

# **A fuzzy logic-genetic algorithm approach to modelling public transport users' risk-taking behaviour**

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*Keywords: public transport, route choice, genetic algorithm, fuzzy logic*

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## **Abstract**

The objective of this study is to determine the effects of uncertainty in out-of-vehicle times on route choice. Data was collected at two key interchanges in Auckland, New Zealand. Previous work modelled the data using a manual approach to fuzzy logic. This study extends that work by automating the process through defining a black-box function to match the survey data, then employing a genetic algorithm to fine-tune the fuzzy logic model. Results showed that automation and the genetic algorithm improved the model's capability to more accurately predict ridership. The tuning of the membership functions was conducted twice, first using initial fuzzy rules and again after the fuzzy rules had been adjusted to reduce disparity between the output and survey data. The calibrated membership functions provided for operational (transfer waiting and walking time and delay) and physical attributes (safety and seat availability) can be used by practitioners to determine an estimated ridership.

## 1 Introduction and Research Objective

In today's society, for reasons ranging from the increase in demand for employees' flexibility in the labour market to the decline of traditional household travel patterns, private vehicles play a dominant role in travel behaviour. Commuters prefer direct, high-frequency services for public transport (PT), however, not all origins and destinations can be provided by direct routes. As such, a PT network needs to be composed of inter-modal and intra-modal transfers. To reduce the inconvenience associated with transfers, globally, policy makers have been developing strategies to produce an effective integrated multimodal system which is a combination of high and low frequency services (Vassallo et al. 2012). The objective of such integrated systems has been to provide travellers with a wide spectrum of destination choices through a convenient, accessible, comfortable, safe, speedy and affordable PT system (Luk and Olszewski 2003, Ulengin et al. 2007). This can be achieved by strategically positioning transfer points in the network to optimize resources (Navarrete and Ortuzar 2013). Therefore, an important element in the development of such integrated systems is for policy makers and operators to facilitate routes with "seamless" transfers. Ceder defined a well-connected journey to be:

*"An advanced, attractive transit (PT) system that operates reliably and relatively rapidly, with smooth (ease of) synchronized transfers, part of the door-to-door passenger chain".*

It has been well documented that PT users are negatively disposed towards transfers. In modelling, this is represented by a value termed "transfer penalty". The extra effort required in making transfers has deemed them to be a significant contributor to users' journey inconvenience (Hadas and Ranjitkar 2012). Perceived uncertainty associated with transfer connections can cause travellers to completely avoid transfer routes. Users perceive variation in out-of-vehicle times as risk. Variations occur when the actual departure and arrival times deviate from the scheduled times. This problem is amplified in chained trips as missed connections can cause the total journey time to substantially increase. Due to the difficulties in providing a consistent high level of reliability for connections, it is inevitable that a certain amount of variability is likely to occur. Previous work by the authors (Ceder et al. 2013) adopted the cumulative prospect theory and fuzzy logic to model users' perception of risk for out-of-vehicle times. The modelling of fuzzy logic was manually calibrated and validated, using Microsoft Excel. To improve the modelling, in the present study, user's perception of risk for out-of-vehicle times will be modelled using fuzzy logic, automated in MatLab, and with membership functions calibrated using a genetic algorithm (GA). The results are expected to assist planners and operators to determine ridership of a route involving transfer given the degree of variability in out-of-vehicle times.

Hereafter, Section 2 provides literature review, Section 3 is a description of the survey data, Section 4 gives the fuzzy logic-genetic algorithm model's process, Section 5 provides the results and lastly, Section 6 is discussion and conclusion.

## 2 Literature Review

### 2.1 Out-of-vehicle time attributes

There are two types of transfers, direct transfer and transfer including a walk (Parbo et al. 2014). Direct transfer includes only waiting time for the next vehicle to make the connection. There is much support for transfer waiting times being valued higher than transfer walking times. Sparing and Goverde (2013) discussed that operators attempt to minimise long transfer waiting times through timed transfers. The study suggested the adoption of *guaranteed* timed transfers; such transfers are when a departing vehicle waits for moderately delayed arriving vehicles. This type of connections was seen to improve the travel experience of transferring passengers. Due to the variable nature of transfer waiting time, it can effect users' route decision. Cats and Gkioulou (2014) adopted an agent-based model to determine users' route choice based on wait-time uncertainty. The study found that route selection is based on past experience as well as perceived reliability of static and real-time information. Parbo et al. (2014) discussed the importance of timetable offset, which determines transfer waiting time, on users' travel experience at any connection point. The study developed a bi-level timetable optimisation approach to minimise waiting time from users' transferring to and from bus lines. Users' perceived waiting time has been shown to be more onerous than the actual waiting

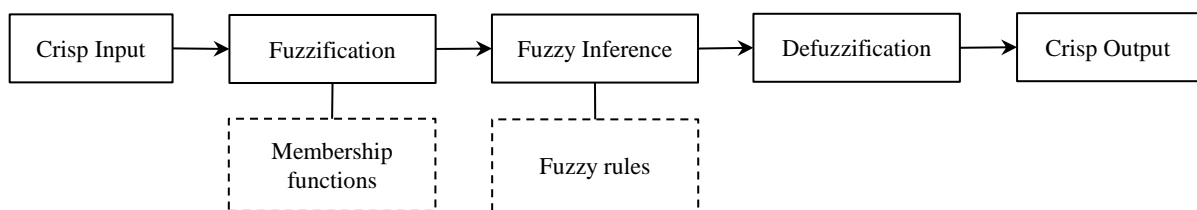
time. Perceived waiting time is dependent on waiting conditions such as personal safety, reliability of connection and comfort (Iseki and Smart 2011). As for transfer walking time, factors which influence it are the physical connection between terminals such as covered walk-ways and information provisions such a guide signs and maps. Female users penalise transfer walking times 4.05 more times than men (Navarrete and Ortuzar 2013). Unfamiliar facilities and/or low quality information can lead travellers making a transfer to wander, stress and feel uncertain about “how to make a transfer, where to transfer, on which corner or bus stop or platform to wait and so on” (Iseki and Taylor 2009).

The importance of personal safety at terminals has been echoed in several travel behaviour studies (Atkins 1990, Volinski and Page 2006, Iseki and Taylor 2008). Fear and apprehension about personal safety can affect all aspects of travel, including mode and route choice. Security is primarily measured at station areas as these are points of highest crime occurrence and greatest passenger vulnerability (Volinski and Page 2006). It was seen that travellers are more likely to feel unsafe during out-of-vehicle times than in-vehicle times (Hiscock et al. 2002). Feeling safe on one’s streets and trust in the local community have some effect on perception of personal safety when using PT (Delbosch and Currie 2012). Hale and Miller (2013) explained that station environment plays an important role in the PT users’ journey experiences and therefore the conceptualisation effort needs to be a design task, particularly for multimodal stations. The design aspects identified are: access and connection, way-finding, direct customer service, layout of station (ease of internal movement), platform conditions, aesthetics and overall comfort.

## 2.2 Fuzzy logic: application in transportation

Fuzzy logic has also been well established in the transportation field. Fuzzy logic, first introduced in 1965 (Zadeh 1965), allows the formation of logical statements to compute vagueness in subjective judgment. Using the concept of “approximate reasoning”, fuzzy logic makes it possible to model imprecision in human reasoning and thus, decision making. A number of route and mode choice studies have shown that fuzzy logic is capable of modelling ambiguity in perception and appraisal of trip attributes (Ridwan 2004, Manju et al. 2008, Postorino and Versaci 2008). Recently, Kumar et al. (2013) developed a mode choice model using fuzzy logic. The study examined travellers’ commuting patterns and their willingness to select PT. Each fuzzy logic system can be divided into three stages: fuzzification, fuzzy inference and defuzzification. Figure 1 shows the link among the stages and the input and output of each stage.

A disadvantage of fuzzy logic is the task of fine-tuning the membership functions and adjusting the fuzzy rules. Construction of the membership functions and the fuzzy rules is a trial-and-error process until an appropriate fit of the input-output set is achieved. This process can be simplified by use of learning algorithms in programs such as MatLab for tuning (Postorino and Versaci 2008). Vythoukas and Koutsopoulos (2003) developed a neuro-fuzzy framework which gives a weight to the fuzzy rules and applied the framework to determine mode choice. Ridwan (2004) used FiPV (Fuzzy individuelle Präferenzen von Verkehrsteilnehmern) to model route choice of individual drivers for traffic assignment. Andrade et al. (2006) proposed a hybrid model (multinomial logit model with neuro-fuzzy utility functions) to determine mode choice between PT modes and cars. Postorino and Versaci (2008) used an adaptive neuro-fuzzy inference system to investigate the decision criteria followed by users when they select a transport mode. Hanaoka and Kunadhamraks (2008) developed a fuzzy logic model using multi-criteria decision making approach, Analytic Hierarchy Process (AHP) to assess the decision process of operators.



**Figure 1: Fuzzy Logic Systems**

### **3 Data Collection**

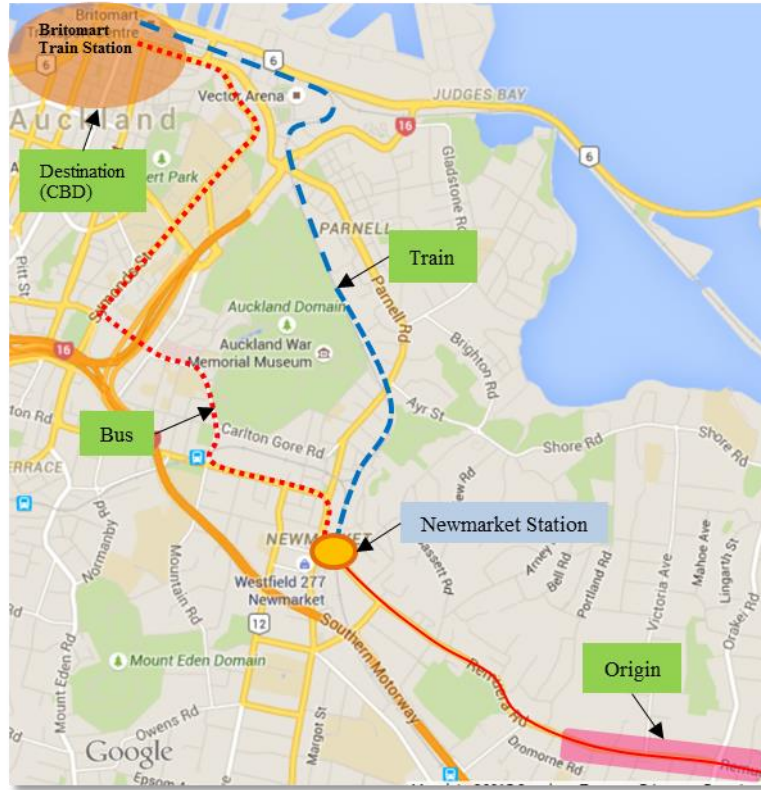
#### **3.1 Research methodology and survey locations**

Subjective judgment has been shown to be present when dealing with route choice (Teodorovic 1999). The amount of uncertainty in out-of-vehicle times, such as the possibility of delays in connecting vehicles, has been shown to play a key role in PT users' decision to ride routes involving transfers (Iseki and Taylor 2009). An example of such a route choice in Auckland, New Zealand is offered in New Lynn Transport Centre and Newmarket Train Station; both interchanges offer commuters with a choice between a direct route without a transfer and a route with a transfer. Figure 2 illustrates the two route choice for the Newmarket Train Station. Commuters can either ride the bus from the origin (a residential suburb) to the destination (Auckland CBD) or alternatively transfer from a bus to a train at the interchange. The alternative choice provides travel time savings between 5 to 10 minutes. Provided enough demand shifts from the direct routes to the transfer routes will allow the direct routes to be terminated, thereby increasing the efficiency of the PT network and reducing operational cost. Currently, approximately 30% of the commuters make a transfer at Newmarket.

Two survey locations were selected to conduct the user preference survey, New Lynn Transport Centre and Newmarket Train Station. Section 3.2 provides a discussion about the questionnaire. Newmarket Train Station is Auckland city's second busiest terminal and is a key junction in the rail network. The station caters to the Southern and Western lines of the Auckland railway network (Auckland Transport 2011). This allows for intra-modal transfers. High frequency bus stops located within 5 minutes walking distance from the interchange facilitates inter-modal transfers. The New Lynn Transport Centre is the main transport hub for the western part of Auckland. It includes both train and bus services. The train service includes the Western line of the railway network. Commuters are able to make inter-modal transfers within the interchange. The survey was conducted for 20 working days from 7 am to 10 am to capture commuters. Respondents were invited to participate in the survey while waiting for the arrival of their vehicle.

#### **3.2 Questionnaire Design**

As discussed in Section 2.1, several studies have identified personal safety, reliability of connections, and transfer walking and waiting times as the most sensitive indicators for PT users' perception of out-of-vehicle times when selecting a route which involves transfers (Zhou et al. 2007, Muller and Furth 2009, Kumar et al. 2011). For the present study, trip attributes selected to assess users' perception of out-of-vehicle times are: reliability of service (delay time), transfer walking time and transfer waiting time. PT users' perception of personal security and comfort were measured for a given transfer waiting time. The participants of the survey were presented with a total of 15 hypothetical cases, three cases (I, II, III) for each of the trip attributes. Each case consisted of a direct route (Current route) and two transfer routes (Route A and B) with an equal travel time saving of 15-20 minutes in comparison to the direct route. The routes with transfers (Route A and B) were designed as one route with higher variability but less time in comparison to the other route which has less variability but greater time.



**Figure 2: Route choice for commuters passing Newmarket Train Station (Google map)**

Figure 3 illustrates one of the cases for transfer waiting time. Respondents were instructed to select one of the three scenarios for each case. Each case has varying probabilities of uncertainty to better assess the effect of variation out-of-vehicle times on users' decision to transfer. Personal safety was defined as the users' probable waiting time to reach a security guard when feeling unsafe. Comfort was defined as the probable waiting time to get an available seat in the station during peak hour periods. Cases for personal safety and comfort were measured under the assumption that the transfer waiting time is 10 minutes.

## 4 Fuzzy logic modelling process

### 4.1 Fuzzification

Fuzzification is the process of defining "crisp" inputs as fuzzy linguistic variables by associating the input with membership values (Hawas 2011). The membership function expresses the degree that an element of the universal set belongs to the fuzzy set. A fuzzy set can take any value within the closed interval [0,1]. The grade of the membership represents the confidence that the member belongs to the fuzzy set; larger values (closer to 1) denote higher degrees of membership (Zhang and Prevedouros 2011). For the present study, a triangular shape for the membership function has been adopted. Each trip attribute (input) and the difference in weighted times of the two transfer route scenarios (WT) (input) were classified into three groups: low, moderate and high. PT users' preference for a transfer route scenario (output) was grouped into seven ridership categories: A, B, C, D, E, F, G and H. The ridership categories represent the proportion of users willing to use the route involving a transfer (either Route A or B). Equation 1 gives the mathematical format of the membership function. Let,  $X$  be the route choice set and  $\tilde{A}$  is the fuzzy set of  $X$ , where  $\mu_A(x)$  is the membership function of the fuzzy set  $\tilde{A}$ . The crisp input is denoted as  $x$ . Fuzzy sets are represented by intervals which are called  $\alpha$ -level sets (Mockor 2013). The  $\alpha$ -level sets  $A_\alpha$  of a fuzzy set  $\tilde{A}$  are defined as,

$$A_\alpha = \{x \in X | \mu_A(x) \geq \alpha\} = [\min\{x \in X | \mu_A(x) \geq \alpha\}, \max\{x \in X | \mu_A(x) \geq \alpha\}] \quad (1)$$



**Figure 3: Case I, II and III for transfer waiting time**

#### 4.2 Fuzzy Inference

Fuzzy inference is based on a set of “If-Then” logic statements (Andrade et al. 2006). A typical fuzzy rule has the form:

$$\text{IF } x \text{ is } A \text{ AND } y \text{ is } B \text{ THEN } z$$

where A and B are antecedents and z is the consequent (Postorino and Versaci 2008). Fuzzy inference handles the degree of approximate match between the input and the antecedent of the rule. The number of fuzzy rules is dependent on the combination of input variables (Zhang and Prevedouros 2011). From the survey, a total of 300 participants’ questionnaire was deemed appropriate for analysis. The rules were derived using Route A for all cases. The proportion of respondents who selected the direct route was excluded in development of the fuzzy rules, as the focus is on users who chose to make a transfer. The model therefore reflects users’ preference for the transfer route scenarios, with the output of the fuzzy system being the proportion of users choosing Route A and the remainder is the proportion of users choosing Route B. Each fuzzy rule has two inputs, quality of the trip attribute and the difference in weighted time between two transfer route scenarios. In total, 42 fuzzy rules were developed. The general format for the fuzzy rules is as follows:

**IF** [trip attribute] is  $[x_{TA}]$  and  $[\Delta \text{ weighted time}]$  is  $[x_{WT}]$ , **THEN** ridership is  $[R]$ .

A sample of the rules is given in Table 1. The max-min method is applied for fuzzy inferences and this is expressed by Equation 2.

$$\mu_A(x) = \max\{\min[\mu_1(x), \mu_2(x), \dots \dots \mu_n(x)]\} \quad (2)$$

**Table 1: Fuzzy rules (sample set) for 300 data-points**

Fuzzy rules for Route A scenarios	
Rule no.	Transfer waiting time (TWT <sub>1</sub> )
1	IF [TWT <sub>1</sub> ] is [high] and [WT] is [low] THEN [ridership] is [B].
2	IF [TWT <sub>1</sub> ] is [moderate] and [WT] is [low] THEN ridership is [B].
3	IF [TWT <sub>1</sub> ] is [low] and [WT] is [low] THEN ridership is [B].
4	IF [TWT <sub>1</sub> ] is [moderate] and [WT] is [high] THEN ridership is [E].
.	.
.	.
Transfer walking time ( TWT <sub>2</sub> )	
10	IF [TWT <sub>2</sub> ] is [high] and [WT] is [moderate] THEN [ridership] is [E].
11	IF [TWT <sub>2</sub> ] is [moderate] and [WT] is [moderate] THEN ridership is [E].
12	IF [TWT <sub>2</sub> ] is [low] and [WT] is [moderate] THEN ridership is [E].
13	IF [TWT <sub>2</sub> ] is [moderate] and [WT] is [high] THEN ridership is [G].
.	.
.	.
Personal Security	
37	IF [safety] is [high] and [WT] is [high] THEN ridership is [E].
38	IF [safety] is [moderate] and [WT] is [high] THEN ridership is [E].
39	IF [safety] is [low] and [WT] is [high] THEN ridership is [E].
40	IF [safety] is [high] and [WT] is [moderate] THEN ridership is [F].
41	IF [safety] is [moderate] and [WT] is [moderate] THEN ridership is [F].
42	IF [safety] is [low] and [WT] is [moderate] THEN ridership is [F].
43	IF [safety] is [high] and [WT] is [low] THEN ridership is [G].
44	IF [safety] is [moderate] and [WT] is [low] THEN ridership is [G].
45	IF [safety] is [low] and [WT] is [low] THEN ridership is [G].

### 4.3 Defuzzification

Defuzzification is the final stage of the fuzzy system. The process involves converting the fuzzy inference outputs into a crisp value. A common approach is the centre of gravity method (Zhang and Prevedouros 2011). It should be note that the crisp value, denoted  $y^*$  (Equation 3), will change continuously with continuous change in the input values (Van Broekhoven and De Baets 2006). The expression used to derive the crisp output value  $y^*$  is shown below (Zhang and Prevedouros 2011).

$$y^* = \frac{\int \mu(y)y dy}{\int \mu(y)dy} \quad (3)$$

### 4.4 Application of a genetic-algorithm

The calibration or tuning of the fuzzy logic membership functions is an example of black-box optimisation. Parameters defining the membership functions are provided to the fuzzy logic model and the model then uses these membership functions to determine ridership for a set of scenarios. This calculated ridership is then compared to the survey data to provide a measure of performance for the membership functions and the parameters that define them. Hence, both a set of parameters  $x$  and an objective function  $f(x)$  are defined, but it is not clear how a change in  $x$  will affect  $f(x)$  and the iterations are complex. Thus,  $f(x)$  is a black-box function and finding  $x^*$  that optimises  $f(x)$  is a black-box optimisation problem. Meta-heuristic approaches are often appropriate for black-box optimisation and in this study a genetic algorithm (GA) approach was prototyped. Previously, GAs have been used for PT route designs (Cevallos and Zhao 2006) and trip distributions (Kalic and Teodorovic 2003).

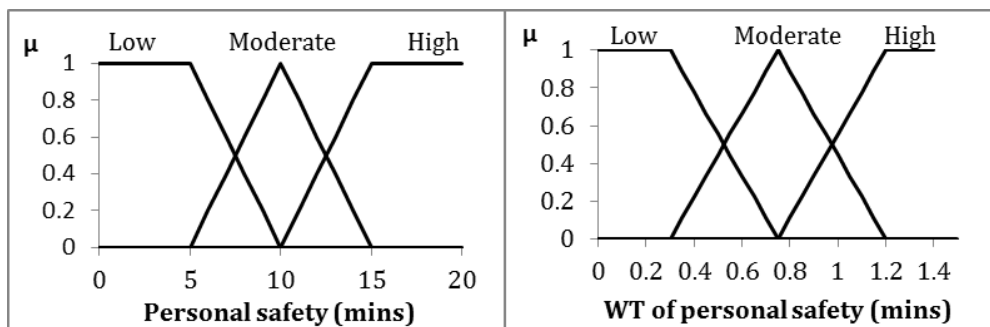
The use of GAs for tuning fuzzy logic models has also been used in previous studies (Thrift 1991, Yuan and Zhuang 1996). The GA implementation used in this study is customised from the MatLab genetic algorithm toolbox (Chipperfield and Fleming 1995).

## 5 Automating the fuzzy logic modelling and results

A GA is used to automatically calibrate the membership functions to optimise the fuzzy ridership output to the corresponding survey data. As stated in Section 4.1, each membership function is triangular in nature and is defined by three points, the threshold values defining the low and high fuzzy group and the range representing the moderate group. Note that each fuzzy rule uses two membership functions: a trip attribute function and a  $\Delta$  weighted time function. There are a total of 30 variables as shown below.

$$5 \text{ trip attributes} \times 2 \text{ memberships functions} \times 3 \text{ points} = 30 \text{ variables}$$

Also, the three points of a membership function must be increasing; thus the points themselves are not variables within the GA, rather the distance between points are the variables (with the first variable being the distance from 0). Consider the membership functions depicted in Figure 4, the variable values for the Personal Safety membership function will be 5, 5 and 5, which gives  $5, 5 + 5 = 10, 10 + 5 = 15$  as the points defined in the triangular membership function. Similarly, the variable values for the WT of Safety (i.e.,  $\Delta$  weighted time for Safety) will be 0.3, 0.45, 0.45 which gives 0.3, 0.75, and 1.2 as the points that define the triangular membership function.



**Figure 4: Fuzzy logic membership functions for Safety, adopted from Ceder et al. (2013)**

Given the membership function definitions, any interval of trip attributes and an associated  $\Delta$  weighted time can be fuzzified and defuzzified to get a ridership percentage for the parameters of a given route. For example, consider the parameters [7, 12] for Personal Safety with the associated weighted time of 0.8. Using linear interpolation,  $\mu$  values for Low, Moderate, and High fuzzy groups can be determined. Table 2 provides the membership values,  $\mu$ , for the example.

**Table 2: Example of fuzzification**

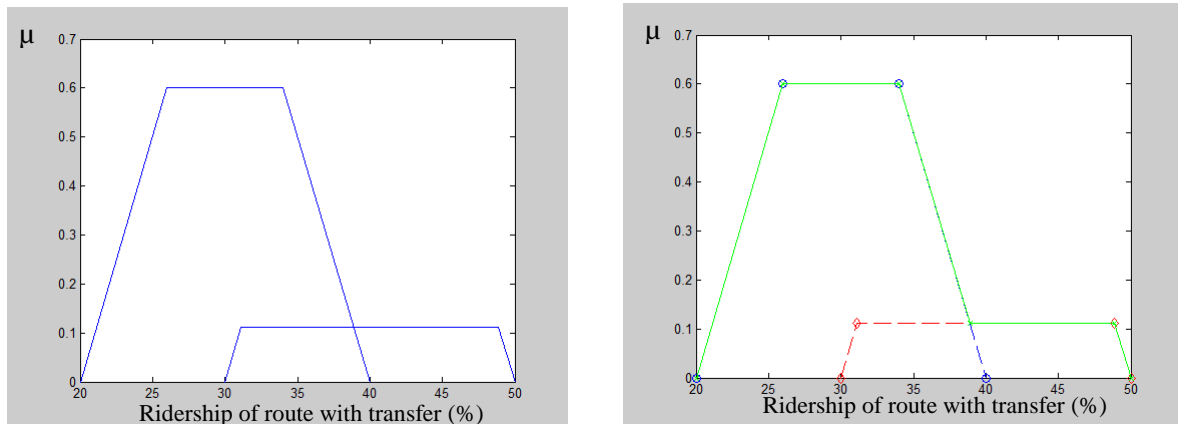
Parameter	Low	Moderate	High
Personal Safety = 7	0.6	0.4	-
Personal Safety = 12	-	0.6	0.4
WT of Safety = 0.8	0	0.89	0.11

Applying the max-min composition method to the fuzzy rules derives the ridership percentage; see Ceder et al. (2013) for further details. For this example, the results of the fuzzy interference process are:

- Ridership F at 0.6; and
- Ridership E at 0.11.



These  $\mu$  values for each fuzzy group of the output fuzzy membership function define the overall ridership profile by “peak shaving” the corresponding fuzzy output groups (F and E). Figures 5a and 5b show the two “peak shaved” ridership functions and the combined profile.



**Figure 5(a): Ridership F function at 0.6 (on left) and ridership E function at 0.11 (on right)**      **Figure 5(b): Combined ridership profile (in green) from ridership profiles for F (blue) and E (red)**

By linearly interpolating the combined profile, the centre of gravity of the ridership can be calculated to give the overall ridership percentage. For this example it is 31.67%. This percentage is then compared to the corresponding survey percentage to see how well the membership function represents the actual ridership. The comparison metric is the squared difference between the calculated ridership and the actual ridership from the survey. This calculation is repeated for all surveyed trip attributes intervals (and associated  $\Delta$  weighted time) to give an overall “estimate of fit” for all the membership functions. This measure of fit is the evaluation of the membership function parameters and is the sum of the squared difference between the calculated ridership levels and the ridership levels from the survey.

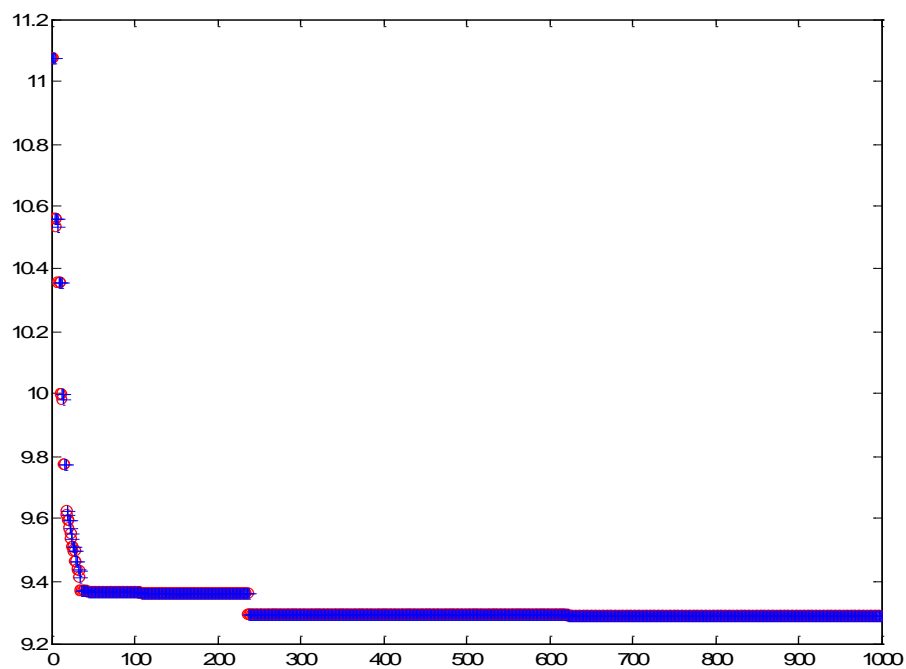
The entire process from fuzzification of the inputs to evaluation forms the black-box function for the GA. Bounds of 20 for the trip attribute variables ( a max of 60 for the trip attributes final points) and 3 for the associated  $\Delta$  weighted time variables (a max of 9 for the associated  $\Delta$  weighted time final points) were determined by looking at the membership functions in the previous work (Ceder et al. 2013). The GA was run for 500 generations with 100 individuals per generation using default functions for selection, recombination, and mutation. The best membership functions from the GA give outputs as shown in Table 3. The progress of the best function value from the GA is shown in Figure 6.

## 6 Discussion and Conclusion

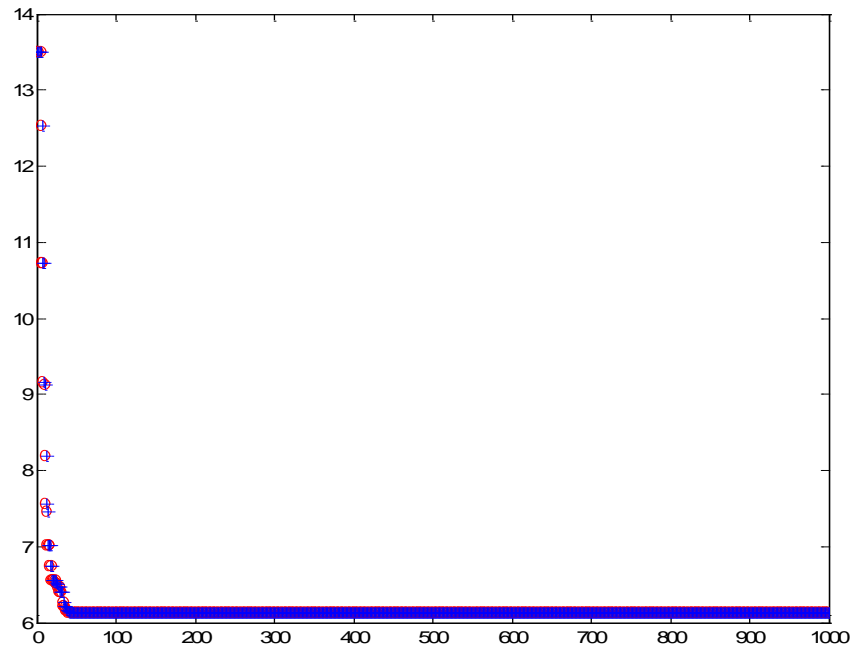
Table 3 provides a comparison of each scenario presented to participants for the fuzzy output results, before and after GA tuning, against the survey data. Performing a goodness-of-fit measure using the root mean square error (RMSE) showed that the model provides a better fit after being tuned by the GA. The RMSE for the fuzzy output before tuning was 11 people (rounded to whole people) while for the model with GA it is 9 people (also rounded to whole people). Figure 6 shows the progress of the GA in terms of reducing the RMSE as the population of solutions evolves and, hence, the membership functions are tuned. Automation of the process improves the model’s capability to more accurately predict ridership. After the first round of tuning there were some cases in which the difference between the tuned fuzzy outputs and the survey data was  $\geq 10$ . The fuzzy rules for these cases were re-adjusted to run a second round of tuning. The new model (with revised fuzzy rules and re-tuned membership functions) produced a RMSE of 6 people. Figure 7 shows the progress of the re-tuning GA. The iterative process of tuning the model with the GA, examining the match between the fuzzy outputs and the survey data, adjusting the fuzzy rules, and then re-tuning with the GA reduced disparities between the fuzzy outputs and the survey data.

**Table 3: Comparison between fuzzy system outputs and survey data**

Trip Attribute	Case	Scenario	Fuzzy Output Before Tuning	Fuzzy Output After (GA) Tuning	Survey Data
Transfer waiting time	A	S1	192	192	203
		S2	82	82	71
	B	S1	110	110	115
		S2	166	166	161
	C	S1	109	109	103
		S2	163	163	169
Transfer walking time	A	S1	110	105	111
		S2	166	171	165
	B	S1	110	105	96
		S2	166	171	180
	C	S1	55	68	68
		S2	221	208	208
Transfer delay time	A	S1	67	66	66
		S2	209	210	210
	B	S1	82	82	95
		S2	192	192	179
	C	S1	82	82	92
		S2	193	193	183
Comfort	A	S1	138	138	160
		S2	137	137	115
	B	S1	137	137	153
		S2	137	137	121
	C	S1	55	63	63
		S2	221	213	213
Safety	A	S1	110	110	113
		S2	166	166	163
	B	S1	62	74	74
		S2	214	202	202
	C	S1	55	63	63
		S2	221	213	213



**Figure 6: Progress of best objective function (red circle is the current best value in the generation and blue cross is the current global best, they coincide so the GA keeps the global best in the population at all times)**



**Figure 7: Progress of best objective function when re-tuning the membership functions. Note that the starting solution is the best membership functions from the initial tuning, but as the fuzzy rules have changed the RMSE has deteriorated from (approx.) 9.3 to (approx.) 13.5. However, the new fuzzy rules provide more “scope” for improvement to the re-tuned membership functions have a lower RMSE of (approx.) 6.1 than the tuned membership functions (approx. 9.3)**

The use of automated fuzzy logic model combined with the GA for tuning provided several improvements in comparison to the previous manual modelling process. Using the GA to tune the membership functions not only improved the initial model, but also enabled the refinement of the fuzzy rules by identifying the cause of disparities. This refinement then enabled re-tuning which produced improved outputs (decrease in a RMSE error of 11 to 9 and then 6). It was observed that in the second round of re-tuning, membership functions changed significantly for “transfer waiting time” and “safety”, but with no improvement to the RMSE for these attributes. The re-tuned membership functions changed slightly for “transfer walking time”, “transfer delay time”, and “seat availability” with a slight improvement in the RMSE for “transfer walking time” and significant improvement in the RMSE for “transfer delay time” and “seat availability”. This phenomenon was interesting as the fuzzy rules were only changed for “transfer delay time” and “seat availability”. The explanation is that variability in the membership functions for “transfer waiting time” and “safety” does not worsen the RMSE with the unchanged fuzzy rules, thereby the randomness of the GA enables them to change significantly during the second round of re-tuning without adversely affecting the outputs. To demonstrate that some membership functions can vary without affecting the outputs, the membership functions for “transfer walking time”, “transfer waiting time” and “safety” were reverted to their initially tuned values and the resulting RMSE was unchanged.

Figure 8 provides the original membership functions, the tuned membership functions and the re-tuned membership functions for “transfer delay time”, and “seat availability” (as these changes are the only ones that significantly provide improved RMSE). The diagram shows the previous function in grey dotted lines, the tuned function in black dashed lines, and the re-tuned function in black solid lines. It is intended that these calibrated membership functions for operational (transfer waiting and walking time and delay) and physical attributes (personal safety and comfort) can be used by planners to determine an estimated ridership for a given route. It should be noted that the output fuzzy membership function was not tuned using the GA, as this was developed using the survey data. The contribution of the final membership functions is two-fold. First, future researchers can use this as a basis to improve their understanding of out-of-vehicle travel behaviour. Secondly, planners can use the membership functions in conjunction with the rules to attain an indicative ridership for a given route. Overall, the contribution of this study lies in both the results of the final fuzzy logic model and the automation of the fuzzy logic along with its combination with a GA. The automation/GA

combination enables the calibration of the membership functions and manual improvement of the fuzzy rules. Future research will include automation of the both the fuzzy logic and fuzzy rules combined with a GA to enable the entire fuzzification to de-fuzzification process to be tuned simultaneously.

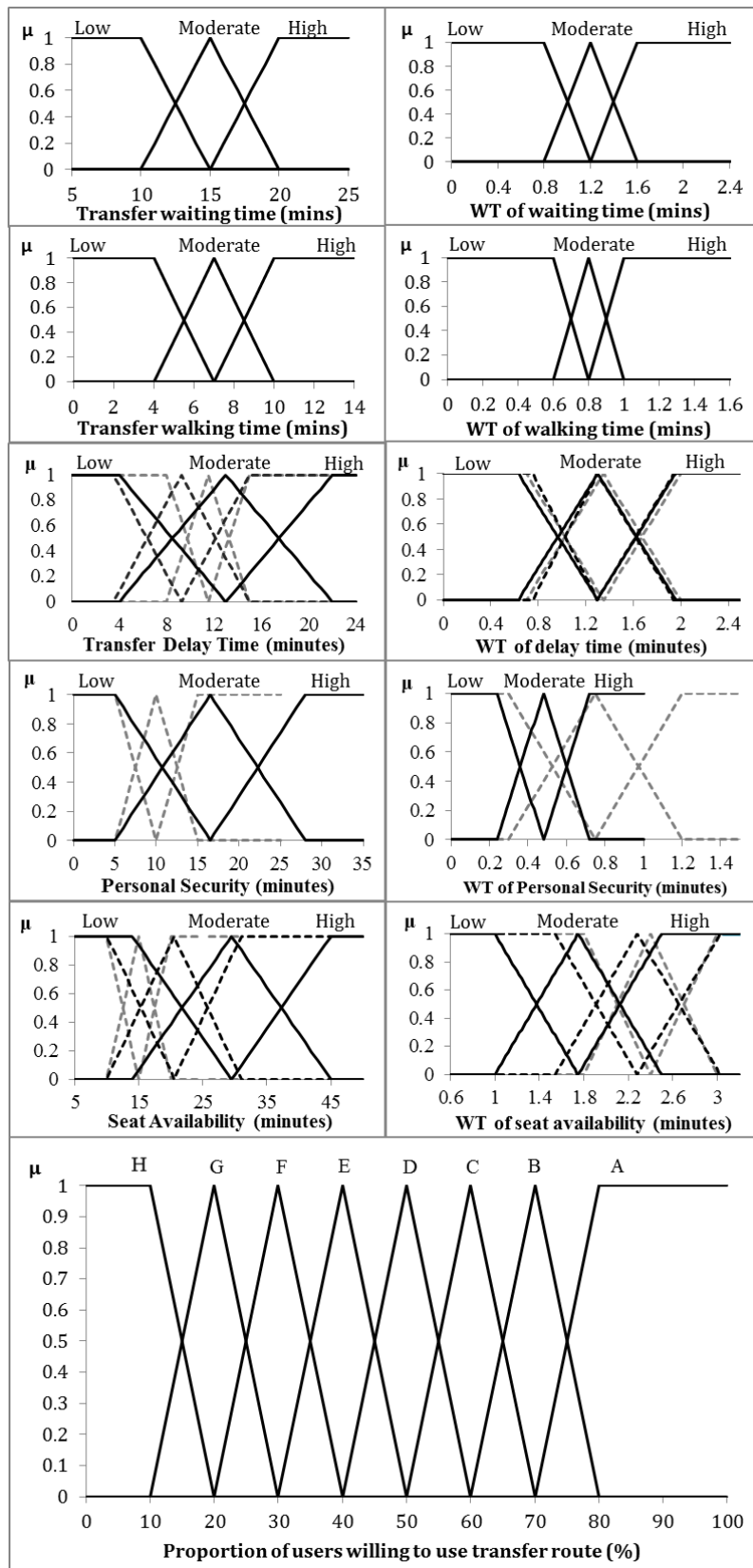


Figure 8: Membership functions after Fuzzy GA tuning

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