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Fuzzy Logic Application to Model Uncertain Route Choice Behaviour of Bus Users in Dhaka City

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Abstract

This paper aims at addressing uncertain human behavior of selecting any particular route based on the predefined road attributes. The study has focused on the route choice behavior of individual road users. This phenomenon of choosing any particular route may depend on number of variables and the influences of variables are different and uncertain on different road users for selecting any route. The study has been conducted on users of five different bus routes of Dhaka City having same origin-destination. Bus users have been asked question regarding the factors that influence each individual's choice of any particular route. The survey has been conducted for both weekday and weekend. Fuzzy logic approach has been used to model such uncertain behavior and Neuro-fuzzy logic has been used to calibrate the fuzzy logic based model. Results have shown that travel time and waiting time are two most significant factors to influence route choice behavior. Other factors, such as the comfort, safety, security and regularity are also found significantly important. The output results of model have been validated against the surveyed data and it has revealed that Fuzzy Logic model can predict the route choice pattern (route share) to a significant level.

Introduction

Dhaka being one of the busiest mega cities of the world and capital of Bangladesh is experiencing rapid growth for the last couple of decades. The Dhaka Metropolitan Area (DMA) has the population of 9.15 million (DHUST, 2011) and is seriously suffering from congestion problem. The transportation network needs to be designed for handling both current and future traffic loads so that it can minimize the possibility of traffic congestion. Route choice plays a critical role in many transportation related problems most importantly in the congestion (Arslan and Khisty, 2006: 571). In the context of the present congested scenario, route choice modeling should receive emphasis in transport sector to forecast demand for different routes. Route choice models not only help analyzing and understanding travelers' behavior, but also constitute the essential part of traffic assignment methods (Prato, 2009: 65).

In order to make a tangible decision about future road infrastructure requirements, it is essential to understand how individual people choose their routes. Such inventory of individual's route choice behavior is important part of transport planning. Choosing any

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particular route depends on individual road user's perception about different factors such as, travel time, waiting time, comfort level etc. However, such perception varies from person to person. Any particular factor may be perceived differently by different people. Therefore, it is very important to adopt a method to address such uncertainty in selecting any particular route. In this study, fuzzy logic technique has been used to develop a method for identifying individual's route choice behavior and route share. Fuzzy logic method has been chosen for its strength to deal with the uncertain, vague, imprecise or ambiguous data and to mimic how a person would make decisions much faster (Kaehler, 1998).

Previous Studies

Several studies have been done in transportation sector to handle fuzzy perceptions in explaining route choice behavior from behavioral point of view (Arslan and Khisty, 2006: 571) and to address the improvement of route choice model by adding realistic behavioral assumptions (Ben-Elia et al, 2007). A psychological research stated that different generalizations imply deviations in different directions, specifically; different choices arise when decisions are taken on the basis of information compared to those taken on the basis of personal experience (Ben-Elia et al, 2007). Some other studies developed route choice utility model by neuro-fuzzy approach and calibrating the model using user opinion information (Hawas, 2004: 171; Chandran et al, 2013: 09).

To calculate the utility of each route and to choose different route, different studies have used different factors. For example, one study used travel time, queue time, familiarity, speed and pavement condition (Chandran et al, 2013) to calculate the utility of each route but other researchers incorporated variables related to network topology, complementing those found in traditional models based on service levels and users' socio-economic and demographic character to develop a route choice model for public transit networks (Grange et al, 2011:138). Binetti and De Mitri developed a path choice model using random utility models where they utilized only one parameter for representing the imprecision of the costs with the hypothesis that the choice of users depends on the comparison of the estimated cost of all the paths and these values are affected by imprecision, vagueness and uncertainty (Binetti and De Mitri, 2002). Henn proposed a new route choice model based on a fuzzy representation of costs and using possibility comparison by using fuzzy logic (Henn, 2000:77).

Very few studies have been done in route choice modeling in Bangladesh. As a result, the study had to face the lacking of necessary information and support in local context. No study has been done by using Fuzzy Logic to address the issue of how people choose their route in Bangladesh, more precisely in Dhaka city. As such, the main objective of this study was to calculate the road user's route share for network assignment using fuzzy logic.

The paper is divided into six sections. Section 1 illustrates the background of the study and the literature review. Section 2 introduces the methodology used for data collection and surveys. Fuzzy logic model development methods and neuro-fuzzy training of the model have been discussed in Section 3. Section 4 describes the validation of the developed model and model result analysis. Conclusion and Recommendations of the study have been presented in Section 5.

Data Collection

Two trip production/attraction points were chosen and only bus routes were selected to conduct the study. It is because more than one route is available to travel between the two selected trip production/attraction points and due to time and resource constraint. However, it is anticipated that studying only bus user's behavior will fulfill the objective of the study.

The data needed for the study was collected by conducting a questionnaire survey. The questionnaire was designed to extract information regarding the particular route one user was using at the time of conducting the survey and the reasons behind choosing the particular route. The reasons or variables which significantly influence the individual's route choice behavior were selected based on the literature review. Since bus routes were considered for this study, only bus users' socio economic characteristics and travel attributes (both route attributes and bus attributes) were considered as the influential indicators for route choice. The selected variables are presented in the Table 1.

Table 1: Description of variables

Variable No.	Variable Name	Definition	Denoted in FLM
Socio Economic Variables			
1	Age	Age of the Travelers	Age
2	Gender	Gender of the Travelers	Gender
3	Income	Monthly Income of the Travelers	Income
Travel Variables			
4	Distance	Length of the Route	Distance
5	Travel Cost	Cost of the travel in taka	T_Cost
6	Travel Time	Total time needed to accomplish a trip in minute	T_Time
7	Waiting Time	Total waiting time for the bus	W_Time
8	Comfort level	Comfort level of the bus	Comfort
9	Safety Level	Safety level of the bus	Safety
10	Security Level	Security level of the bus	Security
11	Regularity Level	Regularity level of the bus	Regularity

Mirpur Section 1, a residential location, was chosen as origin point where more than one bus route was available to reach the origin point; and Motijheel Commercial Area, a commercial and business hub of Dhaka City, was chosen as destination point. The target population of this study is the people who travel from Mirpur 1 to Motijheel daily or at least for three days in a week. The survey was conducted only for the morning peaks due to the nature of the origin/destination location.

Model Development

Development of Fuzzy Logic Model (Flm)

Fuzzy Logic Model (FLM) was developed using the Fuzzy TECH 5.55i. Unlike other models, the FLM has the strength to work with imprecise or vague data with linguistic relations (*4*). The development of FLMs and selection of final model were done in three steps- first, development of pure FLMs; second, use of neuro-fuzzy techniques for FLM calibration, and third, FLM validation and selection of final FLM. FLMs were developed for both weekday and weekend to understand the route choice behavior on the both days.

Initial Flm Development

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).

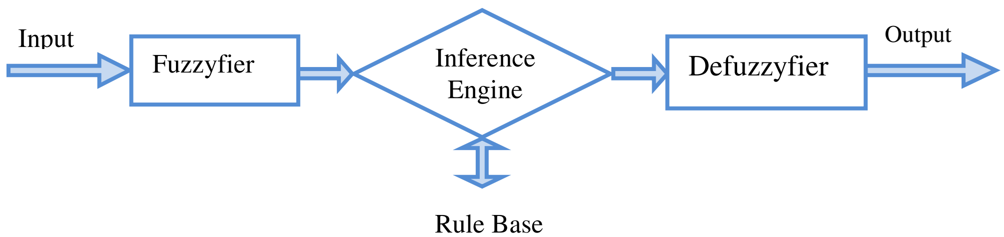


Fig. 1: Block Diagram of Fuzzy inference systems

Fuzzification

Some of the input variables, for example, travel cost, travel time, waiting time, distance etc are numeric. But, users always perceive these variables as linguistic. For example, the cost is often perceived as *high* or *low*, distance as *long* or *close* rather than their actual numeric values. The other input variables, such as comfort, safety, security, etc. are linguistic in nature and were converted into two linguistic terms *low* and *high*. The rest of the input variable values were converted into three linguistic terms as *low, medium* and *high*. The linguistic term for the output variables i.e. the choice of any particular route were *true* (for selected route) or *false* (other routes). Table 2 shows the linguistic terms for input and output variables.

The 'L-shape' membership function (MBF) was used for all variables. The MBFs were generated using the "Compute MBF" fuzzification method. Figure 2 is showing the membership function for 'Travel Time' input variable for weekday as an example. For this particular variable, the ranges of linguistic terms were defined as (75, 142.5), (108.75, 176.25) and (142.5, 210) for *low, medium* and *high* term respectively. The probability 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 probability while μ of 1.0 indicates full membership.

Table 2: Input variables and associated linguistic terms

Variable name	Day of the Week	Min	Max	Linguistic terms
Input Variables				
Age	Weekday, Weekend	1	5	Low, medium, high
Gender	Weekday, Weekend	1	2	False, true
Income	Weekday, Weekend	1	5	Low, medium, high
Distance	Weekday, Weekend	12.5	15	Low, medium, high
Travel Cost	Weekday, Weekend	16	20	Low, medium, high
Travel Time	Weekday	75	210	Low, medium, high
	Weekend	40	105	
Waiting Time	Weekday	2	16	Low, medium, high
	Weekend	2	20	
Comfort	Weekday, Weekend	1	5	Low, high
Safety	Weekday, Weekend	1	5	Low, high
Security	Weekday, Weekend	1	5	Low, high
Regularity	Weekday, Weekend	1	5	Low, high
Output Variables				
Route 1	Weekday, Weekend	0	1	True, false
Route 2	Weekday, Weekend	0	1	True, false
Route 3	Weekday, Weekend	0	1	True, false
Route 4	Weekday, Weekend	0	1	True, false
Route 5	Weekday, Weekend	0	1	True, false

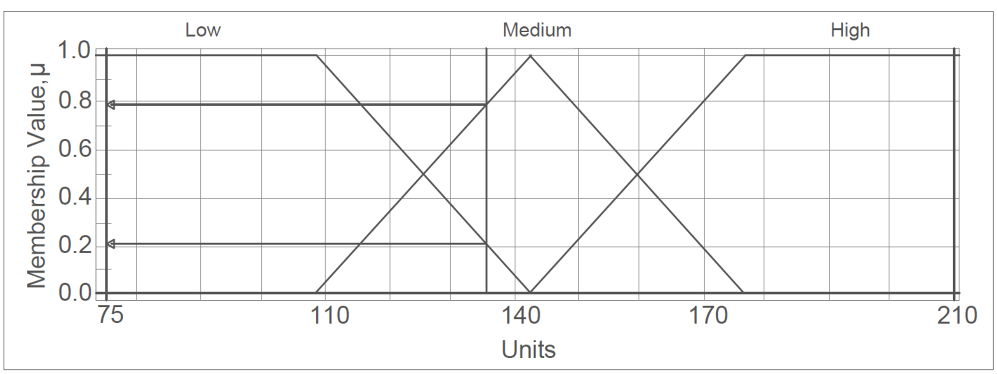


Fig. 2: Membership function for 'Travel Time' input variables

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

After defining the MBFs, the rules (IF-THEN logics) were generated to describe the logical relationship between the input (IF part) and the output (THEN part) variables.

The rules 'IF' part describes the situation, for which the rules are designed. The 'THEN' part describes the response of the fuzzy system in that particular situation. 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 DoSs were set to '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.

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

Input Variables	**Output Variables**									
	Route 1		**Route 2**		**Route 3**		**Route 4**		**Route 5**	
	WD*	WE**	WD	WE	WD	WE	WD	WE	WD	WE
Age	-0.135	-0.086	-0.039	-0.003	-0.240	-0.388	0.200	0.257	0.216	0.220
G1ender	0.003	0.096	-0.056	0.108	0.020	-0.007	-0.005	-0.150	0.038	-0.041
Income	0.052	-0.078	0.056	-0.126	0.044	-0.041	-0.071	0.111	-0.082	0.131
Distance	0.162	0.151	-0.855	-0.847	-0.071	-0.086	0.086	0.077	0.692	0.696
Travel Cost	0.084	0.082	-0.298	-0.284	0.085	0.085	-0.680	-0.692	0.825	0.824
Travel Time	-0.320	0.128	0.441	0.362	-0.529	-0.027	0.191	-0.323	0.218	-0.125
Waiting Time	-0.062	-0.127	-0.402	0.464	-0.125	-0.215	0.383	-0.006	0.209	-0.106
Comfort	-0.033	-0.048	0.035	-0.014	0.050	0.092	-0.419	-0.480	0.374	0.462
Safety	0.089	0.203	0.050	-0.013	0.098	0.052	-0.283	-0.348	0.047	0.114
Security	0.034	0.203	-0.014	-0.086	0.030	0.042	-0.131	-0.312	0.083	0.161
Regularity	-0.238	-0.067	-0.040	-0.138	-0.142	-0.130	0.120	0.116	0.302	0.217
*WD**	Weekday									
*WE***	Weekend									

Table 3 shows that Route 1 has very low correlation with all input variables for both weekday and weekend. Route 2 has high negative correlation with distance in both weekday and weekend. Route 3 is negatively correlated with travel time for both weekday and weekend. Route 4 is negatively correlated with travel cost for both weekday and weekend. The used operator type in this study is the 'MIN-MAX' because of its easiness to implement. In this method, the characteristic of each operator type is influenced by an additional parameter. For example:

MIN-MAX, parameter value ()=Minimum Operator (MIN)

The 'MIN-MAX' method tests the magnitude of each rule and selects the highest one. The horizontal coordinate of the 'fuzzy centroid' of the area under the MBFs was taken as the output. This method does not combine the effects of all applicable rules, but produces a continuous output function. The fuzzy composition eventually combines the different rules to one conclusion. The 'BSUM' (Bounded Sum) method was used to evaluate all rules. A total of 360 rules for weekday and 405 rules for weekend were generated. Table 4 shows ten rules for only four travel related input variables as an example with the final adjusted DoSs after the neuro-fuzzy training. Detail of the neuro-fuzzy training are discussed later.

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

IF				THEN									
Distance	Travel Cost	Travel Time	Waiting Time	DoS	Route 1	DoS	Route 2	DoS	Route 3	DoS	Route 4	DoS	Route 5
low	low	Low	Low	1.00	false	1.00	true	0.95	true	0.00	true	1.00	False
medium	low	Low	low	1.00	false	1.00	false	0.00	true	1.00	true	1.00	False
high	low	Low	low	0.09	true	1.00	false	1.00	false	1.00	true	0.00	True
low	medium	Low	low	1.00	false	0.84	true	1.00	true	0.00	true	1.00	False
medium	medium	Low	low	0.00	true	1.00	false	1.00	true	0.00	true	0.00	True
high	medium	Low	low	1.00	true	1.00	false	1.00	true	0.96	true	0.00	True
low	**high**	**Low**	**low**	**1.00**	**false**	**1.00**	**false**	**1.00**	**true**	**1.00**	**false**	**0.56**	**True**
medium	high	Low	low	1.00	true	1.00	false	1.00	true	1.00	false	1.00	True
high	high	Low	low	1.00	true	1.00	false	1.00	true	1.00	false	1.00	True
low	low	Medium	low	1.00	false	1.00	true	1.00	true	0.01	true	1.00	False

The bold row indicates that with less distance, high travel cost, less travel time and waiting time, two routes (Route 3 and Route 5) can be chosen. The strength (DoS) of choosing Route 3 is 1.00, whereas the strength of choosing Route 5 is 0.56.

De-fuzzification

The results of the inference process were the linguistic terms describing the decision of choosing any particular route. As mentioned earlier, two linguistic terms were used for the output results- *true* and *false*. In the de-fuzzification step, all output linguistic terms were transformed into crisp numeric values. This was 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) was used for estimating the output numeric value, Y, as follows:

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

where Y= numeric value representing the decision of choosing any particular route; $\mu_{\mathrm{Result}}(j)$ = membership value of consequence (linguistic terms) j. Y_j is referred to as the *initial decision* of the consequence j. It is the consequence's numeric value corresponding to a μ value of 1.

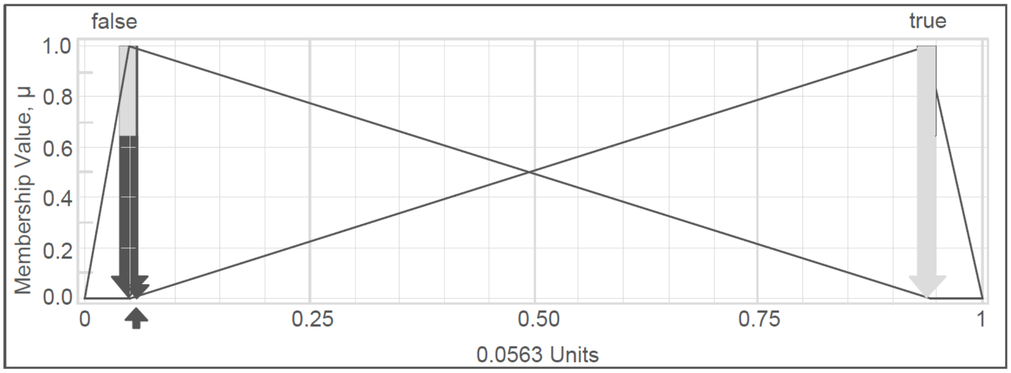


Fig. 3: Membership function for 'Route 5' output variables (weekday)

Figure 3 illustrates MBF for the output variable of Route 5 for weekday using the CoM de-fuzzification procedure as an example. The thick arrows indicate the base decision for Route 5, *Yj* on the horizontal axis and the height of the thick black arrows indicate $\mu_{Result}(j)$. The base values of choosing Route 5 are 0.04742 and 0.93795 respectively. μ_{Result}(false), $\mu_{Result}(true)$ are '0.65' and '0' respectively. The possibility of choosing Route 5 is 0.0563 (indicated by the thin black arrow) was calculated using the Equation (1).

Neuro-Fuzzy Data Training

The initial fuzzy logic models for both weekday and weekend were trained in neuro-fuzzy technique. It is comprised of the three fuzzy logic steps (fuzzification, fuzzy inference and de-fuzzification) with a layer of hidden neurons in each process (Khan and Hawas, 2012). Fuzzy Associative Maps (FAMs) approach is used in neuro-fuzzy technique to train the data. The neuro-fuzzy training was conducted in three steps-firstly, defining the MBFs, rules and DoS for training; secondly, selection of training parameters; and lastly, carrying out training (*Fuzzy Tech 5.5: User's Manual*, 2001).

Initially the default setting of the *Fuzzy Tech* tool was used to define the range of the numeric values for each term. In the first step, all MBFs and rules were selected for the neuro-fuzzy training. As all MBFs and DoSs were selected for optimization, this is regarded as full system setting up. It entails more training effort, but insures best representation of the calibrated FLM. The training of these values was carried out incrementally. Similarly, the DoSs of the rules was optimized iteratively by slightly changing their values with a pre-specified number. A random method was initially selected for picking the MBFs and DoSs for carrying out the optimization first. Following the convergence of the system, the so-called 'real learning method' was selected to fine tune all MBFs and DoSs systematically.

After starting the process, the parameters were set manually to find the optimum solution by reducing the maximum and average deviations. The increment of DoS change was set to 0.1 and the change in MBF was set to 1% for 1000 iteration for both weekday and weekend models.

The training was carried out in one cycles considering minimum increment value of the parameters (DoS values and the MBF definition points). Training the models by increasing the minimum parameter values also increased the training time. But it considered all possible parameter values for training the models. The training results in the calibrated FLMs of the route choice for weekday and weekend. Figure 4 shows the MBF of Route 5 choice decision before and after the neuro-fuzzy training.

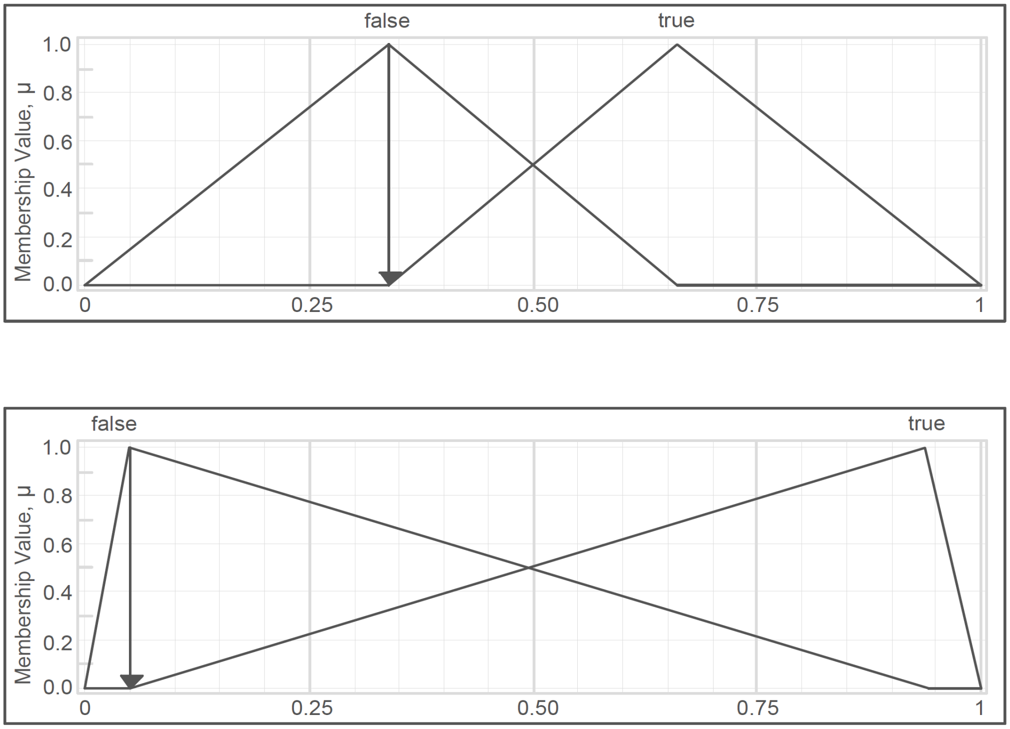


Fig. 4: Membership function of 'Route 5 Choice Decision' (a) before and (b) after neuro-fuzzy training (weekday)

Model Validations and Result Analysis

Validation of the fuzzy logic model results was carried out by comparing the output directly with the field data. It was done so as there is no statistical evidence exists for FLM (Zadeh, 1965: 338). It was found from the first model run that the FLMs were not been able to estimate the route share for all routes for both weekday and weekend. As such, other FLMs were developed using different combination of input variables (IV-11 in total). In total, 13 FLMs for both weekday and weekend were developed. Output (chosen route) of all models was compared with the field survey data to obtain the best model for route choice. Table 5 summarizes different combination of input variables for developing fuzzy logic models.

Table 5: FLMs development criteria (Combination of Input Variables) and output

Name of FL Models	Day of a week	Accuracy rate
Model No-1 (IV_11=A, G, I, D, TC, TT, WT, C, S, SC, R)	Weekday	22% (R2, R3 and R5 not Identified)
	Weekend	38.62% (R3, R4 and R5 not Identified)
Model No-2 (IV_03= A, G, I)	Weekday	28%
	Weekend	37.57%
Model No-3 (IV_08= D, TC, TT, WT, C, S, SC, R)	Weekday	42% (R2 not Identified)
	Weekend	56.08% (R3 not Identified)
Model No-4 (IV_4= D, TC, TT , WT)	Weekday	40% (R2 and R4 not Identified)
	Weekend	**91%**
Model No-5 (IV_4= C, S, SC, R)	Weekday	35%
	Weekend	50.26%
Model No-6 (IV_06= TT, WT, C, S, SC, R)	Weekday	51%
	Weekend	60.85%
Model No-7 (IV_07= A, G, I, C, S, SC, R)	Weekday	20% (R4 not Identified)
	Weekend	46.03%
Model No-8 (IV_9= A, G, I, TT, WT, C, S, SC, R)	Weekday	43%
	Weekend	39.68%
Model No-9 (IV_10= A, G, I, D, TT, WT, C, S, SC, R)	Weekday	49% (R1 and R2 not Identified)
	Weekend	39.15% (R2, R3 and R4 not Identified)
Model No-10 (IV_10= A, G, I, TC, TT, WT, C, S, SC, R)	Weekday	53% (R2 and R3 not Identified)
	Weekend	**70.37%**
Model No-11 (IV_07= D, TT, WT, C, S, SC, R)	Weekday	66% (R3 not Identified)
	Weekend	70.37% (R2 not Identified)
Model No-12 (IV_07= TC, TT, WT, C, S, SC, R)	Weekday	57% (R3 not Identified)
	Weekend	61.38% (R1 not Identified)
Model No-13 (IV_05= TT, WT, C, S, R)	Weekday	**69%**
	Weekend	52.91%
Code used for Naming of Model: IV = Number of Independent Variable Ex = Excluded Variable/s Mrg = Merged Variables '---' = Model selection criteria not fulfilled	**Code used for Naming of Variables** SEV = Socio Economic Variables (Age, Gender, Income) TV = Travel Variables (Distance, Travel Cost, Travel Time, Waiting Time, Comfort, Safety, Security, Regularity)	**Code used for Naming of Variables** A= Age G = Gender I = Income D = Distance TC = Travel Cost TT = Travel Time WT = Waiting Time C = Comfort S = Safety SC= Security R = Regularity

Three criteria were checked to finalize the preferred FLMs for both weekday and weekend. First, predicted routes i.e. if the model is capable of identifying all route share. Second, overall accuracy rate i.e. if the estimated route share is close to the observed route share. Third, the sum of square of the deviation (SSD) was checked for all developed models. It can be seen from Table 8 that Model No. 2, 5, 6, 8 and 13 have predicted all route share with higher accuracy for weekday FLMs. However, Model No. 2, 4, 5, 6, 7, 8, 10 and 13 have estimated all route share for weekend. The SSD has been calculated only for these models using the following formula:

$$SSD = \sum_{1}^{R=5} (ActualRouteShare_R - EstimatedRouteShare_R)^2 \tag{2}$$

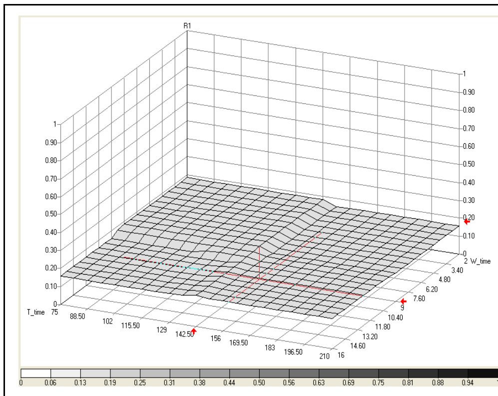
Lower value of SSD indicates better model prediction. Table 6 shows the estimated route share and associated SSD for weekday models as an example. It shows that ***Model No. 13*** has lower SSD, hence this was selected as the preferred model for weekday.

Table 6: Estimated route share and sum of square deviation (SSD) of weekday FL models

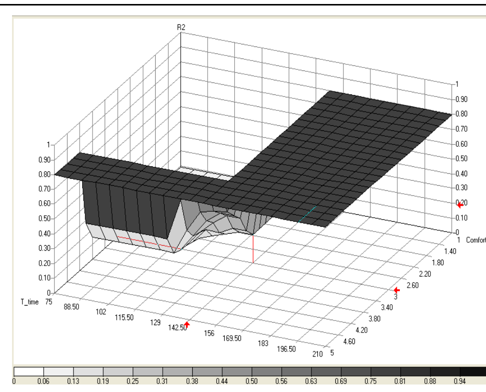
Routes	**Actual Share (%)**	**Model No-2 (%)**	**Model No-5 (%)**	**Model No-6 (%)**	**Model No-8 (%)**	**Model No-13 (%)**	**Model No-2-SSD**	**Model No-5-SSD**	**Model No-6 – SSD**	**Model No-8 - SSD**	**Model No-13-SSD**
R1	19.8	15	15.07	7.55	20	9.03	23.04	22.39	150.13	0.04	116.04
R2	20.3	6.67	17.81	21.7	10	19.44	185.87	6.21	1.95	106.09	0.73
R3	20.3	41.67	5.48	27.36	2.22	25	456.53	219.65	49.82	326.81	22.09
R4	20.3	1.67	20.55	37.74	34.44	26.39	347.20	0.06	304.01	200.07	37.07
R5	19.3	35	41.1	5.66	33.33	20.14	246.49	475.06	186.04	196.93	0.70
Total	100	100	100	100	100	100	1259.13	723.37	691.96	829.94	**176.64**

Same procedures were followed for finalizing the preferred model for weekend. Analysis of weekend model results showed that *Model No. 4* was estimating the route share with lesser SSD. Therefore, *Model No. 4* was chosen as the preferred model for weekend.

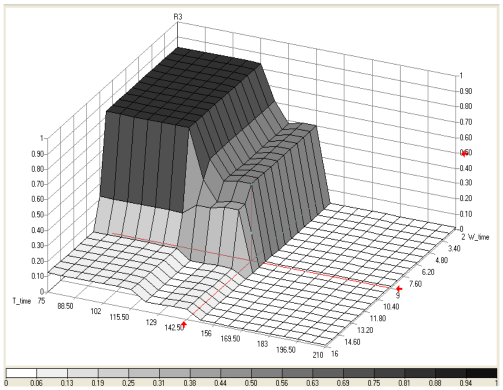
Figure 5 shows the effect of two input variables on choosing any particular route as an example.



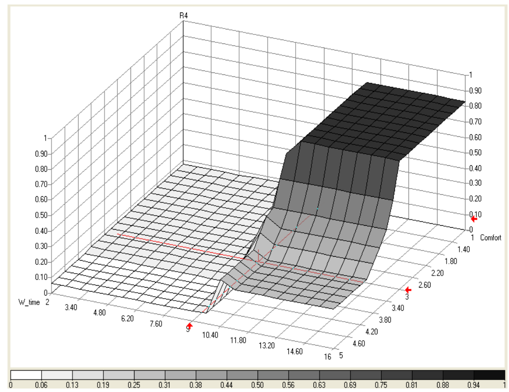
a. Effect of ‘Travel time and Waiting time’ on ‘Route 1’ (Weekday FLM)



b. Effect of ‘Travel time and Comfort’ and ‘Route 2’ (Weekday FLM)



c. Effect of ‘Travel time and Waiting time’ and ‘Route 3’ (Weekday FLM)



d. Effect of ‘Waiting time and Comfort’ and ‘Route 4’ (Weekday FLM)

Fig. 5: Combined Effect of input variables on route choice

Figure 5 (a) illustrates the combined effect of ‘Travel time’ and the ‘Waiting time’ (as input variables) on Route 1 for weekday FLM. As shown in the figure, both the ‘Travel time’ and ‘Waiting time’ variables are negatively correlated with Route 1. The highest possibility of choosing of Route 1 (0.18) is found for lower travel time (75 to 142.5 minute) and lower waiting time (2 to 9 minutes).

Similarly, Figure 5 (b) illustrates the relationship between the ‘Travel time’ and the ‘Comfort’ (as input variables), and ‘Route 2’ using the weekday FLM. As shown in the figure, both ‘Travel time’ and ‘Comfort’ are positively correlated with Route 2.

Figure 5 (c) illustrates the relationship between the ‘Travel time’ and the ‘Waiting time’ (as input variables), and Route 3 for weekday FLM. Like Route 1, the two input variables are negatively correlated with Route 3. It shows that the lower the travel time and/or waiting time, the higher is the possibility to choose Route 3.

Figure 5 (d) illustrates the affect of ‘Waiting time’ and ‘Comfort’ (as input variables) on choosing Route 4 for weekday FLM. The figure illustrates that comfort is negatively related with Route 4 in weekday model which indicates that with increase in comfort level, choice of Route 4 will decrease. The relation between waiting time and Route 4 is shown positively correlated, whereas, it is expected to have a positive correlation with comfort and negative correlation with waiting time. The reason might be that this particular route 4 has very high demand despite of having high waiting time and less comfort. As such, the above mentioned factors may not have any significant impacts on choosing this particular route.

It can be said from the above figures and analysis that fuzzy logic can show the relationship between the input and output variables more realistically. As fuzzy logic handles linguistic terms (a range of numeric values), it is less sensitive to each individual numeric value. This replicates true human nature about perceiving the influential factors for choosing any particular route.

Conclusion

This paper discused the development of fuzzy logic based model for predicting the route choice decision based on some predefined variables. In this study, only 11 variabels were selected to understand such behavior. It was found that travel time, waiting time, safety, regularity and comfort level were the most influential factors for choosing routes for weekday. However, weekend models identified distance, travel cost, travel time and waiting time to be the most influential factors. It was also found that the average accuracy of predicting all routes from Mirpur 1 to Motijheel is 69% and 91% for weekday and weekend FLMs respectively. The factors that were identified to be the most significant for selecting bus routes can also be used in future researches and policy formulation. The models have been developed using proper sample size, hence can be used in predicting the route share of similar bus services and roads. In this study the fuzzy logic model results were compared only with the field data. In future, the same data need to be used to develop other models using different approach (for example, multinomial logit model) and the result of both model approaches need to be compared. Such comparison of FLMs with other models will give more confidence in the FLMs output results. Keeping in mind that the study was conducted only for the bus users, it is suggested to include more road users and more origin/destination points to develop a robust route choice model.

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