whole of the calibration and testing dataset is presented in Appendix C.

4.4.1. Fuzzification Process of the Variables

Fuzzification requires two main stages; derivation of the membership functions for both input and output variables and the linguistic representation of these functions.

Different types of membership functions can be applied such as triangular, trapezoidal, bell shaped, Gaussian, sigmoidal, etc. for fuzzification. Triangular or trapezoidal waveforms could be applied for the systems which has large variation of data. Gaussian or sigmoidal waveforms could be applied for the more sensitive systems that need high control accuracy. Thus, triangular and trapezoidal waveforms were applied for the FL model of the dissertation.

All the input and output data were correlated to develop clusters. The number of the clusters for each variable is deduced from the data distribution of each variable. Through these clusters following fuzzy subsets were constituted for each variable. Mamdani type FIS is selected for the modeling study.

4.4.1.1. Fuzzification of the Input Variables

The variable AAHTL is divided into five triangular and one trapezoidal fuzzy subsets due to the distribution of the data. Figure 4.10 shows the data distribution for AAHTL for the calibration set. As seen in Figure 4.10, the data clusters have centers around 140, 430, 700, 980, 1170 and 1500. Thus, six fuzzy subsets are defined for the variable AAHTL.

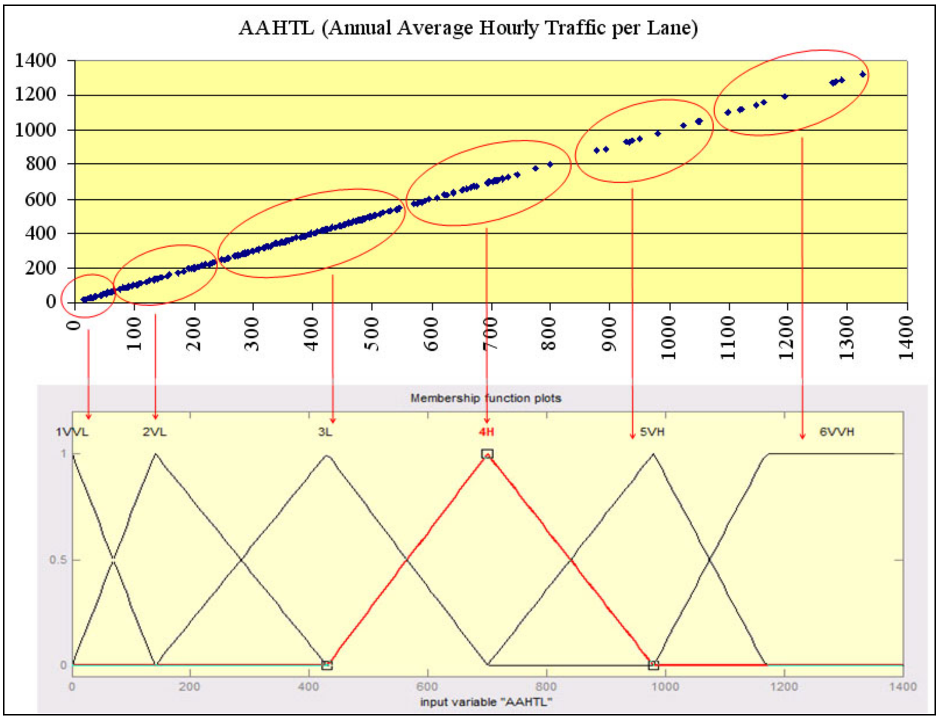

Figure 4. 10. Fuzzification of the input variable AAHTL

<u>Mathematical Expressions of the variable AAHTL:</u>

$$\mu_{VVL}(AAHTL) = \begin{cases} \dfrac{140 - AAHTL}{140}, & If \quad 0 \le AAHTL \le 140 \end{cases} \tag{4.1}$$

$$\mu_{VL}(AAHTL) = \begin{cases} \dfrac{AAHTL}{140}, & If \quad 0 < AAHTL \le 140 \\ \dfrac{430 - AAHTL}{430 - 140}, & If \quad 140 < AAHTL \le 430 \end{cases} \tag{4.2}$$

$$\mu_{L}(AAHTL) = \begin{cases} \dfrac{AAHTL - 140}{430 - 140}, & If \quad 140 < AAHTL \le 430 \\ \dfrac{700 - AAHTL}{700 - 430}, & If \quad 430 < AAHTL \le 700 \end{cases} \tag{4.3}$$

$$\mu_{H}(AAHTL) = \begin{cases} \dfrac{AAHTL - 430}{700 - 430}, & If \quad 430 < AAHTL \le 700 \\ \dfrac{980 - AAHTL}{980 - 700}, & If \quad 700 < AAHTL \le 980 \end{cases} \tag{4.4}$$

$$\mu_{VH}(AAHTL) = \begin{cases} \dfrac{AAHTL - 700}{980 - 700} & If \quad ,700 AAHTL \le 980 \\ \dfrac{1170 - AAHTL}{1170 - 980}, & If \quad 980 < AAHTL \le 1170 \end{cases} \tag{4.5}$$

$$\mu_{VVH}(AAHTL) = \begin{cases} \dfrac{AAHTL - 980}{1170 - 980}, & If \quad 980 < AAHTL \le 1170 \\ 1 \quad , & If \quad 1170 < AAHTL \le 1500 \end{cases} \tag{4.6}$$

The variable AHRT is divided into three triangular and two trapezoidal fuzzy subsets; and the variable RW is divided into one triangular and two trapezoidal fuzzy subsets due to the distribution of the data. Figure 4.11 shows the data distribution for AHRT and RW for the calibration sets. As seen in Figure 4.11, the data clusters have centers around 8.25, 10.58, 12.36, 13.80, 16 for AHRT and 12, 17.50, 25 for RW. Thus, five fuzzy subsets for the variable AHRT and three fuzzy subsets for the variable RW are defined.

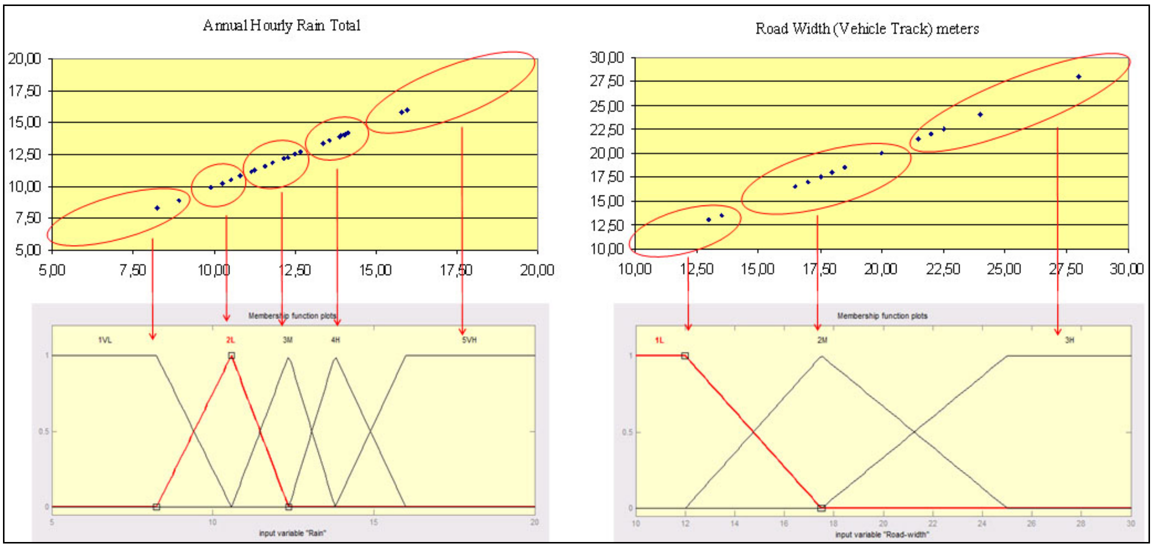

Figure 4. 11. Fuzzification of the input variables AHRT and RW

<u>Mathematical Expressions of the variable AHRT:</u>

$$\mu_{VL}(AHRT) = \begin{cases} 1 \quad , & If \quad 5 \le AHRT \le 8.25 \\ \dfrac{10.58 - AHRT}{10.58 - 8.25}, & If \quad 8.25 < AHRT \le 10.58 \end{cases} \tag{4.7}$$

$$\mu_{L}(AHRT) = \begin{cases} \dfrac{AHRT - 8.25}{10.58 - 8.25}, & If \quad 8.25 < AHRT \le 10.58 \\ \dfrac{12.36 - AHRT}{12.36 - 10.58}, & If \quad 10.58 < AHRT \le 12.36 \end{cases} \tag{4.8}$$

$$\mu_M(AHRT)=\begin{cases}\dfrac{AHRT-10.58}{12.36-10.58}, & If \quad 10.58 < AHRT \le 12.36\\ \dfrac{13.80-AHRT}{13.80-12.36}, & If \quad 12.36 < AHRT \le 13.80\end{cases} \tag{4.9}$$

$$\mu_H(AHRT)=\begin{cases}\dfrac{AHRT-12.36}{13.80-12.36}, & If \quad 12.36 < AHRT \le 13.80\\ \dfrac{16.00-AHRT}{16.00-13.80}, & If \quad 13.80 < AHRT \le 16.00\end{cases} \tag{4.10}$$

$$\mu_{VH}(AHRT)=\begin{cases}\dfrac{AHRT-13.80}{16.00-13.80}, & If \quad 13.80 < AHRT \le 16.00\\ \dfrac{16.00-AHRT}{16.00-13.80}, & If \quad 16.00 < AHRT \le 20.00\end{cases} \tag{4.11}$$

<u>Mathematical Expressions of the variable RW:</u>

$$\mu_L(RW)=\begin{cases}1, & If \quad 10.00 \le RW \le 12.00\\ \dfrac{17.50-RW}{17.50-12.00}, & If \quad 12.00 < RW \le 17.50\end{cases} \tag{4.12}$$

$$\mu_M(RW)=\begin{cases}\dfrac{RW-12.00}{17.50-12.00}, & If \quad 12.00 < RW \le 17.50\\ \dfrac{25.00-RW}{25.00-17.50}, & If \quad 17.50 < RW \le 25.00\end{cases} \tag{4.13}$$

$$\mu_L(RW)=\begin{cases}\dfrac{RW-17.50}{25.00-17.50}, & If \quad 17.50 < RW \le 25.00\\ 1, & If \quad 25.00 < RW \le 30.00\end{cases} \tag{4.14}$$

The variable PM is divided into two triangular and one trapezoidal fuzzy subsets; and the variable BS is divided into three triangular and one trapezoidal fuzzy subsets due to the distribution of the data. Figure 4.12 shows the data distribution for PM and BS for the calibration sets. As seen in Figure 4.12, the data clusters have centers around 0.35, 0.65, for PM and 2.80, 4.50, 7, for BS. Thus, three fuzzy subsets for the variable PM and four fuzzy subsets for the variable BS are defined.

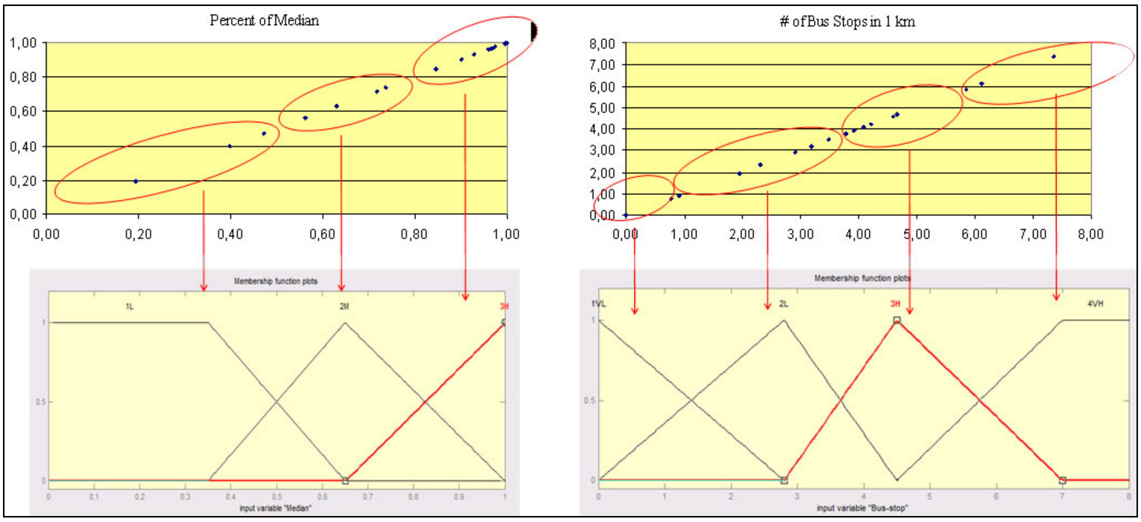

Figure 4. 12. Fuzzification of the input variables PM and BS

<u>Mathematical Expressions of the variable PM:</u>

$$\mu_L(PM) = \begin{cases} 1 \quad , & If \quad 0 \le PM \le 0.35 \\ \dfrac{0.65 - PM}{0.65 - 0.35}, & If \quad 0.35 < PM \le 0.65 \end{cases} \tag{4.15}$$

$$\mu_M(PM) = \begin{cases} \dfrac{PM - 0.35}{0.65 - 0.35}, & If \quad 0.35 < PM \le 0.65 \\ \dfrac{1.00 - PM}{1.00 - 0.65}, & If \quad 0.65 < PM \le 1.00 \end{cases} \tag{4.16}$$

$$\mu_L(PM) = \begin{cases} \dfrac{PM - 0.65}{1.00 - 0.65}, & If \quad 0.65 < PM \le 1.00 \end{cases} \tag{4.17}$$

<u>Mathematical Expressions of the variable BS:</u>

$$\mu_{VL}(BS) = \begin{cases} \dfrac{2.80 - BS}{2.80}, & If \quad 0 < BS \le 2.80 \end{cases} \tag{4.18}$$

$$\mu_L(BS) = \begin{cases} \dfrac{BS}{2.80}, & If \quad 0 < BS \le 2.80 \\ \dfrac{4.50 - BS}{4.50 - 2.80}, & If \quad 2.80 < BS \le 4.50 \end{cases} \tag{4.19}$$

$$\mu_H(BS) = \begin{cases} \dfrac{BS - 2.80}{4.50 - 2.80}, & If \quad 2.80 < BS \leq 4.50 \\ \dfrac{7.00 - BS}{7.00 - 4.50}, & If \quad 4.50 < BS \leq 7.00 \end{cases} \tag{4.20}$$

$$\mu_{VH}(BS) = \begin{cases} \dfrac{BS - 4.50}{7.00 - 4.50}, & If \quad 4.50 < BS \leq 7.00 \\ 1 \quad , & If \quad 7.00 < BS \leq 8.00 \end{cases} \tag{4.21}$$

The variable SJ is divided into three triangular and one trapezoidal fuzzy subsets; and the variable MA is divided into two triangular and two trapezoidal fuzzy subsets due to the distribution of the data. Figure 4.13 shows the data distribution for SJ and MA for the calibration sets. As seen in Figure 4.13, the data clusters have centers around 2.50, 5.10, 12 for SJ and 4, 13.40, 20.40, 29, for MA. Thus, four fuzzy subsets for the variable SJ and four fuzzy subsets for the variable MA are defined.

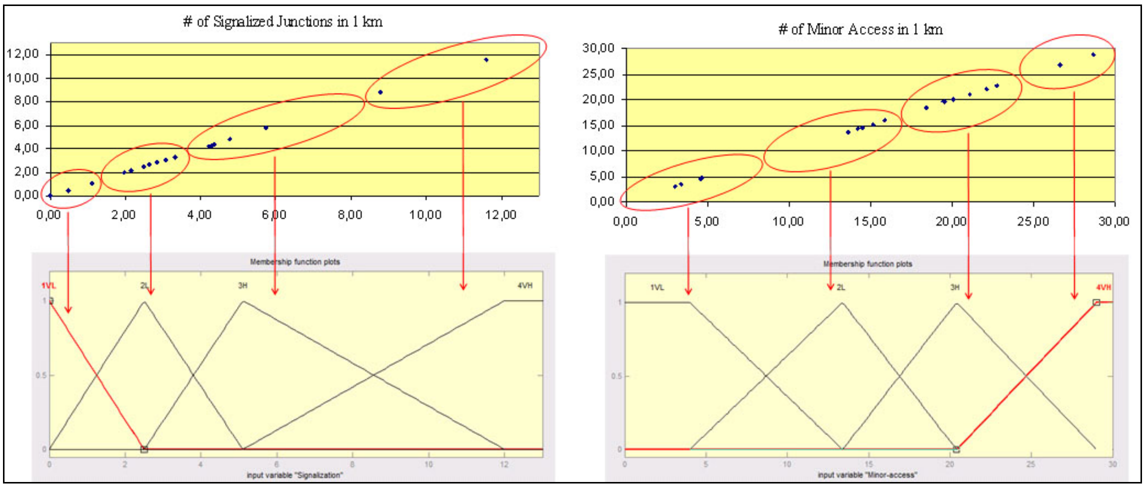

Figure 4. 13. Fuzzification of the input variables SJ and MA

<u>Mathematical Expressions of the variable SJ:</u>

$$\mu_{VL}(SJ) = \begin{cases} \dfrac{2.50 - SJ}{2.50}, & If \quad 0 < SJ \leq 2.50 \end{cases} \tag{4.22}$$

$$\mu_L(SJ) = \begin{cases} \dfrac{SJ}{2.50}, & If \quad 0 < SJ \leq 2.50 \\ \dfrac{5.10 - SJ}{5.10 - 2.50}, & If \quad 2.50 < SJ \leq 5.10 \end{cases} \tag{4.23}$$

$$\mu_H(SJ) = \begin{cases} \dfrac{SJ - 2.50}{5.10 - 2.50}, & If \quad 2.50 < SJ \leq 5.10 \\ \dfrac{12.00 - SJ}{12.00 - 5.10}, & If \quad 5.10 < SJ \leq 12.00 \end{cases} \tag{4.24}$$

$$\mu_{VH}(SJ) = \begin{cases} \dfrac{SJ - 5.10}{12.00 - 5.10}, & If \quad 5.10 < SJ \leq 12.00 \\ 1 \quad , & If \quad 12.00 < SJ \leq 13.00 \end{cases} \tag{4.25}$$

Mathematical Expressions of the variable MA:

$$\mu_{VL}(MA) = \begin{cases} 1 \quad , & If \quad 0 \leq MA \leq 4.00 \\ \dfrac{13.40 - MA}{13.40 - 4.00}, & If \quad 4.00 < MA \leq 13.40 \end{cases} \tag{4.26}$$

$$\mu_L(MA) = \begin{cases} \dfrac{MA - 4.00}{13.40 - 4.00}, & If \quad 4.00 < MA \leq 13.40 \\ \dfrac{20.40 - MA}{20.40 - 13.40}, & If \quad 13.40 < MA \leq 20.40 \end{cases} \tag{4.27}$$

$$\mu_H(MA) = \begin{cases} \dfrac{MA - 13.40}{20.40 - 13.40}, & If \quad 13.40 < MA \leq 20.40 \\ \dfrac{29.00 - MA}{29.00 - 20.40}, & If \quad 20.40 < MA \leq 29.00 \end{cases} \tag{4.28}$$

$$\mu_{VH}(MA) = \begin{cases} \dfrac{MA - 20.40}{29.00 - 20.40}, & If \quad 20.40 < MA \leq 29.00 \\ 1 \quad , & If \quad 29.00 < MA \leq 30.00 \end{cases} \tag{4.29}$$

In the equations and fuzzy sets, VVL represents Very Very Low, VL represents Very Low, M represents Medium, H represents High, VH represents Very High and VVH represents Very Very High for all sets of input variables.

4.4.1.2. Fuzzification of Output Variable

The variable AAA is divided into three triangular and two trapezoidal fuzzy subsets due to the distribution of the data. Figure 4.14 shows the data distribution for

AAA for the calibration set. As seen in Figure 4.14, the data clusters have centers around 1.14, 6.32, 9.96, 17.72, 25.02 and 33. Thus, six subsets are defined for the output variable AAA. Subsets S1 represents the decision of first level safety, S2 represents second level safety, M represents medium, R2 represents second level risk group and R1 represents first level risk group which means the most risky moment for the defined street and time interval.

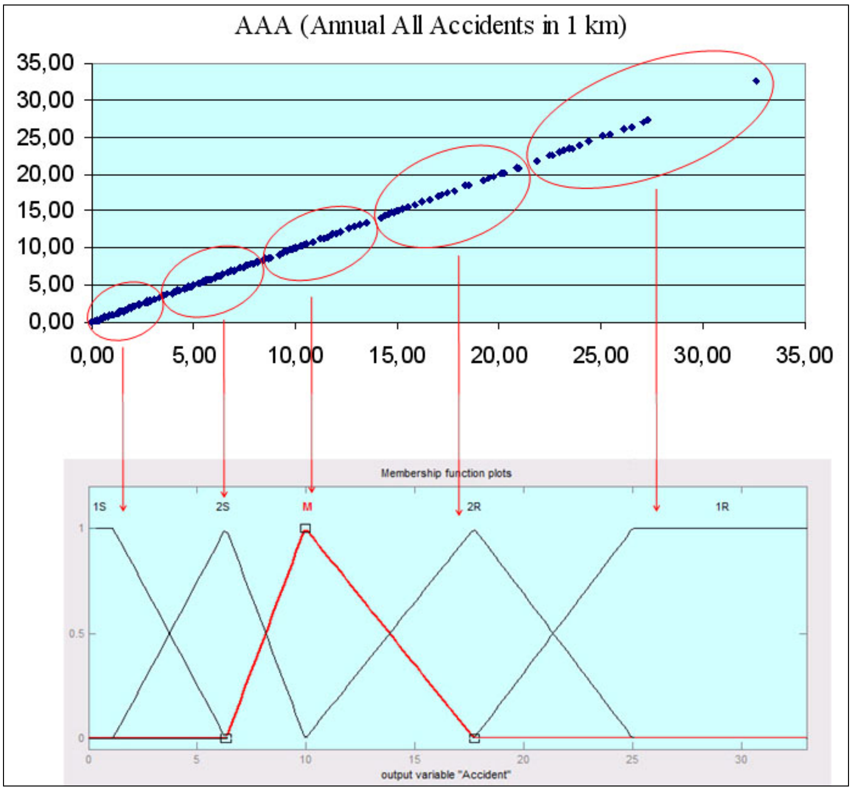

Figure 4. 14. Fuzzification of the output variable AAA

<u>Mathematical Expressions of the variable AAA:</u>

$$\mu_{S1}(AAA) = \begin{cases} 1 \quad , & If \quad 0 \le AAA \le 1.14 \\ \dfrac{6.32 - AAA}{6.32 - 1.14}, & If \quad 1.14 < AAA \le 6.32 \end{cases} \tag{4.30}$$

$$\mu_{S2}(AAA) = \begin{cases} \dfrac{AAA - 1.14}{6.32 - 1.14}, & If \quad 1.14 < AAA \le 6.32 \\ \dfrac{9.96 - AAA}{9.96 - 6.32}, & If \quad 6.32 < AAA \le 9.96 \end{cases} \tag{4.31}$$

$$\mu_M(AAA) = \begin{cases} \dfrac{AAA - 6.32}{9.96 - 6.32}, & If \quad 6.32 < AAA \leq 9.96 \\ \dfrac{17.72 - AAA}{17.72 - 9.96}, & If \quad 9.96 < AAA \leq 17.72 \end{cases} \tag{4.32}$$

$$\mu_{R2}(AAA) = \begin{cases} \dfrac{AAA - 9.96}{17.72 - 9.96}, & If \quad 9.96 < AAA \leq 17.72 \\ \dfrac{25.02 - AAA}{25.02 - 17.72}, & If \quad 17.72 < AAA \leq 25.02 \end{cases} \tag{4.33}$$

$$\mu_{R1}(AAA) = \begin{cases} \dfrac{AAA - 17.72}{25.02 - 17.72}, & If \quad 17.72 < AAA \leq 25.02 \\ 1 \quad , & If \quad 25.00 < AAA \leq 33.00 \end{cases} \tag{4.34}$$

Following part describes the *If-Then* rule production of the fuzzy modeling study.

4.4.2. Production of the Rule Base

There are several methods to produce rule base of fuzzy logic model as cited on the third chapter. In this modeling study, fuzzy rules relating input variables to output variable were constructed from the calibration data set according to the *rule-construction-procedure* given in the literature (Bardossy and Dissi 1993; Bardossy and Duckstein 1995; Ozelkan, et al. 1996; Sen 1998; Coppala, et al. 2002; Tayfur 2006). Commonly used Mamdani type of rule system is employed for the study.

As two input variables and two fuzzy subsets for each variable were identified in basic example in Chapter 3, it was possible to evaluate all the possibilities that variables form with each other, and subsequently, four rules were established as a result of (2 x 2 =) 4 relations.

In the case study, seven input variables with its subsets taken altogether, (6 x 5 x 3 x 3 x 4 x 4 x =) 4,320 different relations are mathematically possible. However, in practice it is not possible to define 4,320 fuzzy rules, and thus, the rules were formulated through the combinations of the data separated as calibration group.

Through these combinations, 161 rules were developed, but there were 35 contradictions. Contradicting rules were omitted intuitively and the model constructed with the 126 rules derived from the calibration data. *Summation* operation method is used for aggregation and CoG is applied for defuzzification process of the modeling. Figure 4.15 illustrates the flow chart of rule extraction process of fuzzy modeling.

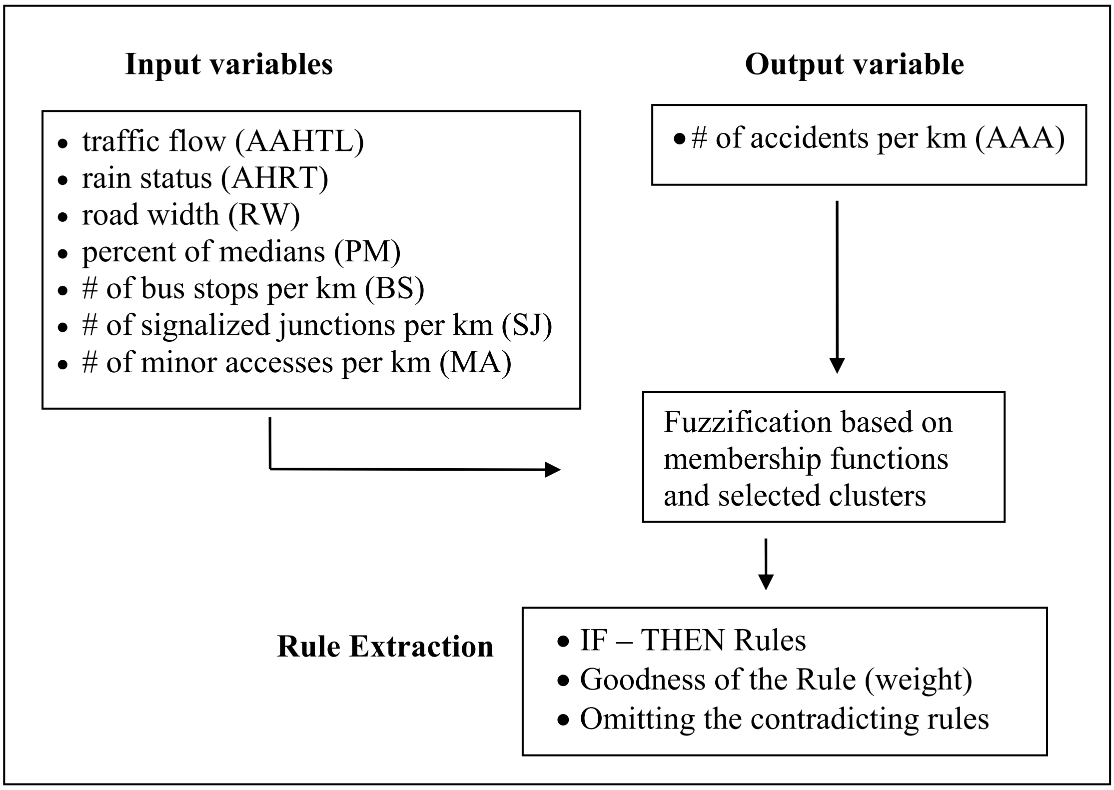

Figure 4. 15. Flow chart of fuzzy rule extraction

Some examples from the rule list (See Appendix D for the table of all rules);

R1 : If AAHTL is VVL, AHRT is L, RW is L, PM is H, BS is VH, SJ is VH and MA is VH then AAA is S1

R2 : If AAHTL is VVL, AHRT is L, RW is M, PM is L, BS is L, SJ is VH and MA is VH then AAA is S1

R3 : If AAHTL is VVL, AHRT is L, RW is M, PM is M, BS is VH, SJ is L and MA is L then AAA is S1

: :

: :

R125 : If AAHTL is VH, *AHRT* is VH, *RW* is H, *PM is H, BS is VL, SJ is VL and MA is VL then AAA is S2*

R126 : If AAHTL is VVH, AHRT is L, RW is H, PM is H, BS is VL, SJ is VL and MA is VL then AAA is R2

As an example R1 (rule one) refers;

IF *Annual Average Hourly Traffic per Lane* is Very Very Low, *Annual Hourly Rain Total* is Low, *Road Width* is Low, *Percent of Median* is High, number of *Bus Stops* per km is Very High, number of *Signalized Junctions* per km is Very High and number of *Minor Access* per km is Very High, THEN the number of *Annual All Accidents* is on the degree of First Safety Level.

Next stage is the defuzzification of all aggregated fuzzy sets into output crisp values. MATLAB 7.4.0.287 - Fuzzy Logic Toolbox is used as a computing tool to obtain the crisp values from the each fuzzy output set. (See Appendix E for MATLAB coding of the Fuzzy Model)

4.4.3. Defuzzification Process

As stated in Chapter 3 this is the process of converting each aggregated fuzzy output into a single crisp value through the developed fuzzy rules. CoG defuzzification method is applied for the model. Following equation is the mathematical expression of the CoG defuzzification method for the discrete fuzzy systems.

$$y^* = \frac{\sum_{i=1}^{n} y_i \cdot \mu_U \cdot (y_i)}{\sum_{i=1}^{n} \mu_U \cdot (y_i)} \tag{4.35}$$

where y^* is the output variable of one set of input variables.

Figure 4.16 shows a sample set of defuzzified data point ALT02 from testing group of data. The model applies a defuzzification process for each data point one by one, as demonstrated in Figure 4.16. The crisp output values obtained by including each input dataset in the testing group are presented in Appendix F.

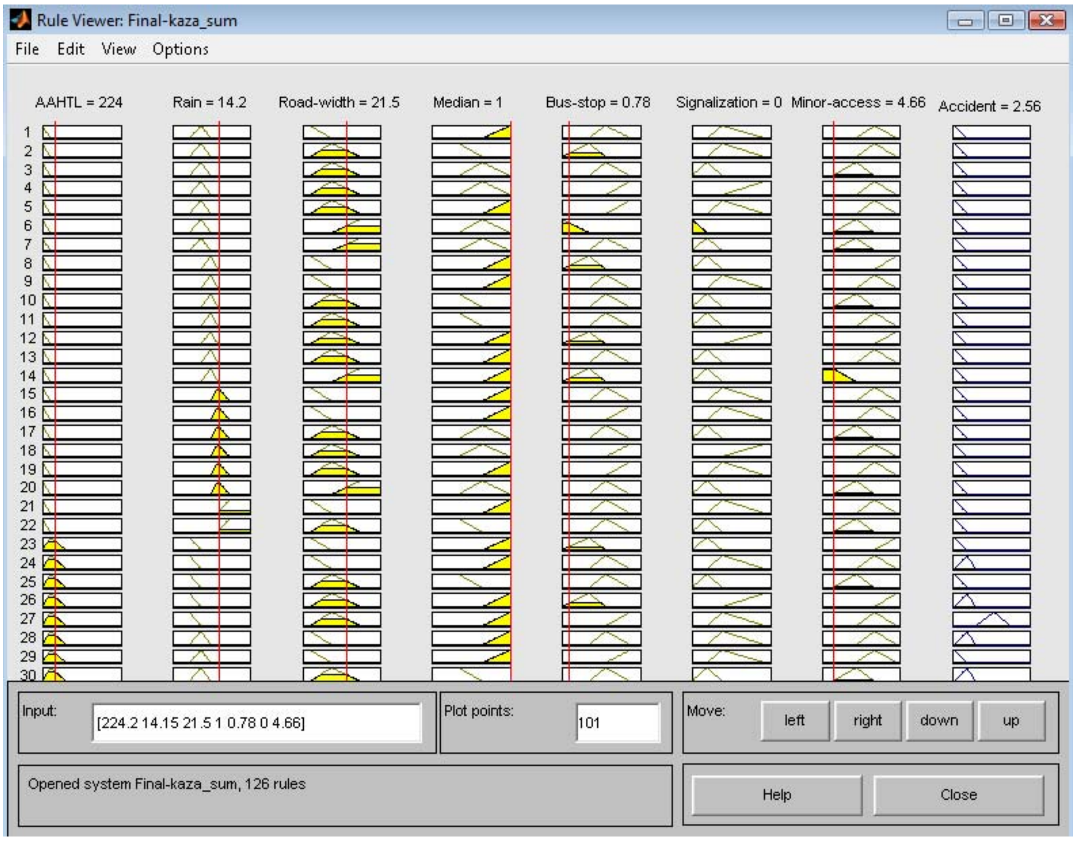

Figure 4. 16. Deffuzification of the data point ALT02 (MATLAB 7.4.0.287 – Fuzzy Logic Toolbox)

Each set of input data was entered to the FIS and output results were taken. Scatter diagram of the model results and the observed data for testing group is expressed in Figure 4.17.

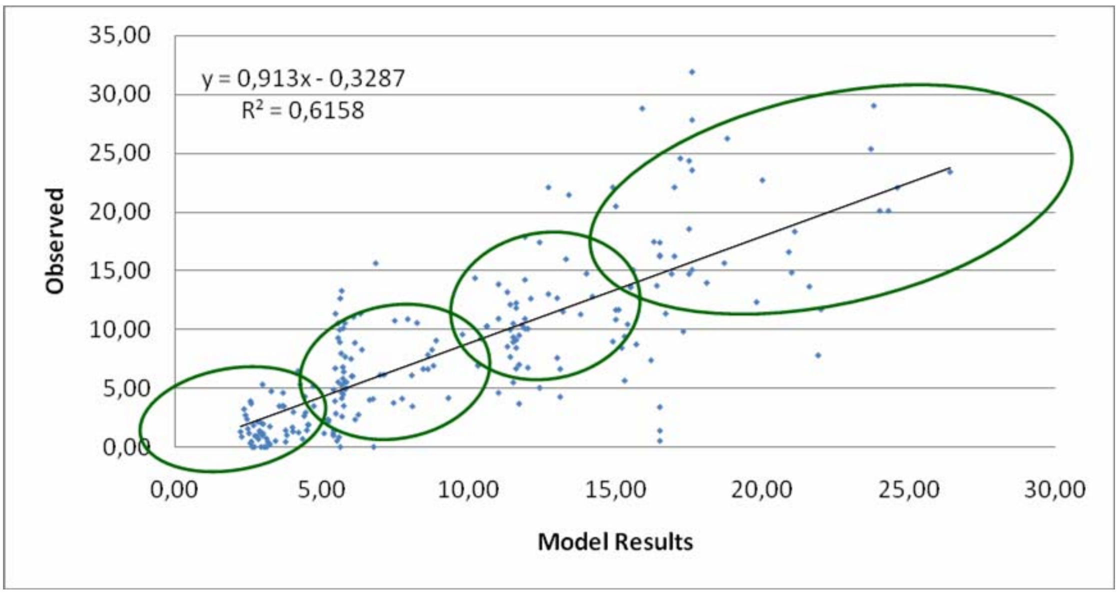

Figure 4. 17. Results of testing group data (R^2 = 0,6158)

4.4.4. Model Results and Discussions

When the model results are examined in detail, it was observed that the time zones during which the streets are safe or risky differ. All the calibration and testing input data is computed to find out the crisp output results and plotted in Figure 4.18. Considering the leaps on the graph, similar to Kononov's LOSS concept, the results were allocated into four clusters in relation to AAA values. According to these clusters, High Safety Level (HSL), Low Safety Level (LSL), Low Risky Level (LRL) and High Risky Level (HRL) time-spaces (streets in relation to the time zones) were determined.

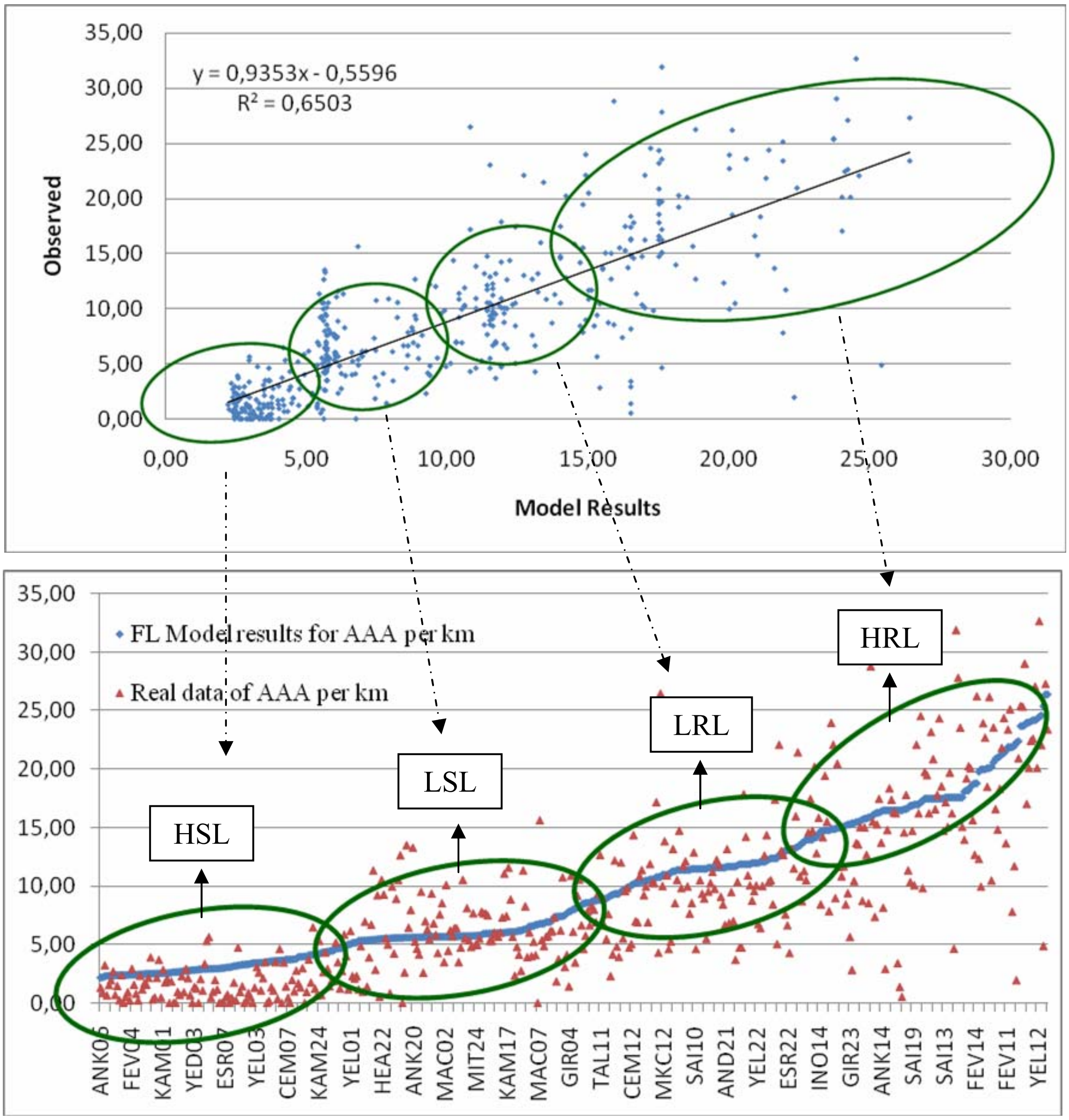

Figure 4. 18. Results of whole data and safety clusters (R^2 = 0,6503)

According to these four level safety clusters;

The streets in the High Safety Level group are:

Altınyol Street between 00:00 – 07:00; Anadolu Street between 00:00 – 07:00; Ankara Street between 00:00 – 07:00; Cemal Gürsel Boulevard between 01:00 – 08:00; Eşrefpaşa Street between 01:00 – 08:00; Fevzipaşa Street between 01:00 – 06:00; Gazi Boulevard between 01:00 – 03:00, 04:00 – 05:00 and 06:00 – 08:00; Girne Boulevard between 00:00 – 03:00 and 04:00 – 07:00; Halide Edip Adıvar Boulevard between 01:00 – 03:00, 04:00 – 05:00 and 06:00 – 08:00; İnönü Street between 01:00 – 06:00; Kamil Tunca Boulevard between 00:00 – 08:00 and 09:00 – 10:00; Mehmet Akif Street between 02:00 – 06:00; Mithatpaşa Street between 00:00 – 07:00, 09:00 – 10:00 and 22:00 – 23:00; Mustafa Kemal Street between 00:00 – 08:00; Mustafa Kemal Sahil Boulevard between 00:00 – 03:00 and 04:00 – 08:00; Şair Eşref Boulevard between 02:00 – 03:00 and 04:00 – 08:00; Talatpaşa Boulevard between 01:00 – 08:00; Yeşildere Street between 00:00 – 07:00; Yeşillik Street between 00:00 – 01:00, 02:00 – 05:00 and 06:00 – 07:00.

The streets in Low Safety Level group are:

Altınyol Street between 07:00 – 08:00, 10:00 – 17:00 and 19:00 – 24:00; Anadolu Street between 07:00 – 08:00; Ankara Street between 07:00 – 08:00, 11:00 – 13:00, and 19:00 – 24:00; Cemal Gürsel Boulevard between 00:00 – 01:00, 09:00 – 10:00 and 21:00 – 24:00; Eşrefpaşa Street between 00:00 – 01:00 and 10:00 – 11:00; Fevzipaşa Street between 00:00 – 01:00 and 06:00 – 08:00; Gazi Boulevard between 00:00 – 01:00, 03:00 – 04:00, 05:00 – 06:00 and 21:00 – 24:00; Girne Boulevard between 03:00 – 04:00 and 07:00 – 08:00; Halide Edip Adıvar Boulevard between 05:00 – 06:00, 09:00 – 10:00 and 21:00 – 24:00; İnönü Street between 00:00 – 01:00, 06:00 – 08:00 and 22:00 – 24:00; Kamil Tunca Boulevard between 08:00 – 09:00 and 10:00 – 22:00; Mehmet Akif Street between 01:00 – 02:00 and 06:00 – 08:00; Mithatpaşa Street between 07:00 – 09:00, 10:00 – 22:00 and 23:00 – 24:00; Mustafa Kemal Street between 08:00 – 11:00, 13:00 – 14:00 and 20:00 – 24:00; Mustafa Kemal Sahil Boulevard between 08:00 – 18:00 and 20:00 – 24:00; Şair Eşref Boulevard between 01:00 – 02:00 and 03:00 – 04:00; Talatpaşa Boulevard between 08:00 – 11:00, 20:00 – 21:00 and 22:00 – 24:00; Yeşildere Street between 07:00 – 08:00, 10:00 –

11:00, 13:00 – 17:00 and 18:00 – 24:00; Yeşillik Street between 01:00 – 02:00, 05:00 – 06:00 and 07:00 – 08:00.

<u>The streets in Low Risky Level group are:</u>

Altınyol Street between 00:08 – 10:00 and 17:00 – 18:00; Anadolu Street between 00:08 – 22:00; Cemal Gürsel Boulevard between 00:08 – 09:00, 10:00 – 18:00 and 20:00 – 21:00; Eşrefpaşa Street between 08:00 – 10:00, 11:00 – 14:00 and 21:00 – 24:00; Fevzipaşa Street between 16:00 – 17:00; Girne Boulevard between 09:00 – 10:00, 12:00 – 13:00, 15:00 – 17:00 and 20:00 – 21:00; Halide Edip Adıvar Boulevard between 00:00 – 01:00, 08:00 – 09:00, 10:00 – 11:00, 12:00 – 14:00, 16:00 – 18:00 and 19:00 – 21:00; İnönü Street between 08:00 – 12:00, 14:00 – 16:00, 18:00 – 20:00 and 21:00 – 22:00; Mehmet Akif Street between 00:00 – 01:00 and 09:00 – 10:00; Mustafa Kemal Street between 11:00 – 13:00 and 14:00 – 20:00; Mustafa Kemal Sahil Boulevard between 18:00 – 20:00; Şair Eşref Boulevard between 00:00 – 01:00, 09:00 – 10:00 and 21:00 – 24:00; Talatpaşa Boulevard between 00:00 – 01:00, 12:00 – 20:00 and 21:00 – 22:00; Yeşildere Street between 08:00 – 10:00, 11:00 – 13:00 and 17:00 – 18:00; Yeşillik Street between 09:00 – 10:00 and 21:00 – 24:00.

<u>The streets in High Risky Level group are:</u>

Altınyol Street between 18:00 – 19:00; Anadolu Street between 22:00 – 24:00; Ankara Street between 08:00 – 11:00 and 13:00 – 19:00; Cemal Gürsel Boulevard between 16:00 – 17:00 and 18:00 – 20:00; Eşrefpaşa Street between 14:00 – 21:00; Fevzipaşa Street between 08:00 – 16:00, 17:00 – 24:00; Gazi Boulevard between 08:00 – 21:00; Girne Boulevard between 08:00 – 09:00, 10:00 – 12:00, 13:00 – 15:00, 17:00 – 20:00 and 21:00 – 24:00; Halide Edip Adıvar Boulevard between 03:00 – 04:00, 11:00 – 12:00, 14:00 – 16:00 and 18:00 – 19:00; İnönü Street between 12:00 – 14:00, 16:00 – 18:00 and 20:00 – 21:00; Mehmet Akif Street between 08:00 – 09:00 and 10:00 – 24:00; Mustafa Kemal Sahil Boulevard between 03:00 – 04:00; Şair Eşref Boulevard between 08:00 – 09:00 and 10:00 – 21:00; Yeşillik Street between 08:00 – 09:00 and 10:00 – 21:00.

Although the results point out that traffic accidents are more affected by dynamic variables such as AAHTL (Annual Average Hourly Traffic per Lane) and AHRT (Annual Hourly Rain Total), it is also observed that Fevzipaşa Street, Gazi

Boulevard, Şair Eşref Boulevard, Yeşillik Street, Girne Boulevard and Ankara Street are often in the high risk level group (HRL). Moreover, streets such as Kamil Tunca Boulevard, Mithatpaşa Street and Mustafa Kemal Street as well belong to the HSL group.

As a result of modeling, four main safety levels were determined. The examination of street-time data points that corresponded to these safety levels would lighten the city and transportation planners about transportation strategies and road designs. The findings of the dissertation will help the design and the strategy of the city planners both in the various scales of the development plans and also in the urban design scale. Besides, these data points would help ITS designers about design of road safety mechanism. Through this point of view similar to Ng et al.'s study following *Accident Risk Assessment Cycle* is created for İzmir urban roads in Figure 4.19.

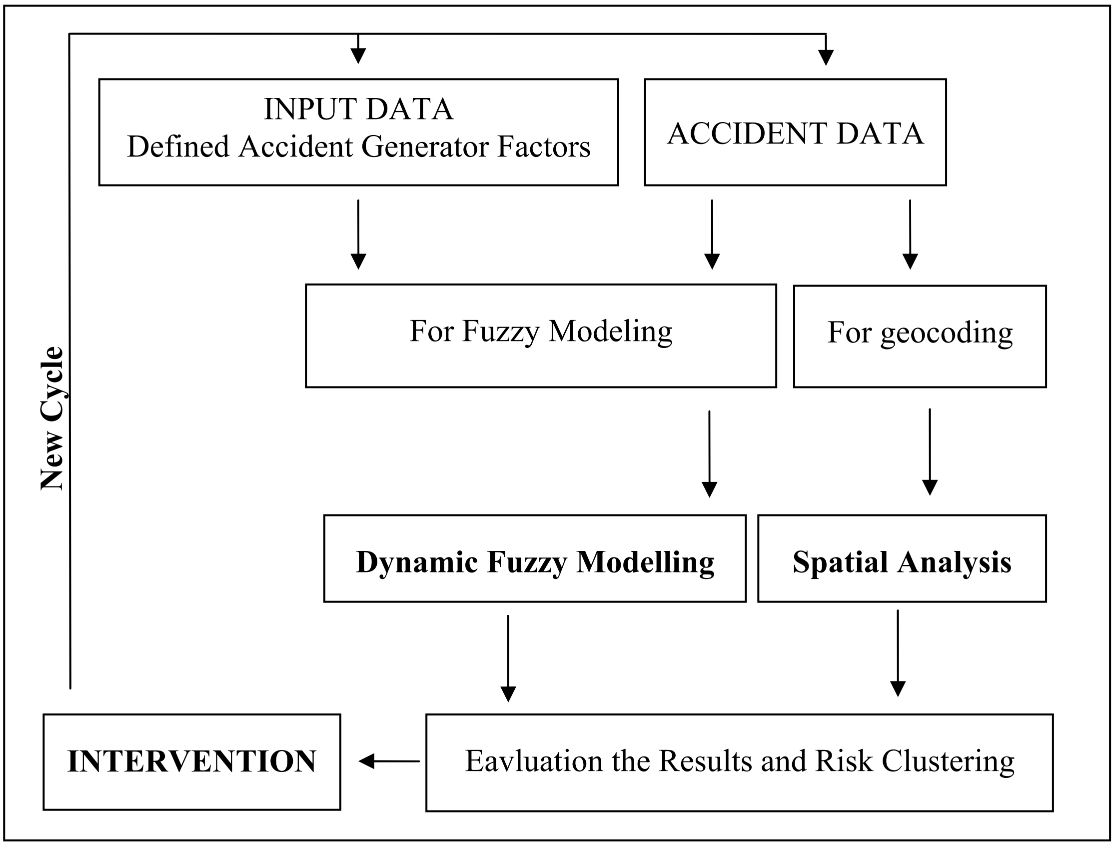

Figure 4. 19. Accident Risk Assessment Cycle

CHAPTER 5

CONCLUSION

Dissertation has dealt with one of the most chaotic events of an urban life that is the traffic accidents. In this study, such a chaotic issue, which is perceived as “faith” especially in our country, was attempted to be predicted through Fuzzy Logic Modeling. Any effort on decreasing the amount of traffic accidents will cause safer urban environments and on the other hand it will provide major savings for the society.

It is believed that this thesis has three contributions to the literature, specifically to Road Safety research field, Transportation Planning practice and to the field of City and Regional Development.

The reason why it contributes to Road Safety research field is that it reveals the reasons related to spatial and traffic characteristics of the accidents, which are generally not dealt with especially in our country. Fuzzy Logic Modeling ascertained the effect of the factors other than the driver and the vehicles. The estimation capacity of the model, which is R^2 = 0,61, could be considered low for engineering but it is nevertheless an important finding that chaotic incidents like traffic accidents are estimated with such precision. Moreover, the Safety Levels groups developed after the model rather than the absolute estimations is sufficient for the scope of this study.

Its contribution to Transportation Planning is related to ITS (Intelligent Transportation Systems). It is seen that changing transportation planning practice parallel to technological developments is supported with ITS systems. The modeling approach developed in the thesis could constitute the Road Safety unit of an advanced intelligent transportation system of an urban area. It would be possible to develop a more solid road safety estimation model with real time datasets. This method would render traceable, and thus, more controllable the roads, which are the dangerous and crucial parts of the city.

ITS applications that are developed parallel to the technological development enable innovative solutions to the problems of urban transportation networks. In future, a controllable transportation network was envisaged for road safety. Here, the emphasis of control is on the movement of motorized vehicles, not the private life of people.

Another contribution of this thesis is familiarizing fuzzy logic approach to the planning discipline. The conformity of fuzzy logic approach that enables modeling through intuitional applications, is its flexibility to achieve uncertainties of planning issues. The contribution of the thesis to City and Regional Planning field is, alongside the creation of a safe urban environment, the presentation of Fuzzy Logic Modeling approach in planning with a case study. Fuzzy Logic approach is a very appropriate method for planning discipline in which one should work with ambiguities, lack of data and linguistic datasets, and sometimes should make intuitive and relative decisions.

This thesis is a preliminary study that produced traffic accident prediction model for the road safety mechanism of urban ITS systems. For an advanced modeling, a system should be established in which output data such as traffic accidents and input data such as traffic flow, weather are collected synchronously. In this system, rule base of the model can have a dynamic structure through updating with new data periodically. To achieve updating, traffic monitoring equipment should be used on important arterials. Another subject that should be studied on is the relation between traffic speed and traffic accidents, which this thesis could not emphasize.

It is observed that during last decade both theoretical and practical studies on reducing traffic accidents especially in the European Union countries have increased. In 2008, as a result of a three-year-study, 21 European members of OECD prepared a report called “Towards Zero: Ambitious Road Safety Targets and the Safe System Approach”. Aiming at reducing the death numbers to zero in 2020, this report includes Turkey as one of the forum participants. However, when the studies conducted and accident statistics of Turkey are observed, it is seen that Turkey is far from this vision. Although Turkey participates in the forum, it is striking that no experts took part in the process of report preparation.

European Union started a campaign with the motto of “vision zero” that was predicted zero deaths on roads for the year of 2020. Thus, there is so much research made on traffic accidents in Europe. However, in Turkey there is not enough research or study on this issue. It is suggested that more importance should be given to the Road Safety issue and academic and practical studies should be increased.

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APPENDIX A

DETAILED SPATIAL ANALYSES

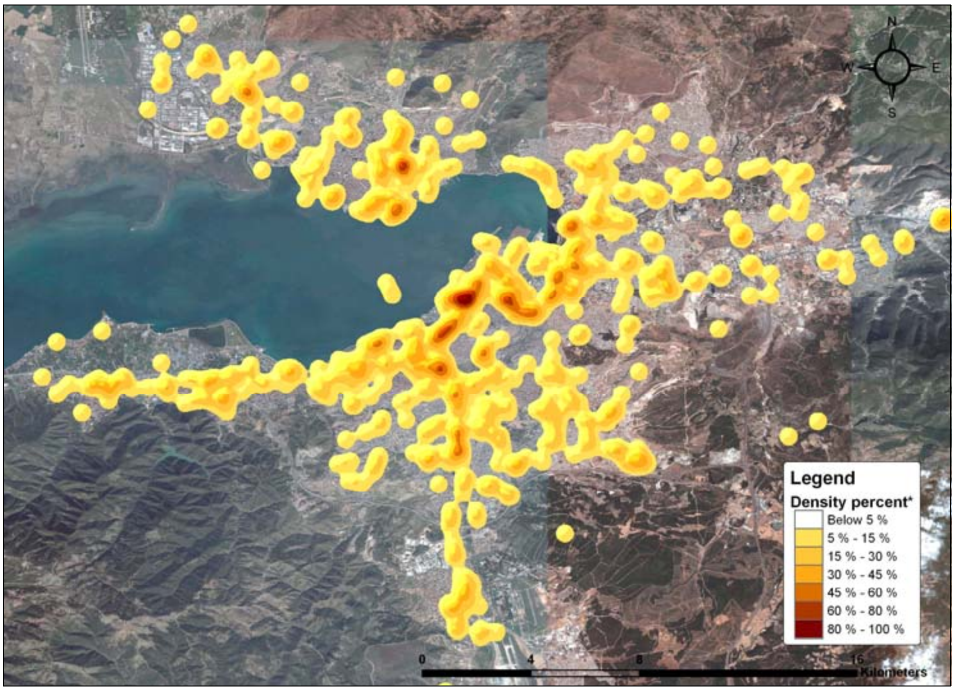

Figure A. 1. Concentration of the killed-injured accidents occurred during peak hour.

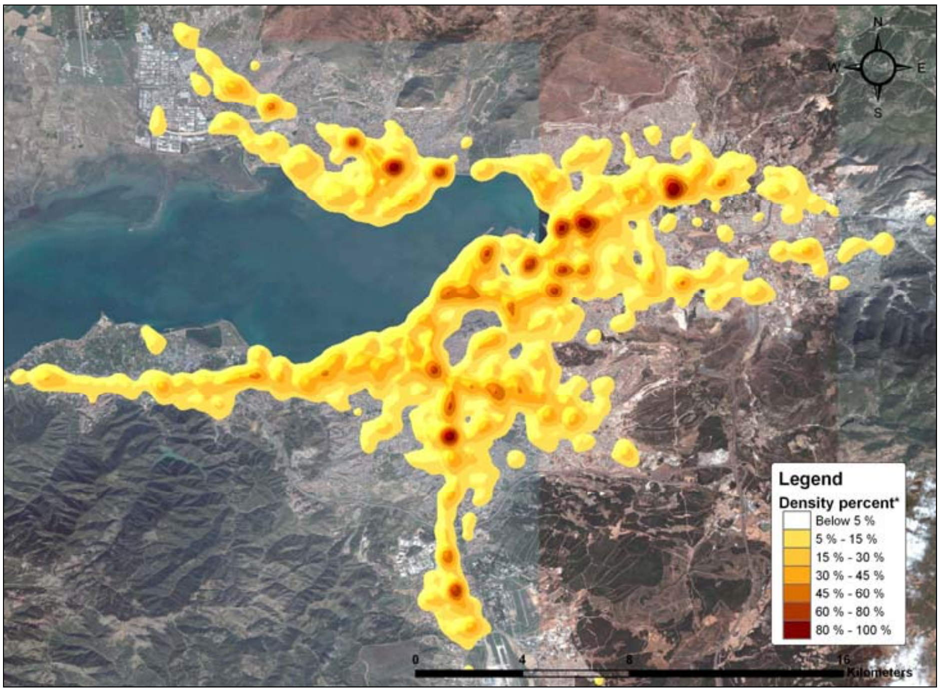

Figure A. 2. Concentration of the damaged-only accidents occurred during peak hour.

* Point objects which drop to each raster cell

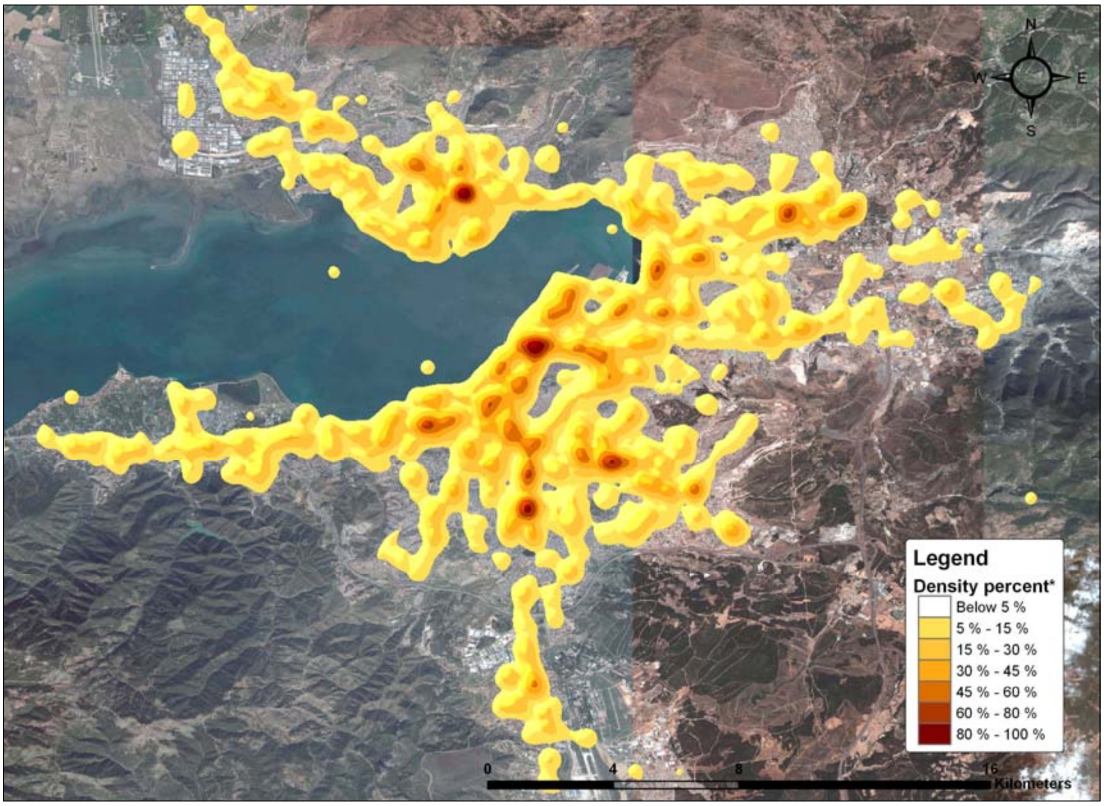

Figure A. 3. Concentration of the killed-injured accidents occurred during off-PH.

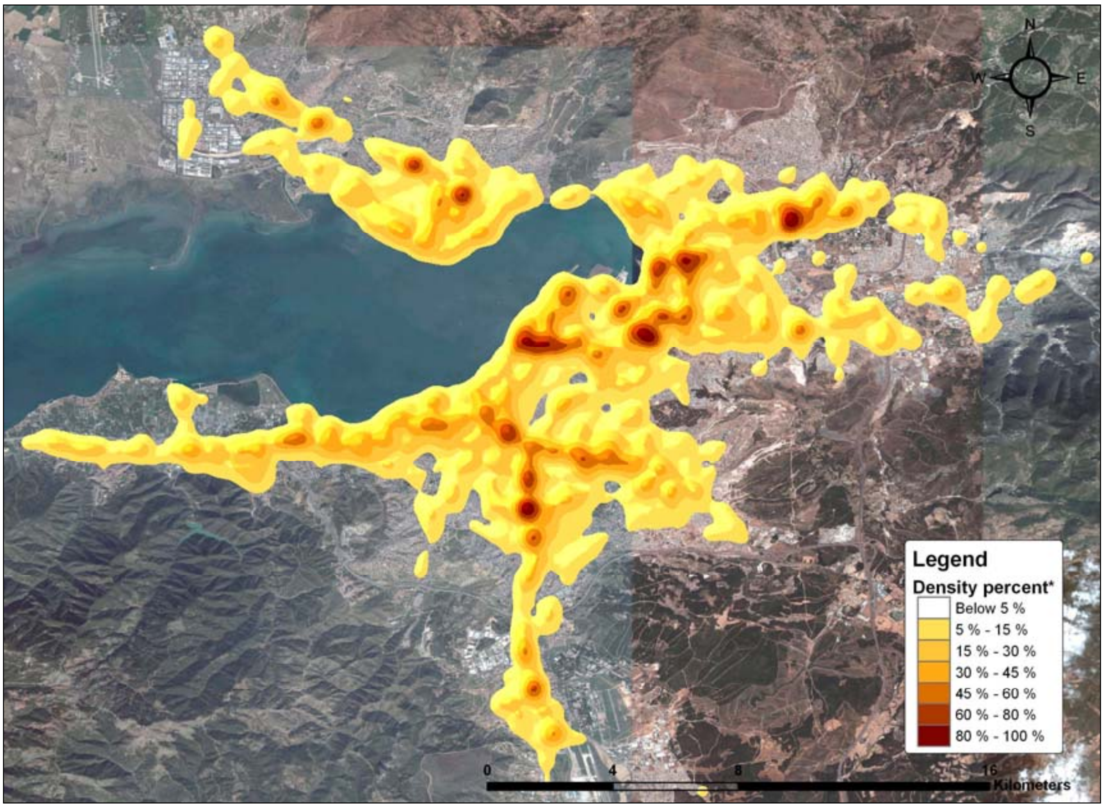

Figure A. 4. Concentration of the damaged-only accidents occurred during off-PH.

* Point objects which drop to each raster cell

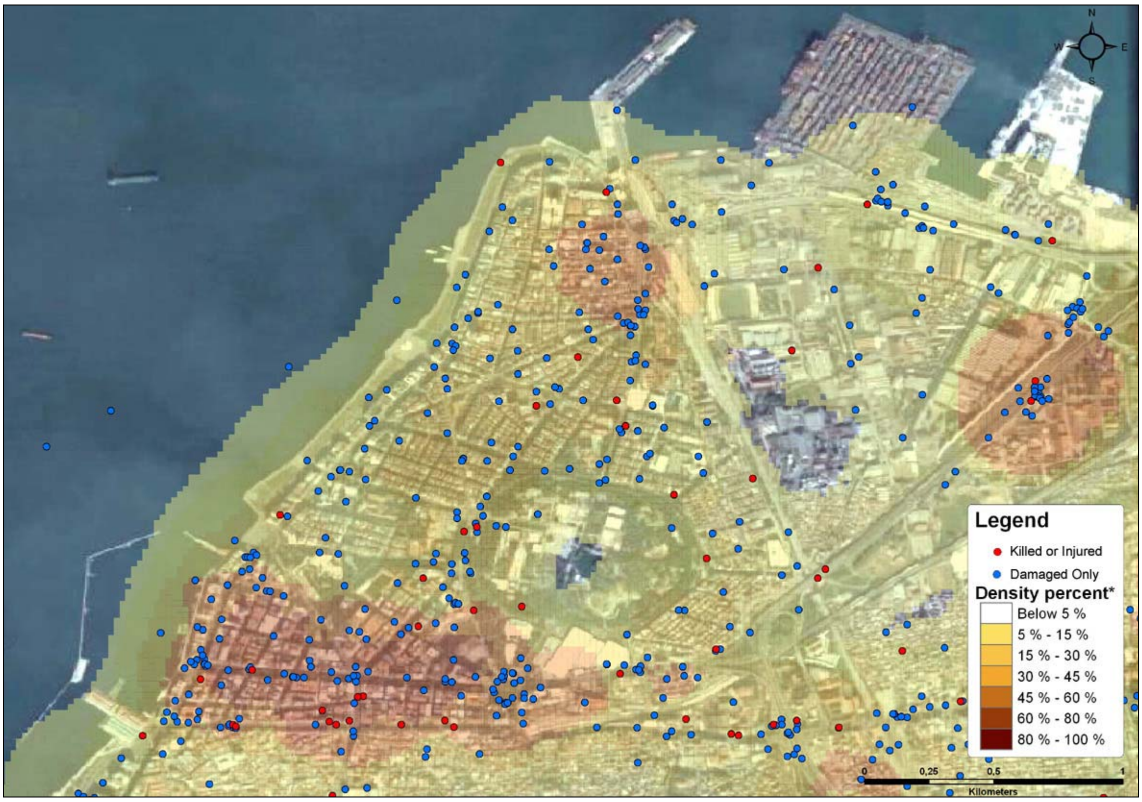

Figure A. 5. Concentration of all accidents in Çankaya – Alsancak region (CBD)

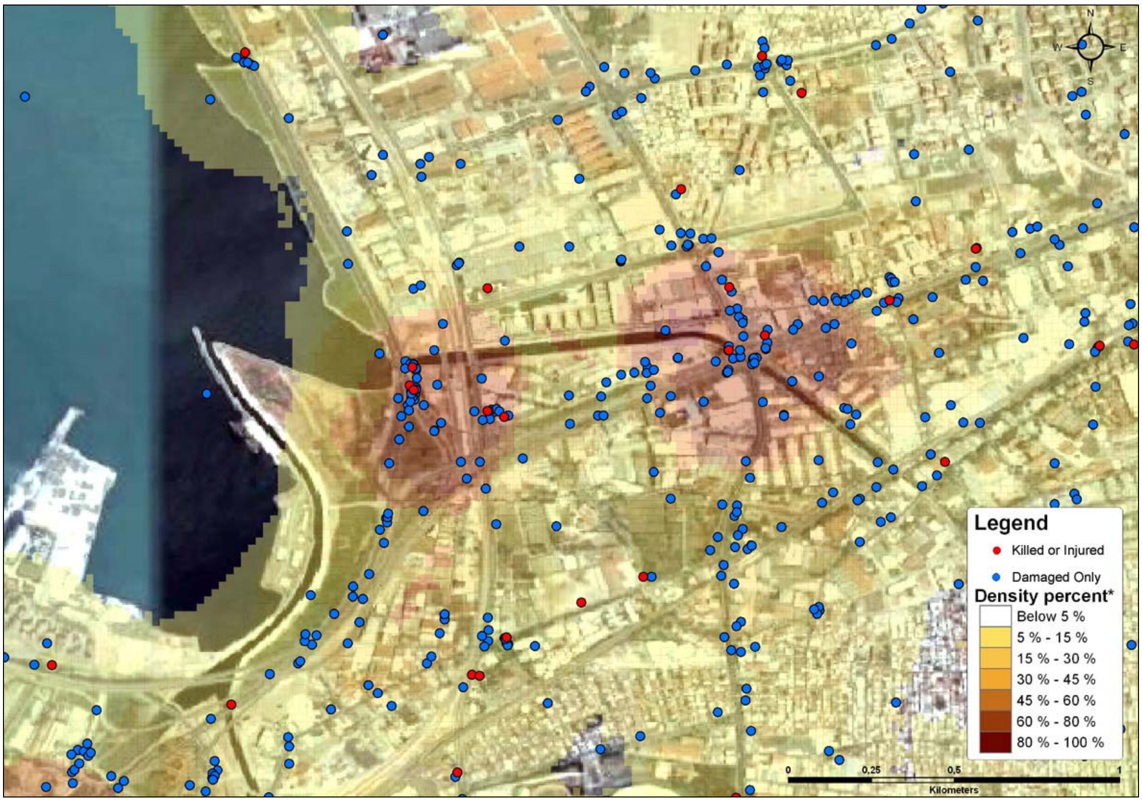

Figure A. 6. Concentration of all accidents around the intersection of Altınyol and Ankara Streets

* Point objects which drop to each raster cell

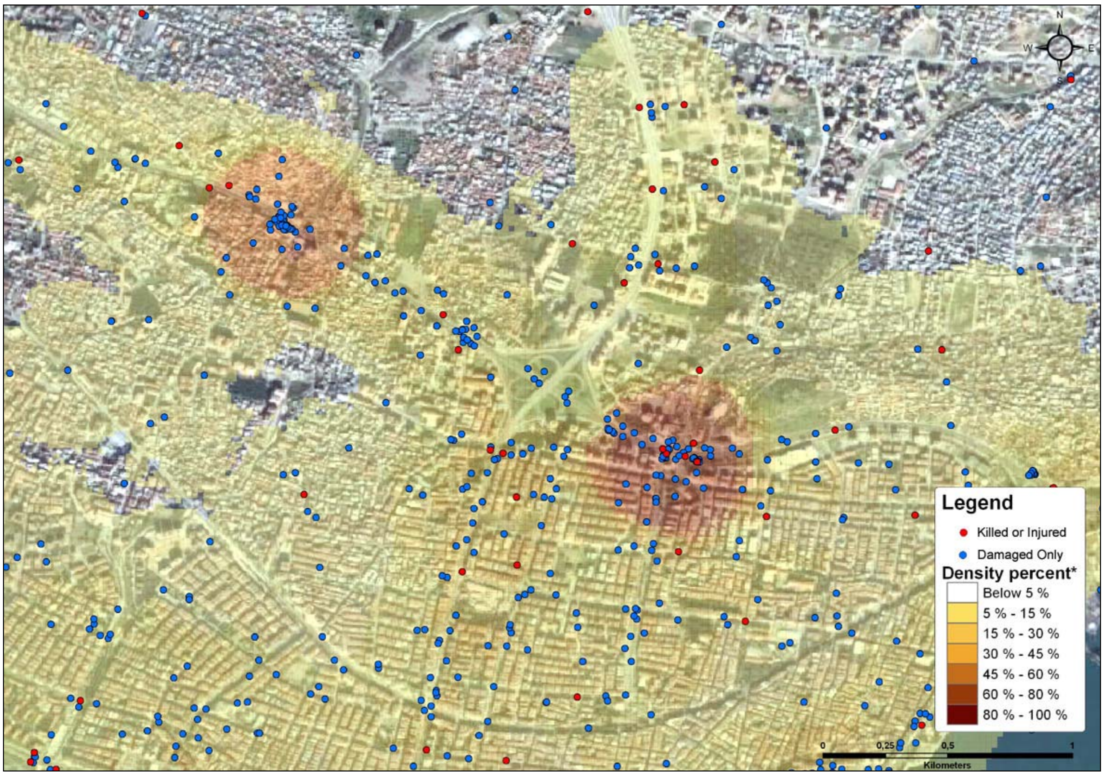

Figure A. 7. Concentration of all accidents around the clover-leaf intersection of Anadolu and Girne Streets. (North of İzmir)

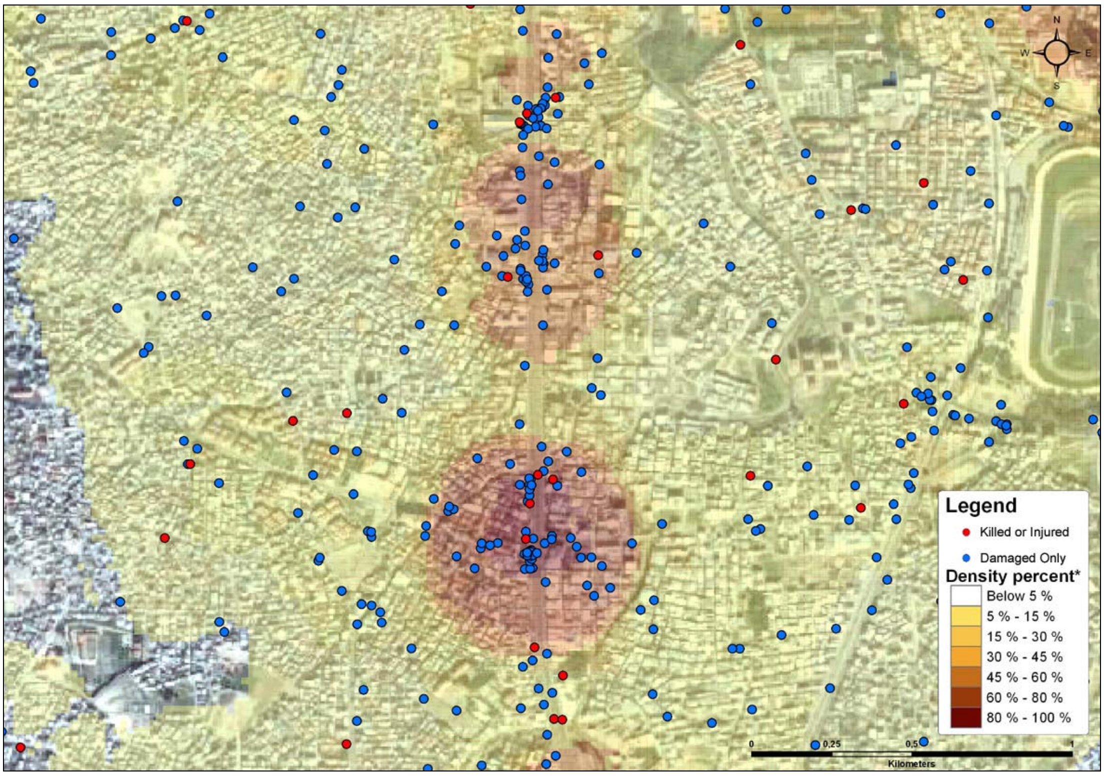

Figure A. 8. Concentration of all accidents around the intersection of Yeşillik Street and Dostluk Boulevard. (South of İzmir)

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* Point objects which drop to each raster cell

APPENDIX B

RAW TRAFFIC COUNT DATA

Table B. 1. Traffic count data of TÜBİTAK project 106Y009 (Elbir, et al., 2007)

Time Interval	AADHT (Annual Average Daily Hourly Traffic)					
	Fevzipaşa Blvd.	Eşrefpaşa Blvd.	Yeşildere St.	H. Edip Adıvar Blvd.	Altınyol St.	İnönü St.
00:00 - 01:00	3,544	6,150	16,721	8,374	17,466	7,964
01:00 - 02:00	2,750	3,554	8,074	4,249	9,417	3,990
02:00 - 03:00	2,432	3,044	4,568	2,588	5,643	2,168
03:00 - 04:00	1,815	1,902	3,412	1,502	4,375	1,251
04:00 - 05:00	1,559	1,605	3,359	1,511	3,785	1,201
05:00 - 06:00	1,224	1,673	6,114	2,177	6,392	1,762
06:00 - 07:00	2,552	3,704	16,157	5,831	15,923	5,184
07:00 - 08:00	5,767	7,778	37,439	14,447	39,011	11,243
08:00 - 09:00	9,078	11,309	43,920	18,355	46,132	13,181
09:00 - 10:00	9,661	10,444	39,887	16,827	43,477	11,911
10:00 - 11:00	10,017	10,065	38,477	16,246	39,347	11,675
11:00 - 12:00	10,823	10,568	38,929	16,486	38,413	12,441
12:00 - 13:00	12,106	11,022	39,169	17,652	39,200	12,970
13:00 - 14:00	12,874	12,479	41,176	18,769	40,651	13,670
14:00 - 15:00	12,758	13,468	43,893	20,086	42,985	14,146
15:00 - 16:00	13,970	13,947	44,036	20,314	43,428	14,165
16:00 - 17:00	12,762	13,641	44,966	20,518	44,169	14,747
17:00 - 18:00	12,008	13,900	47,066	22,540	46,257	17,388
18:00 - 19:00	11,533	13,897	48,292	24,381	50,096	16,604
19:00 - 20:00	11,867	14,175	48,134	24,456	47,436	16,650
20:00 - 21:00	9,986	12,954	40,274	19,797	39,372	15,473
21:00 - 22:00	7,176	10,324	29,731	14,973	31,855	13,218
22:00 - 23:00	6,104	8,628	25,851	13,274	27,671	11,860
23:00 - 24:00	6,547	7,889	24,534	12,386	25,675	10,734
00:00 - 24:00	**190,908**	**218,113**	**734,173**	**337,732**	**748,170**	**255,592**

Time Interval	AADHT (Annual Average Daily Hourly Traffic)						
	Şair Eşref Blvd.	Girne St.	C. Gürsel Blvd.	Yeşillik St.	Gazi Blvd.	M.K. Sahil Blvd.	M.Kemal St.
00:00 - 01:00	6,862	3,175	6,510	10,894	3,828	10,381	3,936
01:00 - 02:00	4,429	1,450	3,470	5,749	2,286	4,968	2,141
02:00 - 03:00	3,418	844	1,693	3,746	1,503	2,540	1,462
03:00 - 04:00	2,483	488	1,011	2,978	1,039	1,487	777
04:00 - 05:00	1,979	386	701	3,522	810	1,187	713
05:00 - 06:00	1,565	464	724	6,033	1,108	1,608	818

(cont. on next page)

Table B.1. (cont.) Traffic count data of TÜBİTAK project 106Y009 (Elbir, et al., 2007)

06:00 - 07:00	3,279	1,731	2,187	14,546	3,000	4,349	2,366
07:00 - 08:00	8,385	6,330	10,568	27,581	9,372	17,953	7,537
08:00 - 09:00	14,501	8,789	17,110	29,679	13,943	22,690	9,950
09:00 - 10:00	14,829	7,886	16,480	27,572	16,138	21,243	9,442
10:00 - 11:00	13,077	7,368	14,966	29,511	16,234	19,967	9,820
11:00 - 12:00	14,479	8,163	14,854	29,926	16,038	19,738	10,422
12:00 - 13:00	15,099	8,310	15,304	30,185	15,950	20,377	10,848
13:00 - 14:00	16,126	8,998	17,078	30,729	16,716	21,728	12,098
14:00 - 15:00	17,029	9,634	17,915	32,557	16,865	22,881	12,840
15:00 - 16:00	17,531	9,797	18,722	31,812	16,994	23,231	12,702
16:00 - 17:00	17,421	10,523	19,636	30,580	18,509	24,746	12,412
17:00 - 18:00	16,706	11,655	20,698	32,998	18,414	28,408	12,515
18:00 - 19:00	16,069	12,799	22,579	33,554	15,681	31,270	13,164
19:00 - 20:00	15,176	11,845	21,231	32,078	14,480	31,038	13,116
20:00 - 21:00	12,302	9,320	16,387	27,935	11,495	26,657	11,528
21:00 - 22:00	9,900	7,512	11,940	20,895	8,184	18,435	8,555
22:00 - 23:00	9,327	6,801	10,202	16,499	6,997	15,646	7,122
23:00 - 24:00	8,936	5,116	8,989	14,729	5,913	14,414	6,133
00:00 - 24:00	**260,903**	**159,379**	**290,948**	**526,283**	**251,493**	**406,936**	**192,409**

Time Interval	*AADHT (Annual Average Daily Hourly Traffic)*					
	Talatpaşa Blvd.	**Anadolu St.**	**Kamil Tunca Blvd.**	**Mehmet Akif St.**	**Mithatpaşa St.**	**Ankara St.**
00:00 - 01:00	5,646	10,190	3,551	12,962	3,700	14,550
01:00 - 02:00	3,697	5,816	2,149	6,552	2,025	8,679
02:00 - 03:00	2,434	3,579	1,294	4,176	1,133	5,703
03:00 - 04:00	1,724	2,775	773	2,523	684	4,475
04:00 - 05:00	1,319	2,878	705	2,659	512	4,056
05:00 - 06:00	891	5,110	1,265	3,655	628	6,664
06:00 - 07:00	1,352	14,556	3,714	8,843	1,816	14,882
07:00 - 08:00	5,447	29,099	8,178	21,097	6,277	40,263
08:00 - 09:00	10,239	28,881	9,661	25,657	8,125	54,157
09:00 - 10:00	10,534	27,470	8,709	21,786	7,156	50,587
10:00 - 11:00	9,895	27,798	9,094	21,228	7,270	48,613
11:00 - 12:00	10,614	28,213	9,551	21,572	7,638	48,168
12:00 - 13:00	11,048	28,793	9,492	22,855	8,813	46,950
13:00 - 14:00	11,824	28,429	9,393	23,943	9,539	48,951
14:00 - 15:00	11,844	29,707	10,009	24,861	9,993	53,538
15:00 - 16:00	12,023	29,848	9,990	25,578	9,995	54,762
16:00 - 17:00	12,032	28,892	9,701	25,378	10,085	55,606
17:00 - 18:00	11,732	29,084	9,515	26,754	10,535	52,926
18:00 - 19:00	11,269	29,904	9,827	26,861	11,319	53,783
19:00 - 20:00	9,867	29,256	9,108	27,330	11,444	46,981
20:00 - 21:00	9,299	25,556	7,756	25,643	10,043	36,851
21:00 - 22:00	7,835	19,512	6,155	21,528	7,390	29,425
22:00 - 23:00	7,649	17,079	5,516	19,653	6,113	24,412
23:00 - 24:00	7,311	14,576	5,403	19,356	5,197	21,659
00:00 - 24:00	**187,520**	**496,997**	**160,503**	**442,445**	**157,424**	**826,636**

APPENDIX C

CALIBRATION AND TESTING DATA SETS

Table C. 1. Calibration dataset of the Fuzzy Model

Data point	*AAHTL*	*AHRT*	*RW*	*PM*	*BS*	*SJ*	*MA*	*AAA*
ALT01	415.85	14.03	21.50	1.00	0.78	0.00	4.66	5.63
ALT03	134.36	12.67	21.50	1.00	0.78	0.00	4.66	2.14
ALT05	90.12	11.57	21.50	1.00	0.78	0.00	4.66	2.33
ALT07	379.11	15.80	21.50	1.00	0.78	0.00	4.66	1.55
ALT09	1098.37	11.15	21.50	1.00	0.78	0.00	4.66	6.41
ALT11	936.83	11.25	21.50	1.00	0.78	0.00	4.66	5.43
ALT13	933.32	12.50	21.50	1.00	0.78	0.00	4.66	4.27
ALT15	1023.44	13.92	21.50	1.00	0.78	0.00	4.66	6.21
ALT17	1051.63	12.28	21.50	1.00	0.78	0.00	4.66	6.21
ALT19	1192.75	14.02	21.50	1.00	0.78	0.00	4.66	8.15
ALT21	937.43	12.13	21.50	1.00	0.78	0.00	4.66	6.99
ALT23	658.83	8.92	21.50	1.00	0.78	0.00	4.66	7.57
AND02	138.48	14.15	28.00	0.72	0.00	1.09	15.16	1.45
AND04	66.07	10.25	28.00	0.72	0.00	1.09	15.16	0.79
AND06	121.67	13.87	28.00	0.72	0.00	1.09	15.16	0.24
AND08	692.83	15.97	28.00	0.72	0.00	1.09	15.16	5.82
AND10	654.04	8.25	28.00	0.72	0.00	1.09	15.16	8.55
AND12	671.74	13.57	28.00	0.72	0.00	1.09	15.16	9.52
AND14	676.88	11.80	28.00	0.72	0.00	1.09	15.16	10.25
AND16	710.65	14.08	28.00	0.72	0.00	1.09	15.16	10.85
AND18	692.48	10.80	28.00	0.72	0.00	1.09	15.16	11.21
AND20	696.57	13.37	28.00	0.72	0.00	1.09	15.16	9.76
AND22	464.56	10.50	28.00	0.72	0.00	1.09	15.16	4.73
AND24	347.04	9.92	28.00	0.72	0.00	1.09	15.16	2.91
ANK01	346.42	14.03	24.00	1.00	0.00	0.00	3.02	2.92
ANK03	135.79	12.67	24.00	1.00	0.00	0.00	3.02	1.94
ANK05	96.57	11.57	24.00	1.00	0.00	0.00	3.02	0.22
ANK07	354.32	15.80	24.00	1.00	0.00	0.00	3.02	0.65
ANK09	1289.44	11.15	24.00	1.00	0.00	0.00	3.02	17.17
ANK11	1157.45	11.25	24.00	1.00	0.00	0.00	3.02	15.01
ANK13	1117.85	12.50	24.00	1.00	0.00	0.00	3.02	13.50
ANK15	1274.71	13.92	24.00	1.00	0.00	0.00	3.02	14.79
ANK17	1323.94	12.28	24.00	1.00	0.00	0.00	3.02	19.76
ANK19	1280.54	14.02	24.00	1.00	0.00	0.00	3.02	18.36
ANK21	877.40	12.13	24.00	1.00	0.00	0.00	3.02	8.53
ANK23	581.24	8.92	24.00	1.00	0.00	0.00	3.02	5.72
CEM02	82.61	14.15	22.50	0.74	3.94	2.84	14.22	1.97
CEM04	24.06	10.25	22.50	0.74	3.94	2.84	14.22	0.22
CEM06	17.23	13.87	22.50	0.74	3.94	2.84	14.22	0.00

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Table C. 1. (cont.) Calibration dataset of the Fuzzy Model

CEM08	251.62	15.97	22.50	0.74	3.94	2.84	14.22	3.72
CEM10	392.37	8.25	22.50	0.74	3.94	2.84	14.22	5.47
CEM12	353.67	13.57	22.50	0.74	3.94	2.84	14.22	5.03
CEM14	406.61	11.80	22.50	0.74	3.94	2.84	14.22	8.75
CEM16	445.76	14.08	22.50	0.74	3.94	2.84	14.22	10.50
CEM18	492.81	10.80	22.50	0.74	3.94	2.84	14.22	10.50
CEM20	505.49	13.37	22.50	0.74	3.94	2.84	14.22	10.06
CEM22	284.27	10.50	22.50	0.74	3.94	2.84	14.22	4.81
CEM24	214.02	9.92	22.50	0.74	3.94	2.84	14.22	3.94
ESR01	219.63	14.03	17.00	0.40	3.79	3.32	22.75	6.64
ESR03	108.71	12.67	17.00	0.40	3.79	3.32	22.75	1.42
ESR05	57.30	11.57	17.00	0.40	3.79	3.32	22.75	0.47
ESR07	132.29	15.80	17.00	0.40	3.79	3.32	22.75	0.47
ESR09	403.88	11.15	17.00	0.40	3.79	3.32	22.75	11.37
ESR11	359.46	11.25	17.00	0.40	3.79	3.32	22.75	7.58
ESR13	393.64	12.50	17.00	0.40	3.79	3.32	22.75	9.95
ESR15	480.98	13.92	17.00	0.40	3.79	3.32	22.75	9.95
ESR17	487.16	12.28	17.00	0.40	3.79	3.32	22.75	19.43
ESR19	496.32	14.02	17.00	0.40	3.79	3.32	22.75	18.48
ESR21	462.63	12.13	17.00	0.40	3.79	3.32	22.75	8.53
ESR23	308.14	8.92	17.00	0.40	3.79	3.32	22.75	4.74
FEV02	98.21	14.15	17.50	0.63	5.85	8.77	19.49	5.85
FEV04	64.80	10.25	17.50	0.63	5.85	8.77	19.49	2.92
FEV06	43.70	13.87	17.50	0.63	5.85	8.77	19.49	0.00
FEV08	205.95	15.97	17.50	0.63	5.85	8.77	19.49	4.87
FEV10	345.04	8.25	17.50	0.63	5.85	8.77	19.49	19.49
FEV12	386.54	13.57	17.50	0.63	5.85	8.77	19.49	24.37
FEV14	459.77	16.55	17.50	0.63	5.85	8.77	19.49	12.67
FEV16	498.91	14.08	17.50	0.63	5.85	8.77	19.49	27.29
FEV18	428.86	10.80	17.50	0.63	5.85	8.77	19.49	22.42
FEV20	423.82	13.37	17.50	0.63	5.85	8.77	19.49	23.39
FEV22	256.27	10.50	17.50	0.63	5.85	8.77	19.49	4.87
FEV24	233.82	9.92	17.50	0.63	5.85	8.77	19.49	1.95
GAZ01	109.37	14.03	18.00	0.90	2.32	11.59	26.65	6.95
GAZ03	42.93	12.67	18.00	0.90	2.32	11.59	26.65	0.00
GAZ05	23.14	11.57	18.00	0.90	2.32	11.59	26.65	0.00
GAZ07	85.71	15.80	18.00	0.90	2.32	11.59	26.65	0.00
GAZ09	398.36	11.15	18.00	0.90	2.32	11.59	26.65	16.22
GAZ11	463.83	11.25	18.00	0.90	2.32	11.59	26.65	23.17
GAZ13	455.71	12.50	18.00	0.90	2.32	11.59	26.65	20.86
GAZ15	481.86	13.92	18.00	0.90	2.32	11.59	26.65	15.06
GAZ17	528.81	12.28	18.00	0.90	2.32	11.59	26.65	19.70
GAZ19	448.01	14.02	18.00	0.90	2.32	11.59	26.65	16.22
GAZ21	328.43	12.13	18.00	0.90	2.32	11.59	26.65	4.63
GAZ23	199.91	8.92	18.00	0.90	2.32	11.59	26.65	8.11
GIR02	51.77	14.15	18.50	0.96	6.11	4.23	22.09	0.94
GIR04	17.43	10.25	18.50	0.96	6.11	4.23	22.09	1.41

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Table C. 1. (cont.) Calibration dataset of the Fuzzy Model

GIR06		16.55	13.87	18.50	0.96	6.11	4.23	22.09		0.94
GIR08		226.05	15.97	18.50	0.96	6.11	4.23	22.09		4.23
GIR10		281.63	8.25	18.50	0.96	6.11	4.23	22.09		14.57
GIR12		291.54	13.57	18.50	0.96	6.11	4.23	22.09		15.51
GIR14		321.34	11.80	18.50	0.96	6.11	4.23	22.09		23.97
GIR16		349.89	14.08	18.50	0.96	6.11	4.23	22.09		20.21
GIR18		416.23	10.80	18.50	0.96	6.11	4.23	22.09		14.57
GIR20		423.02	13.37	18.50	0.96	6.11	4.23	22.09		15.51
GIR22		268.27	10.50	18.50	0.96	6.11	4.23	22.09		10.34
GIR24		182.70	9.92	18.50	0.96	6.11	4.23	22.09		2.82
HEA01		199.38	14.03	20.00	0.98	4.21	2.63	21.06		4.74
HEA03		61.61	12.67	20.00	0.98	4.21	2.63	21.06		1.05
HEA05		35.96	11.57	20.00	0.98	4.21	2.63	21.06		0.53
HEA07		138.82	15.80	20.00	0.98	4.21	2.63	21.06		1.05
HEA09		437.01	11.15	20.00	0.98	4.21	2.63	21.06		13.16
HEA11		386.81	11.25	20.00	0.98	4.21	2.63	21.06		6.85
HEA13		420.27	12.50	20.00	0.98	4.21	2.63	21.06		8.43
HEA15		478.23	13.92	20.00	0.98	4.21	2.63	21.06		15.27
HEA17		488.52	12.28	20.00	0.98	4.21	2.63	21.06		10.53
HEA19		580.49	14.02	20.00	0.98	4.21	2.63	21.06		8.43
HEA21		471.36	12.13	20.00	0.98	4.21	2.63	21.06		14.74
HEA23		316.04	8.92	20.00	0.98	4.21	2.63	21.06		4.74
INO02		142.50	14.15	16.50	0.56	4.67	2.83	15.84		4.00
INO04		44.68	10.25	16.50	0.56	4.67	2.83	15.84		1.33
INO06		62.91	13.87	16.50	0.56	4.67	2.83	15.84		0.67
INO08		401.52	15.97	16.50	0.56	4.67	2.83	15.84		5.00
INO10		425.38	8.25	16.50	0.56	4.67	2.83	15.84		12.00
INO12		444.32	13.57	16.50	0.56	4.67	2.83	15.84		10.84
INO14		488.21	11.80	16.50	0.56	4.67	2.83	15.84		15.84
INO16		505.89	14.08	16.50	0.56	4.67	2.83	15.84		17.17
INO18		620.98	10.80	16.50	0.56	4.67	2.83	15.84		14.17
INO20		594.64	13.37	16.50	0.56	4.67	2.83	15.84		13.17
INO22		472.07	10.50	16.50	0.56	4.67	2.83	15.84		9.84
INO24		383.36	9.92	16.50	0.56	4.67	2.83	15.84		5.67
KAM01		126.80	14.03	13.00	0.97	3.19	2.48	28.69		2.83
KAM03		46.21	12.67	13.00	0.97	3.19	2.48	28.69		0.35
KAM05		25.16	11.57	13.00	0.97	3.19	2.48	28.69		1.06
KAM07		132.64	15.80	13.00	0.97	3.19	2.48	28.69		1.77
KAM09		345.02	11.15	13.00	0.97	3.19	2.48	28.69		5.31
KAM11		324.77	11.25	13.00	0.97	3.19	2.48	28.69		5.31
KAM13		339.00	12.50	13.00	0.97	3.19	2.48	28.69		6.02
KAM15		357.45	13.92	13.00	0.97	3.19	2.48	28.69		7.79
KAM17		346.45	12.28	13.00	0.97	3.19	2.48	28.69		7.44
KAM19		350.95	14.02	13.00	0.97	3.19	2.48	28.69		9.21
KAM21		277.00	12.13	13.00	0.97	3.19	2.48	28.69		5.67
KAM23		196.98	8.92	13.00	0.97	3.19	2.48	28.69		2.13
MAC02		155.99	14.15	18.00	0.47	3.49	4.36	20.07		3.49

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Table C. 1. (cont.) Calibration dataset of the Fuzzy Model

MAC04	60.06	10.25	18.00	0.47	3.49	4.36	20.07	0.00
MAC06	87.02	13.87	18.00	0.47	3.49	4.36	20.07	0.00
MAC08	502.30	15.97	18.00	0.47	3.49	4.36	20.07	2.62
MAC10	518.71	8.25	18.00	0.47	3.49	4.36	20.07	17.45
MAC12	513.61	13.57	18.00	0.47	3.49	4.36	20.07	20.07
MAC14	570.07	11.80	18.00	0.47	3.49	4.36	20.07	19.20
MAC16	609.00	14.08	18.00	0.47	3.49	4.36	20.07	23.56
MAC18	637.00	10.80	18.00	0.47	3.49	4.36	20.07	21.82
MAC20	650.71	13.37	18.00	0.47	3.49	4.36	20.07	26.18
MAC22	512.57	10.50	18.00	0.47	3.49	4.36	20.07	10.47
MAC24	460.86	9.92	18.00	0.47	3.49	4.36	20.07	7.85
MIT01	105.71	14.03	17.00	0.19	4.09	3.06	13.62	2.04
MIT03	32.36	12.67	17.00	0.19	4.09	3.06	13.62	0.85
MIT05	14.61	11.57	17.00	0.19	4.09	3.06	13.62	0.17
MIT07	51.89	15.80	17.00	0.19	4.09	3.06	13.62	0.68
MIT09	232.13	11.15	17.00	0.19	4.09	3.06	13.62	7.66
MIT11	207.70	11.25	17.00	0.19	4.09	3.06	13.62	7.66
MIT13	251.79	12.50	17.00	0.19	4.09	3.06	13.62	7.32
MIT15	285.51	13.92	17.00	0.19	4.09	3.06	13.62	9.19
MIT17	288.13	12.28	17.00	0.19	4.09	3.06	13.62	11.57
MIT19	323.40	14.02	17.00	0.19	4.09	3.06	13.62	9.36
MIT21	286.93	12.13	17.00	0.19	4.09	3.06	13.62	7.32
MIT23	174.66	8.92	17.00	0.19	4.09	3.06	13.62	2.72
MKC02	76.46	14.15	13.50	0.93	3.92	4.79	19.58	2.61
MKC04	27.73	10.25	13.50	0.93	3.92	4.79	19.58	0.00
MKC06	29.20	13.87	13.50	0.93	3.92	4.79	19.58	1.31
MKC08	269.18	15.97	13.50	0.93	3.92	4.79	19.58	1.74
MKC10	337.20	8.25	13.50	0.93	3.92	4.79	19.58	5.22
MKC12	372.20	13.57	13.50	0.93	3.92	4.79	19.58	10.01
MKC14	432.07	11.80	13.50	0.93	3.92	4.79	19.58	12.18
MKC16	453.63	14.08	13.50	0.93	3.92	4.79	19.58	9.57
MKC18	446.96	10.80	13.50	0.93	3.92	4.79	19.58	14.36
MKC20	468.43	13.37	13.50	0.93	3.92	4.79	19.58	10.01
MKC22	305.52	10.50	13.50	0.93	3.92	4.79	19.58	5.66
MKC24	219.02	9.92	13.50	0.93	3.92	4.79	19.58	3.92
MKS01	247.17	14.03	24.00	0.97	2.91	2.15	3.37	2.76
MKS03	60.46	12.67	24.00	0.97	2.91	2.15	3.37	2.15
MKS05	28.25	11.57	24.00	0.97	2.91	2.15	3.37	0.92
MKS07	103.55	15.80	24.00	0.97	2.91	2.15	3.37	1.53
MKS09	540.23	11.15	24.00	0.97	2.91	2.15	3.37	9.51
MKS11	475.40	11.25	24.00	0.97	2.91	2.15	3.37	6.29
MKS13	485.17	12.50	24.00	0.97	2.91	2.15	3.37	5.37
MKS15	544.79	13.92	24.00	0.97	2.91	2.15	3.37	7.97
MKS17	589.18	12.28	24.00	0.97	2.91	2.15	3.37	9.35
MKS19	744.51	14.02	24.00	0.97	2.91	2.15	3.37	9.81
MKS21	634.69	12.13	24.00	0.97	2.91	2.15	3.37	6.44
MKS23	372.51	8.92	24.00	0.97	2.91	2.15	3.37	5.37

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Table C. 1. (cont.) Calibration dataset of the Fuzzy Model

SAI02		158.18	14.15	13.00	0.85	7.36	4.29	18.40		1.84
SAI04		88.68	10.25	13.00	0.85	7.36	4.29	18.40		3.07
SAI06		55.89	13.87	13.00	0.85	7.36	4.29	18.40		0.00
SAI08		299.46	15.97	13.00	0.85	7.36	4.29	18.40		1.23
SAI10		529.61	8.25	13.00	0.85	7.36	4.29	18.40		12.88
SAI12		517.09	13.57	13.00	0.85	7.36	4.29	18.40		16.56
SAI14		575.91	11.80	13.00	0.85	7.36	4.29	18.40		20.25
SAI16		626.11	14.08	13.00	0.85	7.36	4.29	18.40		17.79
SAI18		596.63	10.80	13.00	0.85	7.36	4.29	18.40		23.93
SAI20		542.00	13.37	13.00	0.85	7.36	4.29	18.40		17.79
SAI22		353.57	10.50	13.00	0.85	7.36	4.29	18.40		5.52
SAI24		319.13	9.92	13.00	0.85	7.36	4.29	18.40		4.29
TAL01		201.64	14.03	13.50	0.97	4.60	5.75	19.56		4.60
TAL03		86.93	12.67	13.50	0.97	4.60	5.75	19.56		2.30
TAL05		47.11	11.57	13.50	0.97	4.60	5.75	19.56		0.00
TAL07		48.29	15.80	13.50	0.97	4.60	5.75	19.56		0.00
TAL09		365.68	11.15	13.50	0.97	4.60	5.75	19.56		2.30
TAL11		353.39	11.25	13.50	0.97	4.60	5.75	19.56		12.66
TAL13		394.55	12.50	13.50	0.97	4.60	5.75	19.56		6.90
TAL15		422.98	13.92	13.50	0.97	4.60	5.75	19.56		10.36
TAL17		429.71	12.28	13.50	0.97	4.60	5.75	19.56		26.47
TAL19		402.46	14.02	13.50	0.97	4.60	5.75	19.56		23.01
TAL21		332.09	12.13	13.50	0.97	4.60	5.75	19.56		4.60
TAL23		273.16	8.92	13.50	0.97	4.60	5.75	19.56		5.75
YED02		192.23	14.15	22.00	1.00	0.91	0.46	4.57		0.23
YED04		81.23	10.25	22.00	1.00	0.91	0.46	4.57		0.69
YED06		145.56	13.87	22.00	1.00	0.91	0.46	4.57		0.46
YED08		891.40	15.97	22.00	1.00	0.91	0.46	4.57		5.71
YED10		949.69	8.25	22.00	1.00	0.91	0.46	4.57		11.89
YED12		926.87	13.57	22.00	1.00	0.91	0.46	4.57		5.26
YED14		980.38	11.80	22.00	1.00	0.91	0.46	4.57		4.80
YED16		1048.46	14.08	22.00	1.00	0.91	0.46	4.57		6.40
YED18		1120.62	10.80	22.00	1.00	0.91	0.46	4.57		8.69
YED20		1146.05	13.37	22.00	1.00	0.91	0.46	4.57		10.51
YED22		707.87	10.50	22.00	1.00	0.91	0.46	4.57		4.80
YED24		584.13	9.92	22.00	1.00	0.91	0.46	4.57		4.11
YEL01		259.37	14.03	22.50	0.97	1.95	1.95	14.51		6.14
YEL03		89.19	12.67	22.50	0.97	1.95	1.95	14.51		3.07
YEL05		83.86	11.57	22.50	0.97	1.95	1.95	14.51		1.67
YEL07		346.32	15.80	22.50	0.97	1.95	1.95	14.51		3.35
YEL09		706.63	11.15	22.50	0.97	1.95	1.95	14.51		25.12
YEL11		702.64	11.25	22.50	0.97	1.95	1.95	14.51		20.93
YEL13		718.69	12.50	22.50	0.97	1.95	1.95	14.51		22.61
YEL15		775.17	13.92	22.50	0.97	1.95	1.95	14.51		27.07
YEL17		728.08	12.28	22.50	0.97	1.95	1.95	14.51		32.65
YEL19		798.90	14.02	22.50	0.97	1.95	1.95	14.51		25.40
YEL21		665.12	12.13	22.50	0.97	1.95	1.95	14.51		17.02
YEL23		392.82	8.92	22.50	0.97	1.95	1.95	14.51		11.72

Table C. 2. Testing dataset of the Fuzzy Model

Data point	*AAHTL*	*AHRT*	*RW*	*PM*	*BS*	*SJ*	*MA*	*AAA*
ALT02	224.20	14.15	21.50	1.00	0.78	0.00	4.66	3.69
ALT04	104.17	10.25	21.50	1.00	0.78	0.00	4.66	1.55
ALT06	152.18	13.87	21.50	1.00	0.78	0.00	4.66	1.16
ALT08	928.82	15.97	21.50	1.00	0.78	0.00	4.66	3.49
ALT10	1035.17	8.25	21.50	1.00	0.78	0.00	4.66	8.93
ALT12	914.58	13.57	21.50	1.00	0.78	0.00	4.66	6.79
ALT14	967.88	11.80	21.50	1.00	0.78	0.00	4.66	5.82
ALT16	1033.99	14.08	21.50	1.00	0.78	0.00	4.66	10.09
ALT18	1101.36	10.80	21.50	1.00	0.78	0.00	4.66	7.57
ALT20	1129.43	13.37	21.50	1.00	0.78	0.00	4.66	7.96
ALT22	758.44	10.50	21.50	1.00	0.78	0.00	4.66	2.33
ALT24	611.31	9.92	21.50	1.00	0.78	0.00	4.66	4.46
AND01	242.62	14.03	28.00	0.72	0.00	1.09	15.16	2.36
AND03	85.21	12.67	28.00	0.72	0.00	1.09	15.16	0.67
AND05	68.52	11.57	28.00	0.72	0.00	1.09	15.16	0.30
AND07	346.56	15.80	28.00	0.72	0.00	1.09	15.16	0.97
AND09	687.64	11.15	28.00	0.72	0.00	1.09	15.16	11.82
AND11	661.86	11.25	28.00	0.72	0.00	1.09	15.16	9.09
AND13	685.54	12.50	28.00	0.72	0.00	1.09	15.16	8.43
AND15	707.31	13.92	28.00	0.72	0.00	1.09	15.16	10.91
AND17	687.90	12.28	28.00	0.72	0.00	1.09	15.16	12.25
AND19	711.99	14.02	28.00	0.72	0.00	1.09	15.16	10.25
AND21	608.46	12.13	28.00	0.72	0.00	1.09	15.16	6.67
AND23	406.63	8.92	28.00	0.72	0.00	1.09	15.16	3.39
ANK02	206.64	14.15	24.00	1.00	0.00	0.00	3.02	2.70
ANK04	106.54	10.25	24.00	1.00	0.00	0.00	3.02	0.86
ANK06	158.67	13.87	24.00	1.00	0.00	0.00	3.02	1.30
ANK08	958.64	15.97	24.00	1.00	0.00	0.00	3.02	4.97
ANK10	1204.45	8.25	24.00	1.00	0.00	0.00	3.02	16.31
ANK12	1146.85	13.57	24.00	1.00	0.00	0.00	3.02	12.63
ANK14	1165.50	11.80	24.00	1.00	0.00	0.00	3.02	13.71
ANK16	1303.85	14.08	24.00	1.00	0.00	0.00	3.02	17.39
ANK18	1260.13	10.80	24.00	1.00	0.00	0.00	3.02	23.54
ANK20	1118.60	13.37	24.00	1.00	0.00	0.00	3.02	13.28
ANK22	700.60	10.50	24.00	1.00	0.00	0.00	3.02	5.51
ANK24	515.69	9.92	24.00	1.00	0.00	0.00	3.02	2.59
CEM01	154.99	14.03	22.50	0.74	3.94	2.84	14.22	2.84
CEM03	40.30	12.67	22.50	0.74	3.94	2.84	14.22	1.31
CEM05	16.68	11.57	22.50	0.74	3.94	2.84	14.22	0.00
CEM07	52.06	15.80	22.50	0.74	3.94	2.84	14.22	0.44
CEM09	407.38	11.15	22.50	0.74	3.94	2.84	14.22	10.06
CEM11	356.32	11.25	22.50	0.74	3.94	2.84	14.22	7.66
CEM13	364.38	12.50	22.50	0.74	3.94	2.84	14.22	7.00
CEM15	426.55	13.92	22.50	0.74	3.94	2.84	14.22	10.50

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Table C. 2. (cont.) Testing dataset of the Fuzzy Model

CEM17		467.52	12.28	22.50	0.74	3.94	2.84	14.22	13.56
CEM19		537.60	14.02	22.50	0.74	3.94	2.84	14.22	8.97
CEM21		390.15	12.13	22.50	0.74	3.94	2.84	14.22	5.03
CEM23		242.89	8.92	22.50	0.74	3.94	2.84	14.22	4.16
ESR02		126.91	14.15	17.00	0.40	3.79	3.32	22.75	1.42
ESR04		67.91	10.25	17.00	0.40	3.79	3.32	22.75	0.95
ESR06		59.73	13.87	17.00	0.40	3.79	3.32	22.75	1.90
ESR08		277.77	15.97	17.00	0.40	3.79	3.32	22.75	4.74
ESR10		372.98	8.25	17.00	0.40	3.79	3.32	22.75	10.90
ESR12		377.41	13.57	17.00	0.40	3.79	3.32	22.75	8.53
ESR14		445.66	11.80	17.00	0.40	3.79	3.32	22.75	12.80
ESR16		498.09	14.08	17.00	0.40	3.79	3.32	22.75	12.32
ESR18		496.43	10.80	17.00	0.40	3.79	3.32	22.75	16.59
ESR20		506.25	13.37	17.00	0.40	3.79	3.32	22.75	15.64
ESR22		368.71	10.50	17.00	0.40	3.79	3.32	22.75	6.64
ESR24		281.75	9.92	17.00	0.40	3.79	3.32	22.75	4.27
FEV01		126.55	14.03	17.50	0.63	5.85	8.77	19.49	4.87
FEV03		86.86	12.67	17.50	0.63	5.85	8.77	19.49	2.92
FEV05		55.66	11.57	17.50	0.63	5.85	8.77	19.49	3.90
FEV07		91.14	15.80	17.50	0.63	5.85	8.77	19.49	0.97
FEV09		324.21	11.15	17.50	0.63	5.85	8.77	19.49	11.70
FEV11		357.75	11.25	17.50	0.63	5.85	8.77	19.49	13.65
FEV13		432.36	12.50	17.50	0.63	5.85	8.77	19.49	20.47
FEV15		455.64	13.92	17.50	0.63	5.85	8.77	19.49	23.39
FEV17		455.77	12.28	17.50	0.63	5.85	8.77	19.49	21.44
FEV19		411.89	14.02	17.50	0.63	5.85	8.77	19.49	25.34
FEV21		356.64	12.13	17.50	0.63	5.85	8.77	19.49	12.67
FEV23		217.98	8.92	17.50	0.63	5.85	8.77	19.49	7.80
GAZ02		65.30	14.15	18.00	0.90	2.32	11.59	26.65	1.16
GAZ04		29.67	10.25	18.00	0.90	2.32	11.59	26.65	0.00
GAZ06		31.66	13.87	18.00	0.90	2.32	11.59	26.65	1.16
GAZ08		267.76	15.97	18.00	0.90	2.32	11.59	26.65	3.48
GAZ10		461.09	8.25	18.00	0.90	2.32	11.59	26.65	16.22
GAZ12		458.23	13.57	18.00	0.90	2.32	11.59	26.65	18.54
GAZ14		477.59	11.80	18.00	0.90	2.32	11.59	26.65	27.81
GAZ16		485.54	14.08	18.00	0.90	2.32	11.59	26.65	15.06
GAZ18		526.10	10.80	18.00	0.90	2.32	11.59	26.65	24.33
GAZ20		413.71	13.37	18.00	0.90	2.32	11.59	26.65	16.22
GAZ22		233.83	10.50	18.00	0.90	2.32	11.59	26.65	9.27
GAZ24		168.94	9.92	18.00	0.90	2.32	11.59	26.65	4.63
GIR01		113.39	14.03	18.50	0.96	6.11	4.23	22.09	5.17
GIR03		30.13	12.67	18.50	0.96	6.11	4.23	22.09	1.41
GIR05		13.79	11.57	18.50	0.96	6.11	4.23	22.09	0.00
GIR07		61.82	15.80	18.50	0.96	6.11	4.23	22.09	1.88
GIR09		313.89	11.15	18.50	0.96	6.11	4.23	22.09	15.04
GIR11		263.14	11.25	18.50	0.96	6.11	4.23	22.09	9.40
GIR13		296.79	12.50	18.50	0.96	6.11	4.23	22.09	15.98

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Table C. 2. (cont.) Testing dataset of the Fuzzy Model

GIR15	344.07	13.92	18.50	0.96	6.11	4.23	22.09	22.09
GIR17	375.80	12.28	18.50	0.96	6.11	4.23	22.09	22.09
GIR19	457.11	14.02	18.50	0.96	6.11	4.23	22.09	22.09
GIR21	332.86	12.13	18.50	0.96	6.11	4.23	22.09	11.28
GIR23	242.89	8.92	18.50	0.96	6.11	4.23	22.09	5.64
HEA02	101.17	14.15	20.00	0.98	4.21	2.63	21.06	2.11
HEA04	35.76	10.25	20.00	0.98	4.21	2.63	21.06	0.53
HEA06	51.83	13.87	20.00	0.98	4.21	2.63	21.06	0.53
HEA08	343.96	15.97	20.00	0.98	4.21	2.63	21.06	2.63
HEA10	400.63	8.25	20.00	0.98	4.21	2.63	21.06	10.53
HEA12	392.51	13.57	20.00	0.98	4.21	2.63	21.06	8.43
HEA14	446.87	11.80	20.00	0.98	4.21	2.63	21.06	12.11
HEA16	483.67	14.08	20.00	0.98	4.21	2.63	21.06	7.37
HEA18	536.65	10.80	20.00	0.98	4.21	2.63	21.06	14.22
HEA20	582.29	13.37	20.00	0.98	4.21	2.63	21.06	14.74
HEA22	356.49	10.50	20.00	0.98	4.21	2.63	21.06	10.53
HEA24	294.89	9.92	20.00	0.98	4.21	2.63	21.06	5.27
INO01	284.41	14.03	16.50	0.56	4.67	2.83	15.84	4.00
INO03	77.41	12.67	16.50	0.56	4.67	2.83	15.84	1.67
INO05	42.89	11.57	16.50	0.56	4.67	2.83	15.84	1.00
INO07	185.14	15.80	16.50	0.56	4.67	2.83	15.84	0.83
INO09	470.75	11.15	16.50	0.56	4.67	2.83	15.84	13.00
INO11	416.95	11.25	16.50	0.56	4.67	2.83	15.84	9.34
INO13	463.21	12.50	16.50	0.56	4.67	2.83	15.84	11.67
INO15	505.21	13.92	16.50	0.56	4.67	2.83	15.84	13.17
INO17	526.68	12.28	16.50	0.56	4.67	2.83	15.84	13.67
INO19	593.00	14.02	16.50	0.56	4.67	2.83	15.84	13.84
INO21	552.59	12.13	16.50	0.56	4.67	2.83	15.84	10.84
INO23	423.55	8.92	16.50	0.56	4.67	2.83	15.84	7.84
KAM02	76.75	14.15	13.00	0.97	3.19	2.48	28.69	2.13
KAM04	27.61	10.25	13.00	0.97	3.19	2.48	28.69	0.00
KAM06	45.18	13.87	13.00	0.97	3.19	2.48	28.69	0.71
KAM08	292.07	15.97	13.00	0.97	3.19	2.48	28.69	4.61
KAM10	311.02	8.25	13.00	0.97	3.19	2.48	28.69	5.31
KAM12	341.09	13.57	13.00	0.97	3.19	2.48	28.69	11.34
KAM14	335.46	11.80	13.00	0.97	3.19	2.48	28.69	6.02
KAM16	356.77	14.08	13.00	0.97	3.19	2.48	28.69	11.34
KAM18	339.80	10.80	13.00	0.97	3.19	2.48	28.69	8.86
KAM20	325.29	13.37	13.00	0.97	3.19	2.48	28.69	6.02
KAM22	219.82	10.50	13.00	0.97	3.19	2.48	28.69	3.90
KAM24	192.95	9.92	13.00	0.97	3.19	2.48	28.69	5.31
MAC01	308.62	14.03	18.00	0.47	3.49	4.36	20.07	6.98
MAC03	99.42	12.67	18.00	0.47	3.49	4.36	20.07	3.49
MAC05	63.30	11.57	18.00	0.47	3.49	4.36	20.07	0.00
MAC07	210.55	15.80	18.00	0.47	3.49	4.36	20.07	0.00
MAC09	610.88	11.15	18.00	0.47	3.49	4.36	20.07	22.69
MAC11	505.42	11.25	18.00	0.47	3.49	4.36	20.07	13.96

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Table C. 2. (cont.) Testing dataset of the Fuzzy Model

MAC13		544.17	12.50	18.00	0.47	3.49	4.36	20.07		17.45
MAC15		591.93	13.92	18.00	0.47	3.49	4.36	20.07		14.83
MAC17		604.23	12.28	18.00	0.47	3.49	4.36	20.07		28.80
MAC19		639.55	14.02	18.00	0.47	3.49	4.36	20.07		18.32
MAC21		610.54	12.13	18.00	0.47	3.49	4.36	20.07		11.34
MAC23		467.92	8.92	18.00	0.47	3.49	4.36	20.07		8.73
MIT02		57.86	14.15	17.00	0.19	4.09	3.06	13.62		2.04
MIT04		19.54	10.25	17.00	0.19	4.09	3.06	13.62		0.68
MIT06		17.94	13.87	17.00	0.19	4.09	3.06	13.62		0.51
MIT08		179.34	15.97	17.00	0.19	4.09	3.06	13.62		3.74
MIT10		204.44	8.25	17.00	0.19	4.09	3.06	13.62		6.47
MIT12		218.21	13.57	17.00	0.19	4.09	3.06	13.62		6.13
MIT14		272.54	11.80	17.00	0.19	4.09	3.06	13.62		7.49
MIT16		285.57	14.08	17.00	0.19	4.09	3.06	13.62		10.55
MIT18		300.99	10.80	17.00	0.19	4.09	3.06	13.62		11.06
MIT20		326.97	13.37	17.00	0.19	4.09	3.06	13.62		6.64
MIT22		211.13	10.50	17.00	0.19	4.09	3.06	13.62		4.09
MIT24		148.47	9.92	17.00	0.19	4.09	3.06	13.62		4.94
MKC01		140.55	14.03	13.50	0.93	3.92	4.79	19.58		3.48
MKC03		52.20	12.67	13.50	0.93	3.92	4.79	19.58		1.74
MKC05		25.45	11.57	13.50	0.93	3.92	4.79	19.58		0.00
MKC07		84.48	15.80	13.50	0.93	3.92	4.79	19.58		0.44
MKC09		355.34	11.15	13.50	0.93	3.92	4.79	19.58		6.09
MKC11		350.71	11.25	13.50	0.93	3.92	4.79	19.58		10.88
MKC13		387.41	12.50	13.50	0.93	3.92	4.79	19.58		9.57
MKC15		458.57	13.92	13.50	0.93	3.92	4.79	19.58		17.41
MKC17		443.29	12.28	13.50	0.93	3.92	4.79	19.58		14.36
MKC19		470.13	14.02	13.50	0.93	3.92	4.79	19.58		12.62
MKC21		411.70	12.13	13.50	0.93	3.92	4.79	19.58		8.27
MKC23		254.34	8.92	13.50	0.93	3.92	4.79	19.58		8.27
MKS02		118.27	14.15	24.00	0.97	2.91	2.15	3.37		3.22
MKS04		35.40	10.25	24.00	0.97	2.91	2.15	3.37		1.38
MKS06		38.29	13.87	24.00	0.97	2.91	2.15	3.37		0.92
MKS08		427.45	15.97	24.00	0.97	2.91	2.15	3.37		4.29
MKS10		505.79	8.25	24.00	0.97	2.91	2.15	3.37		7.67
MKS12		469.94	13.57	24.00	0.97	2.91	2.15	3.37		6.13
MKS14		517.32	11.80	24.00	0.97	2.91	2.15	3.37		5.52
MKS16		553.12	14.08	24.00	0.97	2.91	2.15	3.37		9.05
MKS18		676.37	10.80	24.00	0.97	2.91	2.15	3.37		9.97
MKS20		739.00	13.37	24.00	0.97	2.91	2.15	3.37		9.97
MKS22		438.92	10.50	24.00	0.97	2.91	2.15	3.37		5.52
MKS24		343.18	9.92	24.00	0.97	2.91	2.15	3.37		4.14
SAI01		245.07	14.03	13.00	0.85	7.36	4.29	18.40		6.75
SAI03		122.07	12.67	13.00	0.85	7.36	4.29	18.40		1.23
SAI05		70.68	11.57	13.00	0.85	7.36	4.29	18.40		1.84
SAI07		117.09	15.80	13.00	0.85	7.36	4.29	18.40		1.23
SAI09		517.88	11.15	13.00	0.85	7.36	4.29	18.40		9.82

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Table C. 2. (cont.) Testing dataset of the Fuzzy Model

SAI11		467.02	11.25	13.00	0.85	7.36	4.29	18.40		11.66
SAI13		539.23	12.50	13.00	0.85	7.36	4.29	18.40		14.72
SAI15		608.16	13.92	13.00	0.85	7.36	4.29	18.40		24.54
SAI17		622.18	12.28	13.00	0.85	7.36	4.29	18.40		31.90
SAI19		573.88	14.02	13.00	0.85	7.36	4.29	18.40		14.72
SAI21		439.36	12.13	13.00	0.85	7.36	4.29	18.40		10.43
SAI23		333.09	8.92	13.00	0.85	7.36	4.29	18.40		3.68
TAL02		132.02	14.15	13.50	0.97	4.60	5.75	19.56		3.45
TAL04		61.55	10.25	13.50	0.97	4.60	5.75	19.56		2.30
TAL06		31.80	13.87	13.50	0.97	4.60	5.75	19.56		1.15
TAL08		194.54	15.97	13.50	0.97	4.60	5.75	19.56		2.30
TAL10		376.21	8.25	13.50	0.97	4.60	5.75	19.56		3.45
TAL12		379.07	13.57	13.50	0.97	4.60	5.75	19.56		10.36
TAL14		422.27	11.80	13.50	0.97	4.60	5.75	19.56		9.21
TAL16		429.39	14.08	13.50	0.97	4.60	5.75	19.56		11.51
TAL18		419.00	10.80	13.50	0.97	4.60	5.75	19.56		12.66
TAL20		352.39	13.37	13.50	0.97	4.60	5.75	19.56		4.60
TAL22		279.80	10.50	13.50	0.97	4.60	5.75	19.56		6.90
TAL24		261.09	9.92	13.50	0.97	4.60	5.75	19.56		6.90
YED01		398.12	14.03	22.00	1.00	0.91	0.46	4.57		2.97
YED03		108.76	12.67	22.00	1.00	0.91	0.46	4.57		1.37
YED05		79.98	11.57	22.00	1.00	0.91	0.46	4.57		0.46
YED07		384.68	15.80	22.00	1.00	0.91	0.46	4.57		0.23
YED09		1045.70	11.15	22.00	1.00	0.91	0.46	4.57		10.29
YED11		916.12	11.25	22.00	1.00	0.91	0.46	4.57		4.11
YED13		932.58	12.50	22.00	1.00	0.91	0.46	4.57		5.49
YED15		1045.06	13.92	22.00	1.00	0.91	0.46	4.57		6.40
YED17		1070.62	12.28	22.00	1.00	0.91	0.46	4.57		10.74
YED19		1149.81	14.02	22.00	1.00	0.91	0.46	4.57		8.91
YED21		958.89	12.13	22.00	1.00	0.91	0.46	4.57		6.63
YED23		615.50	8.92	22.00	1.00	0.91	0.46	4.57		2.74
YEL02		136.88	14.15	22.50	0.97	1.95	1.95	14.51		6.70
YEL04		70.89	10.25	22.50	0.97	1.95	1.95	14.51		1.95
YEL06		143.63	13.87	22.50	0.97	1.95	1.95	14.51		1.40
YEL08		656.68	15.97	22.50	0.97	1.95	1.95	14.51		15.63
YEL10		656.48	8.25	22.50	0.97	1.95	1.95	14.51		17.86
YEL12		712.52	13.57	22.50	0.97	1.95	1.95	14.51		20.09
YEL14		731.64	11.80	22.50	0.97	1.95	1.95	14.51		20.09
YEL16		757.43	14.08	22.50	0.97	1.95	1.95	14.51		29.03
YEL18		785.65	10.80	22.50	0.97	1.95	1.95	14.51		26.23
YEL20		763.76	13.37	22.50	0.97	1.95	1.95	14.51		22.05
YEL22		497.49	10.50	22.50	0.97	1.95	1.95	14.51		10.05
YEL24		350.68	9.92	22.50	0.97	1.95	1.95	14.51		9.49

APPENDIX D

RULE LIST OF THE FUZZY MODEL

Table D. 1. *If-Then* rule base of the Fuzzy Inference System

Rule #	*AAHTL*	*AHRT*	*RW*	*PM*	*BS*	*SJ*	*MA*	*AAA*
1	VVL	L	L	H	H	H	H	S1
2	VVL	L	M	L	L	H	H	S1
3	VVL	L	M	M	H	L	L	S1
4	VVL	L	M	M	H	VH	H	S1
5	VVL	L	M	H	H	H	H	S1
6	VVL	L	H	M	L	VL	L	S1
7	VVL	L	H	M	H	L	H	S1
8	VVL	M	L	H	L	L	VH	S1
9	VVL	M	L	H	H	H	H	S1
10	VVL	M	M	L	H	L	L	S1
11	VVL	M	M	L	H	L	H	S1
12	VVL	M	M	H	L	VH	VH	S1
13	VVL	M	M	H	H	L	H	S1
14	VVL	M	H	H	L	L	VL	S1
15	VVL	H	L	H	H	H	H	S1
16	VVL	H	L	H	H	H	H	S1
17	VVL	H	M	M	H	L	L	S1
18	VVL	H	M	M	H	VH	H	S1
19	VVL	H	M	H	H	H	H	S1
20	VVL	H	H	M	H	L	L	S1
21	VVL	VH	L	H	H	H	H	S1
22	VVL	VH	M	L	H	L	L	S1
23	VL	VL	L	H	L	L	H	S1
24	VL	VL	L	H	H	H	H	S1
25	VL	VL	M	L	H	L	L	S1
26	VL	VL	M	H	L	VH	VH	S1
27	VL	VL	M	H	VH	H	H	R1
28	VL	L	L	H	H	H	H	S1
29	VL	L	L	H	VH	H	H	S1
30	VL	L	M	L	H	L	L	S1
31	VL	L	M	M	H	L	L	S1
32	VL	L	H	H	VL	VL	VL	S1
33	VL	M	L	H	L	L	VH	S1
34	VL	M	L	H	H	H	H	S1
35	VL	M	M	L	H	L	L	S1
36	VL	M	M	L	H	L	H	S1
37	VL	M	H	H	VL	VL	VL	S1
38	VL	M	H	H	L	L	L	S1
39	VL	H	L	H	L	L	VH	S1

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Table D. 1. (cont.) *If-Then* rule base of the Fuzzy Inference System

40	VL	H	L	H	VH	H	H	S1
41	VL	H	M	L	L	H	H	S1
42	VL	H	M	L	H	L	L	S1
43	VL	H	M	L	H	L	H	S1
44	VL	H	M	M	H	L	L	S1
45	VL	H	M	M	VH	VH	H	S1
46	VL	H	M	H	L	VH	VH	S1
47	VL	H	M	H	H	L	H	S1
48	VL	H	H	M	VL	VL	L	S1
49	VL	H	H	M	H	L	L	S1
50	VL	H	H	H	VL	VL	VL	S1
51	VL	H	H	H	L	L	VL	S1
52	VL	H	H	H	L	L	L	S1
53	VL	VH	L	H	L	L	VH	S1
54	VL	VH	L	H	H	H	H	S1
55	VL	VH	M	L	H	L	H	S1
56	VL	VH	M	M	VH	VH	H	S1
57	VL	VH	M	H	L	VH	H	S1
58	VL	VH	M	H	H	L	H	S1
59	VL	VH	M	H	VH	H	H	S1
60	VL	VH	H	M	H	L	L	S1
61	VL	VH	H	H	L	L	VL	S1
62	L	VL	L	H	H	H	H	S1
63	L	VL	L	H	VH	H	H	M1
64	L	VL	M	L	L	H	H	R1
65	L	VL	M	L	H	L	H	S1
66	L	VL	M	M	H	L	L	M1
67	L	VL	M	M	VH	VH	H	R1
68	L	VL	M	H	H	L	H	S1
69	L	VL	H	M	H	L	L	S1
70	L	VL	H	H	L	L	VL	S1
71	L	VL	H	H	L	L	L	M1
72	L	L	L	H	L	L	H	S1
73	L	L	L	H	VH	H	H	S1
74	L	L	M	M	VH	VH	H	R1
75	L	L	M	H	VH	H	H	R1
76	L	L	H	M	H	L	L	M1
77	L	M	L	H	L	L	VH	S1
78	L	M	L	H	H	H	H	S1
79	L	M	M	L	H	L	H	M1
80	L	M	M	M	H	L	L	R1
81	L	M	M	M	VH	VH	H	M1
82	L	M	M	H	L	VH	VH	R1
83	L	M	M	H	H	L	H	M1
84	L	M	M	H	VH	VH	H	R1
85	L	M	H	M	H	L	L	M1
86	L	M	H	H	L	L	VL	S1

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Table D. 1. (cont.) *If-Then* rule base of the Fuzzy Inference System

87	L	H	L	H	H	H	H	M1
88	L	H	L	H	VH	H	H	R1
89	L	H	M	L	L	H	H	R1
90	L	H	M	L	H	L	L	M1
91	L	H	M	M	VH	VH	H	R1
92	L	H	M	H	L	VH	H	R1
93	L	H	M	H	H	L	H	R1
94	L	H	M	H	VH	H	H	R1
95	L	H	H	M	H	L	L	M1
96	L	H	H	H	L	L	VL	S1
97	L	VH	L	H	VH	H	H	S1
98	L	VH	M	L	L	H	H	S1
99	L	VH	M	M	H	L	L	S1
100	L	VH	H	H	VL	VL	VL	S1
101	L	VH	H	H	L	L	L	S1
102	H	VL	H	M	VL	VL	L	M1
103	H	VL	H	H	VL	VL	VL	S1
104	H	L	L	H	VH	H	H	R1
105	H	L	M	L	L	H	H	R1
106	H	L	M	M	H	L	L	R1
107	H	L	H	M	VL	VL	L	M1
108	H	L	H	H	VL	VL	VL	S1
109	H	M	L	H	VH	H	H	R1
110	H	M	M	L	L	H	H	R1
111	H	M	H	M	VL	VL	L	M1
112	H	M	H	H	L	L	L	R1
113	H	H	L	H	VH	H	H	R1
114	H	H	M	L	L	H	H	R1
115	H	H	M	M	H	L	L	M1
116	H	H	M	H	H	L	H	M1
117	H	H	H	M	VL	VL	L	M1
118	H	H	H	H	L	L	VL	M1
119	H	H	H	H	L	L	L	R1
120	H	VH	H	M	VL	VL	L	S1
121	VH	VL	H	M	VL	VL	VL	M1
122	VH	L	H	M	VL	VL	VL	S1
123	VH	M	H	M	VL	VL	VL	S1
124	VH	H	H	M	VL	VL	VL	S1
125	VH	VH	H	M	VL	VL	VL	S1
126	VVH	L	H	M	VL	VL	VL	R1

APPENDIX E

MATLAB CODES OF THE FUZZY MODEL

<u>MATLAB Fuzzy Logic Toolbox command lines:</u>

```
[System]
Name='Final-kaza_sum'
Type='mamdani'
Version=2.0
NumInputs=7
NumOutputs=1
NumRules=126
AndMethod='min'
OrMethod='max'
ImpMethod='min'
AggMethod='sum'
DefuzzMethod='centroid'

[Input1]
Name='AAHTL'
Range=[0 1400]
NumMFs=6
MF1='1VVL':'trimf',[-140 0 140]
MF2='4H':'trimf',[430 700 980]
MF3='5VH':'trimf',[700 980 1170]
MF4='3L':'trimf',[140 430 700]
MF5='6VVH':'trapmf',[980 1170 1570 1600]
MF6='2VL':'trimf',[0 140 430]

[Input2]
Name='Rain'
Range=[5 20]
NumMFs=5
MF1='2L':'trimf',[8.25 10.58 12.36]
MF2='3M':'trimf',[10.58 12.36 13.8]
MF3='4H':'trimf',[12.36 13.8 16]
MF4='1VL':'trapmf',[-5.585 3.25 8.25 10.58]
MF5='5VH':'trapmf',[13.8 16 20 40]

[Input3]
Name='Road-width'
Range=[10 30]
NumMFs=3
MF1='1L':'trapmf',[2.5 8 12 17.5]
```

```
MF2='2M':'trimf',[12 17.5 25]
MF3='3H':'trapmf',[17.5 25 35 42.5]

[Input4]
Name='Median'
Range=[0 1]
NumMFs=3
MF1='1L':'trapmf',[-0.36 -0.35 0.35 0.65]
MF2='2M':'trimf',[0.35 0.65 1]
MF3='3H':'trimf',[0.65 1 1.65]

[Input5]
Name='Bus-stop'
Range=[0 8]
NumMFs=4
MF1='1VL':'trimf',[-2.8 0 2.8]
MF2='2L':'trimf',[0 2.8 4.5]
MF3='3H':'trimf',[2.8 4.5 7]
MF4='4VH':'trapmf',[4.5 7 9 13.5]

[Input6]
Name='Signalization'
Range=[0 13]
NumMFs=4
MF1='1VL':'trimf',[-2.5 0 2.5]
MF2='2L':'trimf',[0 2.5 5.1]
MF3='3H':'trimf',[2.5 5.1 12]
MF4='4VH':'trapmf',[5.1 12 14 19.1]

[Input7]
Name='Minor-access'
Range=[0 30]
NumMFs=4
MF1='2L':'trimf',[4 13.4 20.4]
MF2='3H':'trimf',[13.4 20.4 29]
MF3='4VH':'trapmf',[20.4 29 31 40]
MF4='1VL':'trapmf',[-13.4 -4 4 13.4]

[Output1]
Name='Accident'
Range=[0 33]
NumMFs=5
MF1='1S':'trapmf',[-6.32 -1.14 1.14 6.32]
MF2='M':'trimf',[6.32 9.96 17.72]
MF3='2R':'trimf',[9.96 17.72 25.02]
MF4='2S':'trimf',[1.14 6.32 9.96]
```

```
MF5='1R':'trapmf',[17.72 25.02 40.98 48.28]

[Rules]
1 1 1 3 3 3 2, 1 (1) : 1
1 1 2 1 2 3 2, 1 (1) : 1
1 1 2 2 3 2 1, 1 (1) : 1
1 1 2 2 4 4 2, 1 (1) : 1
1 1 2 3 4 3 2, 1 (1) : 1
1 1 3 2 1 1 1, 1 (1) : 1
1 1 3 2 3 2 1, 1 (1) : 1
1 2 1 3 2 2 3, 1 (1) : 1
1 2 1 3 3 3 2, 1 (1) : 1
1 2 2 1 3 2 1, 1 (1) : 1
1 2 2 1 3 2 2, 1 (1) : 1
1 2 2 3 2 4 3, 1 (1) : 1
1 2 2 3 3 2 2, 1 (1) : 1
1 2 3 3 2 2 4, 1 (1) : 1
1 3 1 3 3 3 2, 1 (1) : 1
1 3 1 3 4 3 2, 1 (1) : 1
1 3 2 2 3 2 1, 1 (1) : 1
1 3 2 2 4 4 2, 1 (1) : 1
1 3 2 3 4 3 2, 1 (1) : 1
1 3 3 2 3 2 1, 1 (1) : 1
1 5 1 3 3 3 2, 1 (1) : 1
1 5 2 1 3 2 1, 1 (1) : 1
6 4 1 3 2 2 3, 1 (1) : 1
6 4 1 3 3 3 2, 4 (1) : 1
6 4 2 1 3 2 1, 1 (1) : 1
6 4 2 3 2 4 3, 4 (1) : 1
6 4 2 3 4 3 2, 3 (1) : 1
6 1 1 3 3 3 2, 4 (1) : 1
6 1 1 3 4 3 2, 1 (1) : 1
6 1 2 1 3 2 1, 4 (1) : 1
4 1 2 2 3 2 1, 4 (1) : 1
6 1 3 3 1 1 4, 1 (1) : 1
6 2 1 3 2 2 3, 4 (1) : 1
6 2 1 3 3 3 2, 1 (1) : 1
6 2 2 1 3 2 1, 4 (1) : 1
6 2 2 1 3 2 2, 1 (1) : 1
6 2 3 3 1 1 4, 1 (1) : 1
6 2 3 3 2 2 1, 1 (1) : 1
6 3 1 3 2 2 3, 1 (1) : 1
6 3 1 3 4 3 2, 1 (1) : 1
6 3 2 1 2 3 2, 1 (1) : 1
6 3 2 1 3 2 1, 1 (1) : 1
```

131 6 3 2 1 3 2 2, 4 (1) : 1
132 6 3 2 2 3 2 1, 4 (1) : 1
133 6 3 2 2 4 4 2, 4 (1) : 1
134 6 3 2 3 2 4 3, 4 (1) : 1
135 6 3 2 3 3 2 2, 4 (1) : 1
136 6 3 3 2 1 1 1, 1 (1) : 1
137 6 3 3 2 3 2 1, 1 (1) : 1
138 6 3 3 3 1 1 4, 1 (1) : 1
139 6 3 3 3 2 2 4, 1 (1) : 1
140 6 3 3 3 2 2 1, 4 (1) : 1
141 6 5 1 3 2 2 3, 1 (1) : 1
142 6 5 1 3 3 3 2, 1 (1) : 1
143 6 5 2 1 3 2 2, 1 (1) : 1
144 6 5 2 2 4 4 2, 4 (1) : 1
145 6 5 2 3 2 4 3, 1 (1) : 1
146 6 5 2 3 3 2 2, 1 (1) : 1
147 6 5 2 3 4 3 2, 4 (1) : 1
148 6 5 3 2 3 2 1, 1 (1) : 1
149 6 5 3 3 2 2 4, 1 (1) : 1
150 4 4 1 3 3 3 2, 4 (1) : 1
151 4 4 1 3 4 3 2, 2 (1) : 1
152 4 4 2 1 2 3 2, 3 (1) : 1
153 4 4 2 1 3 2 2, 4 (1) : 1
154 4 4 2 2 3 2 1, 2 (1) : 1
155 4 4 2 2 4 4 2, 3 (1) : 1
156 4 4 2 3 3 2 2, 4 (1) : 1
157 4 4 3 2 3 2 1, 4 (1) : 1
158 4 4 3 3 2 2 4, 4 (1) : 1
159 4 4 3 3 2 2 1, 2 (1) : 1
160 4 1 1 3 2 2 3, 4 (1) : 1
161 4 1 1 3 4 3 2, 4 (1) : 1
162 4 1 2 2 4 4 2, 5 (1) : 1
163 4 1 2 3 4 3 2, 3 (1) : 1
164 4 1 3 2 3 2 1, 2 (1) : 1
165 4 2 1 3 2 2 3, 4 (1) : 1
166 4 2 1 3 3 3 2, 4 (1) : 1
167 4 2 2 1 3 2 2, 2 (1) : 1
168 4 2 2 2 3 2 1, 3 (1) : 1
169 4 2 2 2 4 4 2, 2 (1) : 1
170 4 2 2 3 2 4 3, 3 (1) : 1
171 4 2 2 3 3 2 2, 2 (1) : 1
172 4 2 2 3 4 4 2, 5 (1) : 1
173 4 2 3 2 3 2 1, 2 (1) : 1
174 4 2 3 3 2 2 4, 4 (1) : 1
175 4 3 1 3 3 3 2, 2 (1) : 1
176 4 3 1 3 4 3 2, 3 (1) : 1

177 4 3 2 1 2 3 2, 3 (1) : 1
178 4 3 2 1 3 2 1, 2 (1) : 1
179 4 3 2 2 4 4 2, 5 (1) : 1
180 4 3 2 3 2 4 3, 3 (1) : 1
181 4 3 2 3 3 2 2, 3 (1) : 1
182 4 3 2 3 4 3 2, 3 (1) : 1
183 4 3 3 2 3 2 1, 2 (1) : 1
184 4 3 3 3 2 2 4, 4 (1) : 1
185 4 5 1 3 4 3 2, 1 (1) : 1
186 4 5 2 1 2 3 2, 1 (1) : 1
187 4 5 2 2 3 2 1, 4 (1) : 1
188 4 5 3 3 1 1 4, 1 (1) : 1
189 4 5 3 3 2 2 1, 1 (1) : 1
190 2 4 3 2 1 1 1, 2 (1) : 1
191 2 4 3 3 1 1 4, 4 (1) : 1
192 2 1 1 3 4 3 2, 5 (1) : 1
193 2 1 2 1 2 3 2, 5 (1) : 1
194 2 1 2 2 3 2 1, 3 (1) : 1
195 2 1 3 2 1 1 1, 2 (1) : 1
196 2 1 3 3 1 1 4, 4 (1) : 1
197 2 2 1 3 4 3 2, 3 (1) : 1
198 2 2 2 1 2 3 2, 3 (1) : 1
199 2 2 3 2 1 1 1, 2 (1) : 1
200 2 2 3 3 2 2 1, 5 (1) : 1
201 2 3 1 3 4 3 2, 3 (1) : 1
202 2 3 2 1 2 3 2, 5 (1) : 1
203 2 3 2 2 3 2 1, 2 (1) : 1
204 2 3 2 3 3 2 2, 2 (1) : 1
205 2 3 3 2 1 1 1, 2 (1) : 1
206 2 3 3 3 2 2 4, 2 (1) : 1
207 2 3 3 3 2 2 1, 5 (1) : 1
208 2 5 3 2 1 1 1, 4 (1) : 1
209 3 4 3 3 1 1 4, 2 (1) : 1
210 3 1 3 3 1 1 4, 4 (1) : 1
211 3 2 3 3 1 1 4, 4 (1) : 1
212 3 3 3 3 1 1 4, 4 (1) : 1
213 3 5 3 3 1 1 4, 4 (1) : 1
214 5 1 3 3 1 1 4, 3 (1) : 1

APPENDIX F

CRISP RESULTS OF THE FUZZY MODEL

Table F. 1. Crisp results of the Fuzzy Model for calibration set

Data point	AAA Real	AAA Model	Data point	AAA Real	AAA Model
ALT01	2.96	5.63	INO14	14.50	15.84
ALT03	2.56	2.14	INO16	10.80	17.17
ALT05	2.49	2.33	INO18	14.70	14.17
ALT07	2.54	1.55	INO20	13.20	13.17
ALT09	12.10	6.41	INO22	9.89	9.84
ALT11	5.69	5.43	INO24	6.96	5.67
ALT13	5.70	4.27	KAM01	2.59	2.83
ALT15	5.71	6.21	KAM03	3.65	0.35
ALT17	7.44	6.21	KAM05	3.48	1.06
ALT19	16.50	8.15	KAM07	2.59	1.77
ALT21	5.68	6.99	KAM09	5.99	5.31
ALT23	5.70	7.57	KAM11	5.98	5.31
AND02	2.42	1.45	KAM13	6.59	6.02
AND04	2.46	0.79	KAM15	5.85	7.79
AND06	2.42	0.24	KAM17	6.08	7.44
AND08	6.00	5.82	KAM19	5.48	9.21
AND10	11.50	8.55	KAM21	6.02	5.67
AND12	11.60	9.52	KAM23	3.49	2.13
AND14	11.60	10.25	MAC02	5.70	3.49
AND16	10.40	10.85	MAC04	2.85	0.00
AND18	11.60	11.21	MAC06	3.68	0.00
AND20	11.60	9.76	MAC08	5.62	2.62
AND22	11.90	4.73	MAC10	14.00	17.45
AND24	16.50	2.91	MAC12	18.50	20.07
ANK01	2.78	2.92	MAC14	18.20	19.20
ANK03	2.37	1.94	MAC16	20.60	23.56
ANK05	2.48	0.22	MAC18	21.30	21.82
ANK07	2.36	0.65	MAC20	20.10	26.18
ANK09	17.60	17.17	MAC22	20.20	10.47
ANK11	15.80	15.01	MAC24	14.80	7.85
ANK13	5.63	13.50	MIT01	2.59	2.04
ANK15	16.50	14.79	MIT03	3.35	0.85
ANK17	17.50	19.76	MIT05	3.57	0.17
ANK19	16.50	18.36	MIT07	2.70	0.68
ANK21	5.70	8.53	MIT09	5.97	7.66
ANK23	5.71	5.72	MIT11	5.96	7.66
CEM02	3.76	1.97	MIT13	7.39	7.32

(cont. on next page)

Table F. 1. (cont.) Crisp results of the Fuzzy Model for calibration set

CEM04		2.45	0.22		MIT15		8.21	9.19
CEM06		3.54	0.00		MIT17		6.10	11.57
CEM08		4.12	3.72		MIT19		8.84	9.36
CEM10		8.96	5.47		MIT21		6.04	7.32
CEM12		10.10	5.03		MIT23		4.74	2.72
CEM14		12.00	8.75		MKC02		3.47	2.61
CEM16		12.40	10.50		MKC04		3.75	0.00
CEM18		14.00	10.50		MKC06		3.46	1.31
CEM20		17.00	10.06		MKC08		4.14	1.74
CEM22		9.37	4.81		MKC10		6.62	5.22
CEM24		9.37	3.94		MKC12		11.00	10.01
ESR01		8.94	6.64		MKC14		9.36	12.18
ESR03		3.31	1.42		MKC16		12.00	9.57
ESR05		2.55	0.47		MKC18		12.20	14.36
ESR07		3.05	0.47		MKC20		12.10	10.01
ESR09		10.40	11.37		MKC22		6.11	5.66
ESR11		9.09	7.58		MKC24		6.37	3.92
ESR13		10.50	9.95		MKS01		3.80	2.76
ESR15		20.00	9.95		MKS03		2.54	2.15
ESR17		14.80	19.43		MKS05		2.43	0.92
ESR19		20.10	18.48		MKS07		2.36	1.53
ESR21		15.90	8.53		MKS09		5.66	9.51
ESR23		11.90	4.74		MKS11		5.68	6.29
FEV02		4.90	5.85		MKS13		6.82	5.37
FEV04		2.45	2.92		MKS15		8.76	7.97
FEV06		4.01	0.00		MKS17		5.69	9.35
FEV08		6.83	4.87		MKS19		11.40	9.81
FEV10		17.50	19.49		MKS21		5.63	6.44
FEV12		21.40	24.37		MKS23		5.77	5.37
FEV14		18.80	12.67		SAI02		7.42	1.84
FEV16		26.40	27.29		SAI04		7.53	3.07
FEV18		24.10	22.42		SAI06		2.68	0.00
FEV20		21.90	23.39		SAI08		4.71	1.23
FEV22		25.40	4.87		SAI10		11.50	12.88
FEV24		22.30	1.95		SAI12		17.50	16.56
GAZ01		5.38	6.95		SAI14		18.20	20.25
GAZ03		3.44	0.00		SAI16		16.60	17.79
GAZ05		2.43	0.00		SAI18		20.00	23.93
GAZ07		3.02	0.00		SAI20		17.50	17.79
GAZ09		17.50	16.22		SAI22		9.63	5.52
GAZ11		17.50	23.17		SAI24		10.80	4.29
GAZ13		17.50	20.86		TAL01		11.50	4.60
GAZ15		17.60	15.06		TAL03		2.73	2.30
GAZ17		17.60	19.70		TAL05		3.32	0.00
GAZ19		17.60	16.22		TAL07		2.98	0.00
GAZ21		17.60	4.63		TAL09		9.23	2.30
GAZ23		5.77	8.11		TAL11		8.84	12.66

(cont. on next page)

Table F. 1. (cont.) Crisp results of the Fuzzy Model for calibration set

GIR02	4.01	0.94	TAL13	10.50	6.90
GIR04	7.83	1.41	TAL15	12.30	10.36
GIR06	3.27	0.94	TAL17	10.80	26.47
GIR08	5.59	4.23	TAL19	11.50	23.01
GIR10	14.00	14.57	TAL21	8.54	4.60
GIR12	14.80	15.51	TAL23	8.58	5.75
GIR14	14.90	23.97	YED02	3.34	0.23
GIR16	14.20	20.21	YED04	2.40	0.69
GIR18	16.60	14.57	YED06	2.96	0.46
GIR20	16.10	15.51	YED08	6.96	5.71
GIR22	16.90	10.34	YED10	10.60	11.89
GIR24	15.40	2.82	YED12	11.20	5.26
HEA01	9.94	4.74	YED14	5.77	4.80
HEA03	3.63	1.05	YED16	5.71	6.40
HEA05	2.43	0.53	YED18	13.70	8.69
HEA07	2.95	1.05	YED20	5.60	10.51
HEA09	11.70	13.16	YED22	6.16	4.80
HEA11	11.70	6.85	YED24	6.22	4.11
HEA13	12.40	8.43	YEL01	5.06	6.14
HEA15	16.30	15.27	YEL03	3.46	3.07
HEA17	11.40	10.53	YEL05	2.51	1.67
HEA19	14.70	8.43	YEL07	2.95	3.35
HEA21	11.40	14.74	YEL09	21.90	25.12
HEA23	5.75	4.74	YEL11	22.40	20.93
INO02	4.91	4.00	YEL13	24.20	22.61
INO04	3.61	1.33	YEL15	24.20	27.07
INO06	4.19	0.67	YEL17	24.50	32.65
INO08	5.55	5.00	YEL19	23.70	25.40
INO10	9.57	12.00	YEL21	24.00	17.02
INO12	13.50	10.84	YEL23	11.40	11.72

Table F. 2. Crisp results of the Fuzzy Model for testing set

Data point	***AAA***		***Data point***	***AAA***	
	Real	***Model***		***Real***	***Model***
ALT02	3.69	2.56	INO13	11.67	15.10
ALT04	1.55	2.45	INO15	13.17	11.30
ALT06	1.16	2.49	INO17	13.67	15.50
ALT08	3.49	5.72	INO19	13.84	11.00
ALT10	8.93	11.50	INO21	10.84	15.00
ALT12	6.79	5.69	INO23	7.84	8.59
ALT14	5.82	5.69	KAM02	2.13	2.79
ALT16	10.09	5.70	KAM04	0.00	2.90
ALT18	7.57	13.00	KAM06	0.71	3.09
ALT20	7.96	5.63	KAM08	4.61	3.65
ALT22	2.33	6.11	KAM10	5.31	2.95
ALT24	4.46	5.70	KAM12	11.34	6.29
AND01	2.36	2.42	KAM14	6.02	5.99
AND03	0.67	2.81	KAM16	11.34	5.44
AND05	0.30	2.54	KAM18	8.86	6.10
AND07	0.97	2.96	KAM20	6.02	6.02
AND09	11.82	11.60	KAM22	3.90	5.42
AND11	9.09	11.60	KAM24	5.31	4.23
AND13	8.43	11.60	MAC01	6.98	10.30
AND15	10.91	11.00	MAC03	3.49	3.63
AND17	12.25	11.60	MAC05	0.00	3.01
AND19	10.25	10.60	MAC07	0.00	6.74
AND21	6.67	11.60	MAC09	22.69	20.00
AND23	3.39	16.50	MAC11	13.96	18.10
ANK02	2.70	2.37	MAC13	17.45	16.30
ANK04	0.86	2.24	MAC15	14.83	21.00
ANK06	1.30	2.20	MAC17	28.80	15.90
ANK08	4.97	5.79	MAC19	18.32	21.10
ANK10	16.31	16.50	MAC21	11.34	16.70
ANK12	12.63	5.60	MAC23	8.73	15.70
ANK14	13.71	16.40	MIT02	2.04	2.91
ANK16	17.39	16.50	MIT04	0.68	4.32
ANK18	23.54	17.60	MIT06	0.51	3.39
ANK20	13.28	5.65	MIT08	3.74	7.42
ANK22	5.51	5.81	MIT10	6.47	4.16
ANK24	2.59	5.66	MIT12	6.13	6.96
CEM01	2.84	5.45	MIT14	7.49	5.97
CEM03	1.31	3.99	MIT16	10.55	8.22
CEM05	0.00	2.68	MIT18	11.06	6.05
CEM07	0.44	3.74	MIT20	6.64	8.43
CEM09	10.06	11.90	MIT22	4.09	6.72
CEM11	7.66	11.40	MIT24	4.94	5.78
CEM13	7.00	11.70	MKC01	3.48	4.70

(cont. on next page)

Table F. 2. (cont.) Crisp results of the Fuzzy Model for testing set

CEM15		10.50	11.50		MKC03		1.74	3.20
CEM17		13.56	15.50		MKC05		0.00	3.09
CEM19		8.97	14.90		MKC07		0.44	3.13
CEM21		5.03	12.40		MKC09		6.09	8.04
CEM23		4.16	9.29		MKC11		10.88	7.90
ESR02		1.42	4.46		MKC13		9.57	9.77
ESR04		0.95	2.69		MKC15		17.41	12.40
ESR06		1.90	4.50		MKC17		14.36	10.20
ESR08		4.74	3.25		MKC19		12.62	12.10
ESR10		10.90	11.90		MKC21		8.27	8.73
ESR12		8.53	11.30		MKC23		8.27	6.34
ESR14		12.80	14.20		MKS02		3.22	2.32
ESR16		12.32	19.80		MKS04		1.38	16.50
ESR18		16.59	20.90		MKS06		0.92	2.77
ESR20		15.64	18.70		MKS08		4.29	4.40
ESR22		6.64	13.10		MKS10		7.67	5.77
ESR24		4.27	13.10		MKS12		6.13	7.09
FEV01		4.87	5.37		MKS14		5.52	5.76
FEV03		2.92	4.42		MKS16		9.05	8.87
FEV05		3.90	2.54		MKS18		9.97	5.58
FEV07		0.97	5.37		MKS20		9.97	11.40
FEV09		11.70	22.00		MKS22		5.52	5.53
FEV11		13.65	21.60		MKS24		4.14	5.65
FEV13		20.47	15.00		SAI01		6.75	12.00
FEV15		23.39	26.40		SAI03		1.23	2.87
FEV17		21.44	13.40		SAI05		1.84	2.64
FEV19		25.34	23.70		SAI07		1.23	4.18
FEV21		12.67	15.80		SAI09		9.82	17.30
FEV23		7.80	21.90		SAI11		11.66	15.00
GAZ02		1.16	5.05		SAI13		14.72	17.50
GAZ04		0.00	5.60		SAI15		24.54	17.20
GAZ06		1.16	5.36		SAI17		31.90	17.60
GAZ08		3.48	3.52		SAI19		14.72	16.90
GAZ10		16.22	16.50		SAI21		10.43	15.40
GAZ12		18.54	17.50		SAI23		3.68	11.70
GAZ14		27.81	17.60		TAL02		3.45	3.68
GAZ16		15.06	17.60		TAL04		2.30	5.17
GAZ18		24.33	17.50		TAL06		1.15	2.97
GAZ20		16.22	17.00		TAL08		2.30	5.20
GAZ22		9.27	5.53		TAL10		3.45	8.06
GAZ24		4.63	5.65		TAL12		10.36	11.80
GIR01		5.17	4.68		TAL14		9.21	10.40
GIR03		1.41	3.74		TAL16		11.51	13.20
GIR05		0.00	2.60		TAL18		12.66	13.00
GIR07		1.88	4.52		TAL20		4.60	11.00
GIR09		15.04	15.60		TAL22		6.90	10.30
GIR11		9.40	15.30		TAL24		6.90	8.78

(cont. on next page)

Table F. 2. (cont.) Crisp results of the Fuzzy Model for testing set

GIR13		15.98	13.30	YED01		2.97	4.00
GIR15		22.09	14.90	YED03		1.37	2.85
GIR17		22.09	12.70	YED05		0.46	2.57
GIR19		22.09	17.00	YED07		0.23	3.20
GIR21		11.28	13.80	YED09		10.29	10.60
GIR23		5.64	15.30	YED11		4.11	7.71
HEA02		2.11	5.19	YED13		5.49	11.50
HEA04		0.53	16.50	YED15		6.40	5.72
HEA06		0.53	5.49	YED17		10.74	7.46
HEA08		2.63	4.37	YED19		8.91	5.59
HEA10		10.53	5.76	YED21		6.63	8.59
HEA12		8.43	15.20	YED23		2.74	6.22
HEA14		12.11	11.40	YEL02		6.70	5.43
HEA16		7.37	16.20	YEL04		1.95	2.97
HEA18		14.22	11.90	YEL06		1.40	5.38
HEA20		14.74	14.00	YEL08		15.63	6.81
HEA22		10.53	5.53	YEL10		17.86	11.90
HEA24		5.27	5.65	YEL12		20.09	24.30
INO01		4.00	6.60	YEL14		20.09	24.00
INO03		1.67	3.97	YEL16		29.03	23.80
INO05		1.00	3.78	YEL18		26.23	18.80
INO07		0.83	5.56	YEL20		22.05	24.60
INO09		13.00	12.70	YEL22		10.05	12.00
INO11		9.34	11.50	YEL24		9.49	11.70

VITA

Birthplace / Date: Beyşehir, January 26, 1976

e-mail: omerselvi@iyte.edu.tr; redomer@gmail.com

Education:

2002 – 2009 Ph.D Izmir Institute of Technology Faculty of Architecture, Department of City and Regional Planning

Thesis: Traffic Accident Predictions Based on Fuzzy Logic Approach for Safer Urban Environments Case Study: Izmir Metropolitan Area

1998 – 2002 MSc Izmir Institute of Technology Faculty of Architecture, Department of City and Regional Planning

Thesis: Efficiency Analysis of Izmir Metro in its Current State

1994 – 1998 BSc Dokuz Eylul Universitesi Faculty of Architecture, Department of City and Regional Planning

Some Recent Publications:

Duvarcı, Y., Ö. Selvi, H. Murat Günaydın and G. Gür. 2008. Impacts of transportation projects on urban trends in Izmir. *Teknik Dergi (Digest)* December: 1175-1201

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