FUZZY LOGIC APPROACH FOR ESTIMATING 85TH PERCENTILE SPEED BASED ON ROAD ATTRIBUTE DATA

Bayzid Khan[1] and Yaser E. Hawas[1,2]

[1]*Roadway, Transportation and Traffic Safety Research Center,*
United Arab Emirates University, Al Ain, United Arab Emirates

[2]*Department of Civil and Environmental Engineering, United Arab Emirates University, Al Ain, United Arab Emirates*

Keywords: 85th Percentile Speed, Posted Speed Limit, Fuzzy Logic, Neuro-Fuzzy Training.

Abstract: This paper discusses the development of fuzzy logic model for estimating the 85th percentile speed of urban roads. Spot speed survey was conducted on four randomly selected urban road segments for a typical weekday and a weekend. The considered road segment attribute data are length of the road segment, number of access points/intersecting links, number of pedestrian crossings, number of lanes, hourly traffic volume, hourly pedestrian volume and current posted speed limits of the selected roads. Such attribute data were collected and used as input variables in the model. Two models for weekday and weekend were developed based on the field survey data. Both models were calibrated using the neuro-fuzzy technique for optimizing the fuzzy logic model (FLM) parameters. Analyses of estimated results show that the FLM can estimate the 85th percentile speed to a reasonable level.

1 INTRODUCTION

Determining a safer posted speed limit for any given roads/links is one of the major challenges for the researchers and professionals all around the world. Many studies tried to identify the safer speed limit for a road (Manual on Uniform Traffic Control Devices [MUTCD], 2003; Department for Transportation [DfT], 2006; Global Road Safety Partnership [GRSP], 2008). Setting a speed limit is a multi-criteria task. Many road and roadside factors such as the road alignment, section length, traffic volume, pedestrian volume, current speed limit, number of lanes, weather condition, time of the day, law enforcement, purpose and length of the trip, vehicles' characteristics are to be incorporated. (TRB, 1998; Srinivasan, Parker, Harkey, Tharpe and Summer, 2006). Setting the speed limits also requires understanding the drivers' characteristics and their driving pattern. As such, most of the studies suggested the 85th percentile of the operating speed to be set as the posted speed limit (Fitzpatrick, Carlson, Wooldridge and Miaou, 2003).

Studies showed that the chances of involving in a crash is least at 85th the percentile traffic speed (Minnesota Department of Transportation [MNDOT], 2002; American Association of State Highway and Transportation Officials [AASHTO], 1985).

Developing a model to estimate the 85th percentile speed by incorporating all the factors is quite challenging. The individual driver's operating speed depends on individual driver's perception about all of the above mentioned factors. For a given road characteristics, every driver may choose different operating speed. Therefore, it is very important to develop a method to estimate the 85th percentile speed which will also address such uncertain choice behaviour.

Many studies were conducted to determine the factors that influence the choice of the operating speed. Poe, Tarris and Mason (1996) showed that access points, land-use characteristics and traffic engineering features have influences on vehicle speed on low speed urban streets. Haglund and Aberg (2000) showed that the posted speed limit has influence on drivers' speed choice behaviour. Fitzpatrick, Carlson, Brewer and Wooldridge (2001) evaluated the influence of geometric, roadside and traffic control devices on drivers' speed on four-lane suburban arterials and found that posted speed limit was the most significant variable for both curve and straight sections. Wang (2006) demonstrated that the number of lanes, sidewalks, pedestrian movements,

Khan B. and E. Hawas Y..
FUZZY LOGIC APPROACH FOR ESTIMATING 85TH PERCENTILE SPEED BASED ON ROAD ATTRIBUTE DATA.
DOI: 10.5220/0003716300460054
In *Proceedings of the 4th International Conference on Agents and Artificial Intelligence* (ICAART-2012), pages 46-54
ISBN: 978-989-8425-95-9

and access density have significant influences on the drivers' behaviour of choosing operating speed. Fildes, Fletcher and Corrigan (1987) and Fildes, Leening and Corrigan (1989) found that the road width and the number of lanes have the greatest influence on speed choice. Tignor and Warren (1990) showed that the number of access points and the nearby commercial development have the greatest influences on the vehicle speeds. Most of these studies used different model approaches range from simple linear regression models to complex curvilinear regression equations (Wang, 2006; Tarris, Poe, Mason and Goulias, 1996; Poe and Mason, 2000). Most of the existing models attempt to quantify the operating speed based on physical conditions such as road geometric design, roadside development and traffic control devices. All of these models used 85th percentile speed as a representative measures for operating speed.

No studies on the use of FLM to estimate the 85th percentile speed have been found. The FLM approach has the premise to tackle the imprecise, vague and uncertain relationship between the inputs and outputs. The proposed system can be regarded as an expert system or a knowledge base. It is critically important that the design of such system should account for the imprecise, incomplete or not totally reliable information (Zadeh, 1983). The key feature of the FLM is the suitability to incorporate intuition, heuristic and human reasoning (Hawas, 2004) and such technique is useful for problems that entail probabilistic or stochastic uncertainty (human behaviour modeling), or problems that cannot be easily represented by mathematical modeling because of the complexity of the process (Kikuchi and Pursula, 1998). Fuzzy set theory provides a strict mathematical framework in which vague conceptual phenomena can be precisely and rigorously studied (Zimmermann, 1996). The word imprecise or vague does not mean the lack of knowledge of data; rather it indicates the sense of vagueness of the value of parameters.

The objective of this paper is to develop a fuzzy logic based approach to estimate the 85th percentile speed for different urban road segments based on road segments attribute data for weekday and weekend. In doing so, four urban road segments (one local and three arterial roads) of Al Ain city of United Arab Emirates have been selected randomly (termed as 'Site 1' to 'Site 4'). Only four road segments were selected because of limited time and resources for conducting the study. The authors do recognize that the limited data collection cannot be used to make general conclusions on the validity of the devised FLM for a general network. We emphasize here that the main contribution of this study is the introduction of the concepts and the procedure to develop the FLM that can be generalized to any network given that adequate data collection on a representative sample size is fulfilled.

This paper is divided into five sections. The second section provides a brief overview on data collection methodology. In third section, the structure of the proposed FLM is discussed in brief. The inference engine and fuzzy operators, and neuro-fuzzy training procedure are also discussed. The fourth section discusses the FLM validation and analysis of results. Concluding remarks on the use of the FLM for estimating the 85th percentile speed to set the speed limit are provided in the last section.

2 DATA COLLECTION

Spot speed survey were conducted on selected four sites for five different time periods of the day, for a typical weekday and weekend and for both directions. The five time periods include both peak (AM, MD, PM) and off-peak periods (15 minutes within each time period). Only passenger vehicles (excluding trucks and busses) were selected randomly for the survey, keeping in mind that a minimum of 50 vehicles should be observed for spot speed study (Ewing, 1999) on each selected road segments. The 85th percentile speed of the spot speed data was calculated for 40 different cases (4 sites*2directions*5 time periods) for two days (one typical weekday and one weekend).

The detailed road attribute data including the length of the road segment, number of access points/intersecting links, number of pedestrian crossings, number of lanes, traffic count and pedestrian count data (15 minutes count), and the current posted speed limit for each road were collected. The length of Site 1 is 2.78 km, has 8 access points and 3 pedestrian crossings on each direction. The traffic volume is relatively high, but number of pedestrian is low on both weekday and weekend. Site 2 is 0.46 km long with 4 access points and 3 pedestrian crossings on each direction. This site has the highest pedestrian volume with the lowest traffic volume among the four sites. The length of Site 3 is 2.15 km. It has 11 and 8 access points on direction 1 and direction 2, respectively. The site has the highest traffic volume (among the four sites) on both weekday and weekend. Pedestrian volume is also high at this site. Site 4 is

2.94 km long, 4 access points on both directions with no pedestrian crossing. The traffic volume is moderate with very little pedestrian activity. The traffic and pedestrian count data were converted to hourly volume data prior to developing the FLM. It is to be noted that all road attribute data are fixed for each road segments for different time periods and for weekday and weekend except the traffic volume and pedestrian data. The current posted speed limits for site1, site 2, site 3 and site 4 are 40, 60, 80 and 80 km/hr, respectively.

3 DEVELOPMENT OF FLM FOR 85TH PERCENTILE SPEED ESTIMATION

The development of the FLM starts with preparing the data sets for both weekday and weekend. The road attribute data collected from the fields were used as the input variables. The estimated 85th percentile of the operating speed was used as the output variable. The input and output variables and their corresponding modified name used in the FLM are shown in Table 1. Two separate models were developed (for weekday and weekend). It is to be noted that volume to capacity ratio was also calculated from the hourly traffic volume to incorporate in the FLM development.

Table 1: Input and output variables and their corresponding modified name in fuzzy logic.

Variable category	Variable name	Denoted in FLM
Input variables	Length	Length
	Number of access points/intersecting links	IntLnks
	Number of pedestrian crossings	PedCros
	Volume to capacity (V/C) ratio	VCRat
	Hourly pedestrian volume	PedVol
	Posted speed limit	PostSp
Output variable	85th percentile speed	SpEF

The FLM development was done in two stages using the tool *FuzzyTech* (INFORM, 2001)- first, initial models were developed for both weekday and weekend by setting the memberships (fuzzy sets' parameters) and the knowledge base (rules) intuitively (using some correlation analysis). Secondly, to overcome the limitations of intuitive setting of knowledge base, the neuro-fuzzy logic (integrated fuzzy and neural nets) (Hawas, 2004) was used.

3.1 Development of Initial Fuzzy Logic Model

The development of initial models involves three major steps- fuzzification (converting numeric variables into linguistic terms), fuzzy inference (knowledge base- 'IF-THEN' logics) and de-fuzzification (converting linguistic terms into numeric output values) (Figure 1).

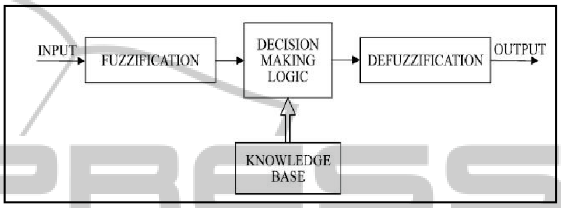

Figure 1: Conceptual block diagram of the proposed FLM.

3.1.1 Fuzzification

The input and output variables are numeric in nature. The drivers mostly perceive these as linguistic terms. For example, the traffic volume may be perceived as *high* or *medium* or *low* rather than its actual numeric values. As such, the numeric values of each input variables were converted into three linguistic terms and the values of the output variable has been converted into five linguistic terms (Table 2). The minimum and maximum values of each variable were determined from the survey results. It is to be noted that the variability of data for the output variable is high and grouping these data into more linguistic terms might result in more accurate estimation of the output variable. On the other hand, three terms have been selected for the input variables due to low variability of the data. It will also reduce the number of rule bases and neuro-fuzzy training time.

The 'L-shape' membership function (MBF) was used for all variables. The MBFs were generated using the "Compute MBF" fuzzification method. Figure 2 shows the MBF for the *Hourly Pedestrian Volume* input variable for weekday. For this particular variable, the ranges of linguistic terms were set as (0, 92), (42.465, 138) and (92, 184) for the *low, medium* and *high* terms, respectively. The possibility that a numeric level belongs to a linguistic term's range is denoted by the membership degree, μ (Y axis in Figure 2). A μ of 0.0 indicates zero possibility, while μ of 1.0 indicates full membership.

Table 2: The proposed FLM variables term definitions.

Variable name	Day of the Week	Min	Max	Linguistic terms
Length	Weekday, Weekend	0.46	2.94	Low, medium, high
IntLnks	Weekday, Weekend	4	11	Low, medium, high
PedCros	Weekday, Weekend	0	3	Low, medium, high
VCRat	Weekday	0.08	1.03	Low, medium, high
	Weekend	0.07	1.13	
PedVol	Weekday	0	184	Low, medium, high
	Weekend	0	156	
PostSp	Weekday, Weekend	40	80	Low, medium, high
SpEF	Weekday	13.9	109.9	Very low, low, medium, high, very high
	Weekend	22.36	124.89	

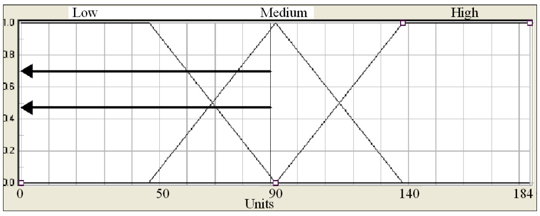

Figure 2: Membership function for 'hourly pedestrian volume' input variable.

3.1.2 Fuzzy Inference (knowledge base- 'IF-THEN' logics)

The rules (IF-THEN logics) were generated to describe the logical relationship between the input variables (IF part) and the output variable (THEN part). The degree of support (DoS) was used to weigh each rule according to its importance. A 'DoS' value of '0' means non-valid rules. Initially, all the DoS's were set to a fixed value of '1'. The IF-THEN rules were formed exhaustively based on the correlation of the input and output variables considering all possible combinations of input and output terms. The neuro-fuzzy training capability was activated in later stage to eliminate non-valid rules (the ones with DoS approaching zero value).

Two correlation matrices were developed for both weekday and weekend to define the relationship between the input and output variables (Table 3) in the fuzzy inference system..

Table 3: Correlation values between input and output variables for both weekday and weekend.

	85^{th} percentile speed	
	Weekday	Weekend
Length	0.87	0.82
Number of access points/intersecting links	0.15	0.11
Number of pedestrian crossings	-0.64	-0.35
Volume to capacity (V/C) ratio	0.27	0.08
Hourly pedestrian volume	-0.84	-0.57
Posted speed limit	0.77	0.53

It is to be noted that some of the correlation values is showing unexpected signs (e.g. V/C ratio to 85^{th} percentile speed shows positive relation). This is because of Site 2 (a local road), which has very low 85^{th} percentile speed (low posted speed limit of 40 km/hr) and very low traffic volume. Including the data of this particular road segment in calculating the correlation values affects the overall results, particularly because of the limited data (only four segments). Site 2 data were kept for calculating the correlation values to have representation of both road categories in the devised FLM, keeping in mind that increasing the sample road segments may result in better correlation values.

The used operator type for generating the fuzzy rules has been the 'MIN-MAX'. The 'MIN-MAX' method tests the magnitude of each rule and selects the highest one.

The fuzzy composition eventually combines the different rules to one conclusion. The 'BSUM' (Bounded Sum) method was used as it evaluates all rules. A total of 729 rules were generated for both weekday and weekend models. Table 4 shows six rules as an example with the final adjusted DoS's after the neuro-fuzzy training. Detail of the neuro-fuzzy training will be discussed later.

The bold row indicates that for a road segment with *low* length, *low* number of intersecting links, *low* number of pedestrian crossings, *medium* hourly traffic volume, *medium* hourly pedestrian volume and *low* posted speed limit, the estimated 85^{th} percentile speed is *medium* and the strength for this rule (DoS) is 0.90.

Table 4: Examples of (IF-THEN) rules.

IF						THEN	
Length	IntLnks	PedCros	VCRat	PedVol	PostSp	DoS	SpEF
low	low	low	low	low	low	0.90	med.
low	low	low	low	med.	low	1.00	med.
low	low	low	low	high	low	1.00	med.
low	low	low	med.	low	low	1.00	low
low	**low**	**low**	**med.**	**med.**	**low**	**0.90**	**med.**
low	low	low	med.	high	low	0.90	med.

3.1.3 Defuzzification

The results of the inference process are the linguistic terms describing the 85th percentile speed. As mentioned above, five linguistic terms were used for the output results- *very low* through *very high* 85th percentile speed*)*. In the defuzzification process, all output linguistic terms are transformed into crisp numeric values. This is done by aggregating (combining) the results of the inference process and then by computing the fuzzy centroid of the combined area. The 'Center-of-Maximum (CoM) method (Ross, 1995) is used for estimating the output numeric value, Y, as follows:

$$Y = \left(\sum_j \mu_{\mathrm{Result}}(j) * Y_j\right) \Big/ \left[\sum_j \mu_{\mathrm{Result}}(j)\right] \quad (1)$$

Where Y= numeric value representing the 85th percentile speed; $\mu_{\mathrm{Result}}(j)$ = membership value of consequence (linguistic terms) j. Y_j is referred to as the *base* value of the consequence j. It is the consequence's numeric value corresponding to a μ value of 1.

Figure 3 illustrates MBF for the output variable (85th percentile speed) for weekday using the CoM de-fuzzification procedure. The thick arrows indicate the 85th percentile speed base values, Yj on the horizontal axis and the height of the thick black arrows indicate $\mu_{\mathrm{Result}}(j)$. The base values of the five 85th percentile terms are 29.9, 45.9, 61.9, 77.9 and 93.9 respectively. $\mu_{\mathrm{Result}}(medium)$, $\mu_{\mathrm{Result}}(high)$ are 1 and 0.95, respectively. The μ_{Result} values of all other terms are zeros. The 85th percentile speed of 69.68 km/hr (indicated by the thin black arrow) was calculated using the Eq. (1).

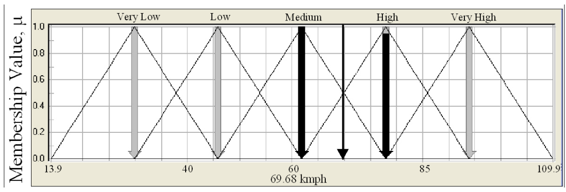

Figure 3: Membership function for the '85th percentile speed' output variable.

3.2 Neuro-fuzzy Data Training

The initial fuzzy logic models for both weekday and weekend were trained in neuro-fuzzy technique. Neuro-fuzzy technique is the combination of neural nets and fuzzy logic. It is comprised of the three fuzzy logic steps (fuzzification, fuzzy inference and de-fuzzification) with a layer of hidden neurons in each process (Hawas, 2004). Fuzzy Associative Maps (FAMs) approach is commonly used in neuro-fuzzy technique to train the data. A FAM is a fuzzy logic rule with an associated weight. This enables the use of a modified error back propagation algorithm with fuzzy logic. The neuro-fuzzy training have been conducted in three steps- defining the MBFs, rules and DoS for training, selection of training parameters, and carrying out training (INFORM, 2001).

Initially the default setting of the *FuzzyTech* tool was used to define range of the numeric values for each term. The rules were formed exhaustively with all DoS values of 1. Therefore in the first step, all MBFs and rules were selected for the neuro-fuzzy training to find the optimized fuzzy logic model. Then the parameters (step width for DoS and terms) were selected for the training. The whole neuro-fuzzy training was carried out for five cycles with each cycle for 1000 iterations.

The step width for the DoS values has been set to 0.1 for each cycle. The step width for the terms has been set to 5% in the first cycle, which was increased by 5% in later cycles. The maximum and average deviations were observed after completion of each cycle. The cycle, for which the deviation values are less, was selected as the final FLM. The process was run for both weekday and weekend models. After the training phase, the MBFs and the DoS values were determined as shown in Table 4 and Figure 4. It can be seen from the Figure 4 that the initial 85th percentile speed terms were set uniformly over the variable's range [Figure 4(a)]. The *base* value for *high* 85th percentile speed is 77.9 km/hr (indicated by black arrow). The training algorithm examines the effect of introducing a pre-specified shift to the term's base value (+5% in this case). If the base shift results in a reduction in the deviation, a new *base* is identified [71.5 in this case as shown with black arrow in Figure 4(b) for weekday model].

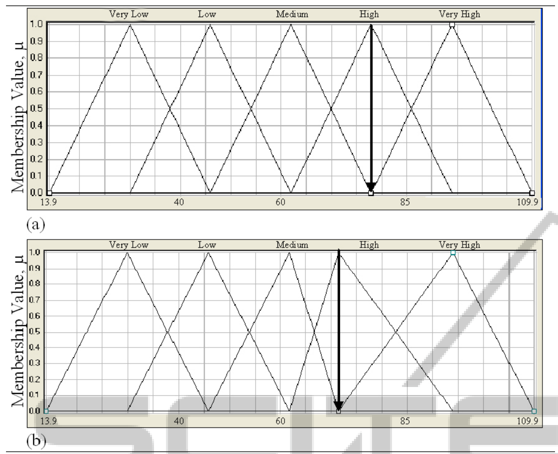

Figure 4: Membership function of '85th percentile speed' (a) before and (b) after neuro-fuzzy training.

4 MODEL VALIDATION AND RESULT ANALYSIS

After completing the training phase, the 85th percentile speeds were estimated (for both weekday and weekend) with the same set of input data which were used to develop the models. As the notion of fuzzy sets are completely non statistical in nature (Zadeh, 1965), the residual values (Figure 5) were used to compare both weekday and weekend model results. The x axis of the figure represents a specific road segment and a time period. It can be seen from the figure that the number of positive and negative deviations are almost same for both weekday and weekend models. The maximum deviations for weekday and weekend are 57.63% and 81.44%, respectively. This results in higher average deviation for weekend (19.65% for weekend compared to 14.90% for weekday).

Figure 5 also shows that the number of residuals with values of 15% or less represent 62.5% and 75% of all the residuals for weekday and weekend, respectively. It can be said that both models estimate the 85th percentile speed to a reasonable level for such limited number of sample size.

The estimated values of the 85th percentile speed were classified according to their corresponding current posted speed limits. A comparative descriptive analysis of the estimated (model results) and actual (field data) values of the grouped data for both weekday and weekend models are presented in Table 5.

It is evident in Table 5 that the mean, median, minimum, maximum and standard deviations of the estimated model results are very close to those of the actual data in case of lower posted speed limit (40 km/hr) for both weekday and weekend models. On the other hand, some variations on these values can be observed in both models' results for road segments with higher posted speed limits (60 km/hr and 80 km/hr).

Figures 6 through 8 illustrate the combined effects of two input variables on the 85th percentile speed data.

Figure 6 shows the effects of 'number of pedestrian crossings' and 'length' on the 85th percentile speed for weekday model. As indicated in the figure, the 'length' variable is positively correlated with the 85th percentile speed. On the other hand, the 'number of pedestrian crossings' is negatively correlated with the 85th percentile speed. The highest 85th percentile speed (71.50 km/hr) is found for highest 'length' (2.9 km) and least 'number of pedestrian crossings' (0-1).

Similarly, Figure 7 illustrates the effects of the 'Posted Speed Limit' and the 'Hourly Pedestrian Volume' (as input variables) on the '85th Percentile Speed' for weekday. As shown, the posted speed limit is positively correlated and hourly pedestrian volume is negatively correlated with the 85th percentile speed. As can also be seen, the effect of the posted speed is not quite noticeable if it exceeds 60 km/hr in cases of high pedestrian volumes.

As shown, the posted speed limit is positively correlated and hourly pedestrian volume is negatively correlated with the 85th percentile speed. As can also be seen, the effect of the posted speed is not quite noticeable if it exceeds 60 km/hr in cases of high pedestrian volumes.

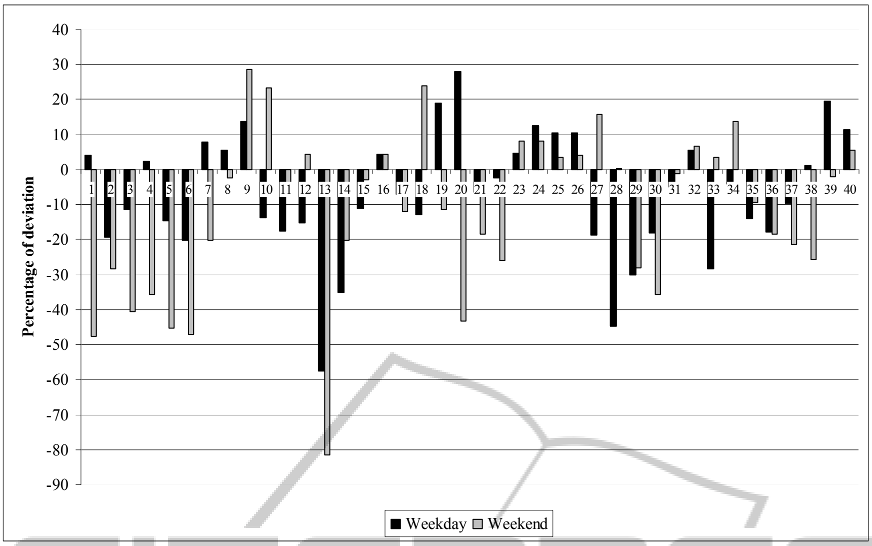

Figure 5: Percentages of deviations for both weekday and weekend FLMs.

Table 5: Comparison of descriptive statistics between the actual field data and the estimated FLM results for both weekday and weekend.

	Weekday						Weekend					
	40 km/hr		60 km/hr		80 km/hr		40 km/hr		60 km/hr		80 km/hr	
	S. Data*	E. Data**	S. Data*	E. Data**	S. Data*	E. Data**	S. Data*	E. Data**	S. Data*	E. Data**	S. Data*	E. Data**
Mean	38.2	38.94	67.82	69.77	68.7	75.89	44.79	50.55	84.71	80.89	70.1	83.74
Median	36.55	38.94	66	69.97	73	73.99	45.1	51.16	87.1	80.41	71.5	84.18
Min	29.9	29.9	55	68.78	48	71.5	39.45	40.48	52.2	79.69	47	81.61
Max	50	45.9	82	70.66	93.9	81.14	51.5	56.54	107.8	84.18	93	84.18
S.D. ***	6.37	6.07	9.6	0.93	11.36	4.12	4.49	6.32	18.66	1.48	13.61	0.91

*S. Data= Survey Data ;**E. Data= Estimated Data;***S.D.= Standard Deviation

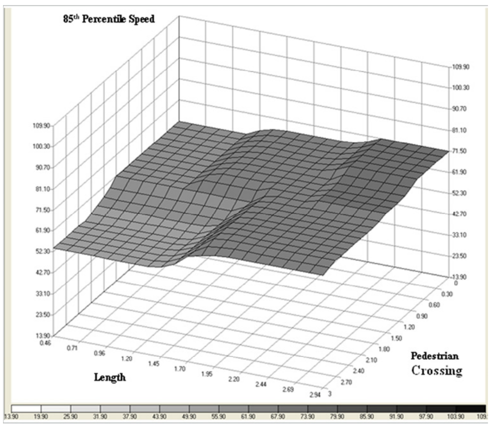

Figure 6: Effects of 'Length and Number of Pedestrian Crossings' on the '85th Percentile Speed' (weekday model).

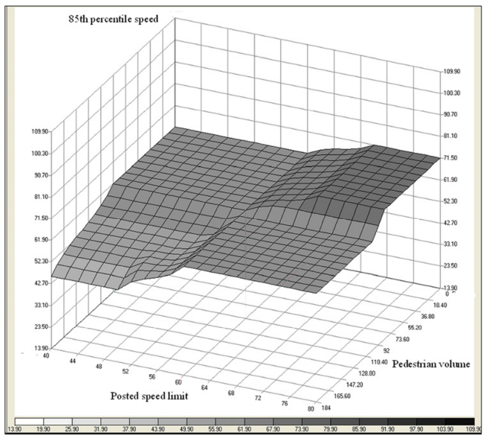

Figure 7: Effects of 'Posted Speed Limit and Hourly Pedestrian Volume' on the '85th Percentile Speed' (weekday model).

Figure 8 illustrates the relationship between the 'Length' and 'Posted Speed Limit' (as input variables), and the '85th Percentile Speed' for weekday. The two input variables are positively correlated with the 85th percentile speed. The higher the length and/or the posted speed limit, the higher is the 85th percentile speed.

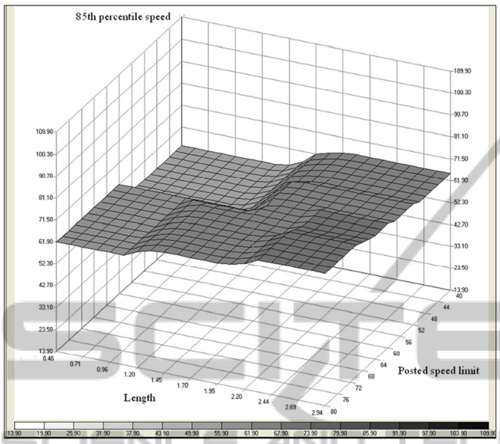

Figure 8: Effects of 'Length' and 'Posted Speed Limit' on the '85th Percentile Speed' (weekday model).

It can be said that regardless limited number of data, fuzzy logic shows the relationship between the input and output variables realistically. As fuzzy logic handles linguistic terms (for a range of numeric values), it is less sensitive to each individual numeric value. This replicates true human nature about perceiving factors on the roads. For example, it is clear from Figure 6 that drivers' choice of operating speed (represented by 85th percentile speed) is influenced by the length of the road segment or pedestrian volume. With larger length, the operating speed tends to be higher.   such changes do not occur for every one km change of length. In reality, the decision of choosing any particular range of operating speed tend to be stable for range of length (say between 0 to 1 km). Fuzzy logic predicts such relationship very realistically.

5 CONCLUSIONS

This paper discussed the development of the FLM for estimating the 85th percentile speed based on six road attributes data. The advantage of fuzzy logic is its ability to address the uncertain nature of human thinking (perception). The same road (road attribute data) can be perceived differently by different drivers and choose their operating speed accordingly. The other advantage is the using the neuro-fuzzy which can be utilized to automate the development of the knowledge base.

The FLMs are widely known for describing the vagueness and nonlinearity in the human behaviour relationships between inputs and output. However, such models are generally only valid in situations for which data are available to calibrate the model. If the FLM is to be used to assess the choice behaviour that is not covered in the data for calibration, the applicability of the model for estimating the 85th percentile speed might be questionable. As such, the data for calibration should thoroughly cover the entire range of (input and output) variables for better and more accurate estimation.

Identifying and setting appropriate posted speed limit for a given road segment is a complex task which involves studying the speed behaviour pattern of the drivers, the characteristics of road environment, road geometry, etc. This study focused on only one aspect; the drivers' speeding behaviour based on the basic road characteristics, the traffic intensity and pedestrian activities for a very limited number of road segments.

One may argue the necessity to develop such models while such 85th percentile speed can be actually measured in the field. In response to such argument is that tremendous savings in the resources (that would be needed to carry on actual field survey measures over an entire network) can be materialized. It is envisioned that these models can be developed with a reasonable representative sample of road segments in a typical network. The derived models can then be validated and subsequently applied to the entire network.

Keeping in mind the limited data set used in the study (due to the resources constraints), that likely contributes to deficiencies in representing the various road characteristics and environmental factors (with only few data points); it is legitimate to assume that the richness in data collection will ultimately lead to better more statistically significant models. Along this line, it is suggested that a systematic sampling approach should be adopted in selecting the road segments to include in the data set to use for models' calibration. The principles of the minimum sample size should be observed. It is suggested that a stratified sampling procedure to be used in selecting the road segments for spot speed field observations.   All the network roadway segments may be stratified based on their intrinsic characteristics of posted speed, length, traffic volume, pedestrian intensity, etc. A representative stratified sampling procedure with a minimum sample size according to a pre-specified confidence level and interval should be observed in generalizing the fuzzy logic modeling approach.

ACKNOWLEDGEMENTS

This research is part of M.Sc. thesis entitled 'Assessing the Methodology of Setting Posted Speed Limit in Al Ain-UAE' funded by Roadway, Transportation and Traffic Safety Research Center, United Arab Emirates University.

REFERENCES

American Association of State Highway and Transportation Officials (AASHTO), 1985. Synthesis of Speed Zoning Practice. *Technical Summary, Report No. FHWA/ RD-85/096*, Subcommittee on Traffic Engineering, Federal Highway Administration, US Department of Transportation.

Department for Transportation (DfT), 2006. Setting Local Speed Limits. Retrieved from: http://www.dft.gov.uk/pgr/roadsafety/speedmanagement/dftcircular106/dftcircular106.pdf.

Ewing, R., 1999. Traffic Calming Impacts. In *ITE (Institute of Transportation Engineers) Traffic Calming: State and Practice*. Washington, D.C., pp.99–126.

Fildes, B. N., Fletcher, M. R. and Corrigan, J. McM. (1987). Speed Perception 1: Driver's Judgments of Safety and Travel Speed on Urban and Rural Straight Roads. *Report CR54*, Federal office of road safety, Department of transport and communications, Canberra.

Fildes, B. N., Leening, A.C. and Corrigan, J. McM. (1989). Speed Perception 2: Driver's Judgments of Safety and Travel Speed on Rural Curved Roads and at Night. *Report CR60*, Federal office of road safety, Department of transport and communications, Canberra.

Fitzpatrick, K., Carlson, P., Wooldridge, M. D. and Miaou, S., 2003. Design Speed, Operating Speed, and Posted Speed Practices. *NCHRP Report 504*, Transportation Research Board, National Research Council, Washington D.C.

Fitzpatrick, K., Carlson, P., Brewer, M. and Wooldridge, M., 2001. Design Factors That Affect Driver Speed on Suburban Streets. *Transportation Research Record*, 1751, 18-25.

GRSP (Global Road Safety Partnership), 2008. *Speed Management: A Road Safety Manual For Decision Makers and Practitioners*. World Health Organization, World Bank.

Haglund, M. and Aberg, L., 2000. Speed Choice in Relation to Speed Limit and Influences from Other Drivers. *Transportation Research Part F: Traffic Psychology and Behavior*, 3, 39-51.

Hawas, Y. E. 2004. Development and Calibration of Route Choice Utility Models: Neuro-Fuzzy Approach. *Journal of Transportation Engineering*, 130 (2).

INFORM (2001). *FuzzyTech 5.5: User's Manual*. GmbH/Inform Software Corporation, Germany.

Kikuchi, S. and Pursula, M. (1998). Treatment of Uncertainty in Study of Transportation: Fuzzy Set Theory and Evidence Theory. *Journal of transportation Engineering*, 124 (1), 1-8.

Minnesota Department of Transportation (MNDOT), 2002. Speed Limit? Here is your answer. Office of Traffic Engineering and Intelligent Transportation System, Minnesota Department of Transportation. Retrieved from: http://www.dot.state.mn.us/speed/SpeedFlyer2002.pdf.

Manual on Uniform Traffic Control Devices (MUTCD), 2003. *The Manual on Uniform Traffic Control Devices 2003 Edition*. approved by Federal Highway Administrator.

Poe, C. M., Tarris, J. P. and Mason, J. M., 1996. Influence of Access and Land Use on Vehicle Operating Speeds Along Low-Speed Urban Streets, In *The 2nd National Access Management Conference*, Vail, Colorado.

Poe, C. M. and Mason, J. M., 2000. Analyzing Influence of Geometric Design on Operating Speeds along Low-Speed Urban Streets: Mixed-Model Approach. *Transportation Research Record*, 1737, 18-25.

Ross, T. J., 1995. *Fuzzy logic with engineering applications*. New York: McGraw-Hill.

Srinivasan, R., Parker, M., Harkey, D., Tharpe, D. and Summer, R., 2006. Expert System for Recommending Speed Limits in Speed Zones. *Final Report, Project No. 3-67*, NCHRP, National Research Council.

Tarris, J. P., Poe, C.M., Mason, J. M., and Goulias, K. G., 1996. Predicting Operating Speeds on Low-Speed Urban Streets: Regression and Panel Analysis Approaches. *Transportation Research Record*, 1523, 46–54.

Tignor, S. C. and Warren, D. (1990) Driver Speed Behavior on U.S. Streets and Highways. Compendium of Technical Papers, Institute of Transportation Engineers, Washington, D. C.

Transportation Research Board (TRB), 1998. Managing Speed: Review of Current Practice for Setting and Enforcing Speed Limit. *Special Report No. 254*, National Research Council, Washington, D.C.

Wang, J., 2006. Operating Speed Models for Low Speed Urban Environments Based on In-Vehicle Data. Ph. D. Georgia Institute of Technology.

Zadeh, L., 1965. Fuzzy Sets. *Information and Control*, 8, 338-353

Zadeh, L. A., 1983. The role of fuzzy logic in the management of uncertainty in expert systems. *Fuzzy Sets and Systems*, 11(1-3), 197-198.

Zimmermann, H. J., 1996. *Fuzzy Set Theory and Its Applications*. USA: *Kluwer Academic*.