Comparative Evaluation of Models of Route Choice and Driver Compliance with Traffic Information

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1 Introduction

Driver behaviour models that can be used to dynamically estimate or predict the degree of drivers' compliance with traffic information can be thought of as a classification problem. The inputs to the model comprise drivers' individual socio-economic characteristics and other variables that may influence their route choice behaviour; and the output a binary integer (1,0) representing whether drivers comply with travel advice or not, respectively. Two approaches are available for developing such models: discrete choice models and artificial neural network (ANN) techniques. Detailed information about the theoretical foundations of these techniques is beyond the scope of this paper. However, a comprehensive treatment of discrete choice models and their applications can be found in Greene (2000) and a detailed review of artificial neural networks and their applications in the transportation field can be found in Dougherty (1995). Hawas (2004) provides a state-of-the-art review of route choice models where he discusses the strengths and weaknesses of the two approaches and presents recent advances in model formulations aimed at addressing their limitations. The review clearly points to the limitation of the discrete choice approach in modelling the vagueness (or fuzziness) of driver behaviour. Evidence of the potential for using neural network models can be found in a number of studies which conducted comparative evaluations of the discrete choice and neural network approaches (e.g. Hensher and Ton, 2000, Pang et al., 1999). These studies showed that neural networks can provide comparable if not better approximations to discrete choice problems. The main advantages of ANNs include the ability to deal with complex non-linear relationship (Narendra and Paethasarathy, 1990); fast data processing (Maren et al., 1990); handling a large number of variables (Smith, 2003) and fault tolerance in producing acceptable results under imperfect inputs (Hecht-Nielsen, 1990). ANNs are also suitable for modelling reactive behaviour which is often described using rules, linking a perceived situation with appropriate action (Panwai and Dia, 2005a, Panwai and Dia, 2005b). Given only a set of inputs and outputs during the training process, the neural network is able to determine all the rules relating the input and output patterns based on the given data set (Palacharla and Nelson, 1999). The combination of fuzzy logic and neural networks is also seen as a viable approach for incorporating human expert' decision to deal with complex problems and to capture uncertainty in drivers' behaviours (Pang et al., 1999, Hawas, 2004). In this approach, fuzzy logic is used for knowledge representation (both precise and imprecise) while neural networks are implemented for data processing and to provide the learning capability. An application of this approach relevant to modelling behavioural rules which is part of drivers' decision process under the influence of real time traffic information has been recently reported in (Panwai and Dia, 2006).

This paper will mainly deal with binary choice and ANN models of route choice and driver compliance with traffic information. This work is part of a study aimed at incorporating driver compliance models within traffic simulation tools to improve their accuracy in evaluating Intelligent Transport Systems (ITS) applications (Dia and Panwai, 2006). It is worthwhile to note that a comparative evaluation of the modelling approaches of driver route choice and compliance with traffic information, based on the same data set, has not been reported in the literature. For this study, neural techniques were developed to predict drivers' compliance with travel information and compared against the traditional utility models using the same data set of commuter behaviour.

2 Travel Behaviour Framework

For the purpose of this study, it is assumed that a travel behaviour framework similar to that proposed by Khattak *et al.* (1996) applies. This framework takes into account that individuals attempt to find the best alternative route using the limited information available to them. Various aspects of travel information influence travellers' decisions. The processing of information depends on its content or meaning, format or presentation style, its nature and type (Schofer et al., 1993).

An example of a dynamic driver behaviour modelling framework is shown in Figure 1 (Ben-Akiva et al., 1991). Drivers set out with goals to travel between an origin and destination within a given period of time while incurring the lowest possible cost. They acquire information about the performance of the road system through direct observation or by having access to electronic information systems. Drivers process and interpret the information in light of their current knowledge and in accordance with their ability to combine and process a variety of information concerning road conditions. The interpretation translates into perceptions of travel times and delays. Perceptions, restrictions and individual characteristics also form preferences for certain alternatives (modes, routes and departure times). These preferences will also depend on the previously acquired knowledge, stored in the memory, and on certain thresholds whereby motorists only switch from their current path if the improvement in travel time exceeds some threshold level. These preferences result in observable choices that have outcomes (e.g. arrival time at work). If the outcome is satisfactory, then the same choice is likely to be repeated on the following trip forming a commute pattern (Ben-Akiva et al., 1991). The repetition of a choice in the commute context also depends on the future or anticipated outcomes. These outcomes also provide feedback to the memory in the form of knowledge updates. In unexpected delay situations, the anticipated outcomes are often unsatisfactory triggering review of preferences and changes in normal travel patterns on a real-time and day-to-day basis (Ben-Akiva et al., 1991).

As was mentioned earlier, various aspects of travel information influence drivers' decisions. The processing of information depends on its content or meaning, nature, type (whether it is quantitative or qualitative) and presentation style. In addition, drivers are more likely to rely on relevant and accurate information. For example, under incident congestion, the perception of delay and the quality of real-time information are critically important in influencing travel behaviour. Obviously, the success of driver behavioural models will depend to a large extent on capturing the different parameters mentioned above. Most previous research on driver behaviour modelling has focused on modelling travel response decisions based on data from travel surveys or travel simulators (e.g. Koutsopoulos et al., 1995). These behavioural models mostly used drivers' socio-economic characteristics and attributes of usual travel patterns as explanatory variables.

The work reported here extends previous research efforts (Dia and Panwai, 2006, Dia, 2002, Panwai and Dia, 2006) and will be based on real data comprising the complete set of drivers' choices as determined from a driver behavioural survey.

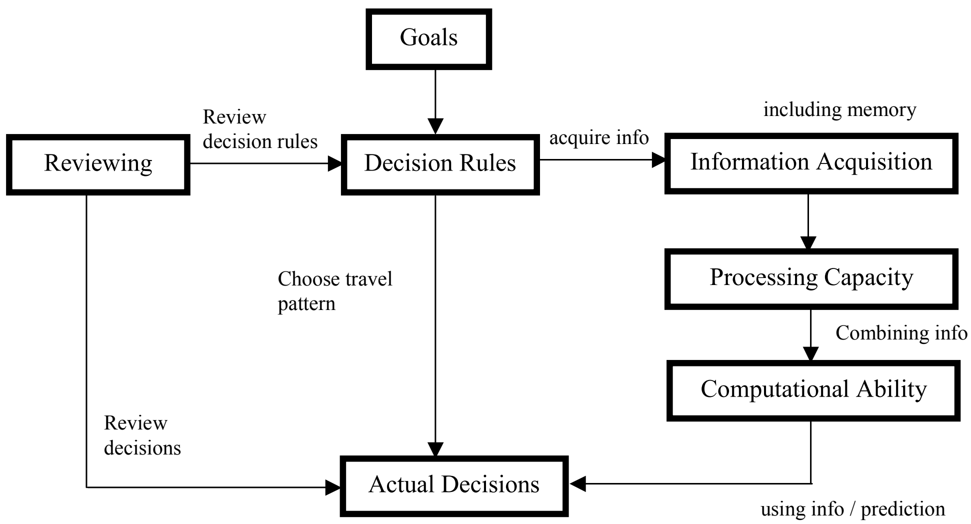

Figure 1. Driver Decision Process (Ben-Akiva et al., 1991)

3 Behavioural Survey of Drivers on a Congested Commuting Corridor

Behavioural surveys of drivers during congested traffic conditions are best suited to developing behavioural models under the influence of travel information. Properly designed surveys that capture the interactions in the travel behaviour model would allow for the investigation of the influence of (a) unexpected and expected congestion, (b) the various types and quality of information received about congestion and (c) drivers' experiences with congestion and related information on the whole spectrum of pre-trip and en-route decisions. In particular, these behavioural surveys allow for the relationship between a driver's response to information to be modelled in combination with actual behaviour. User response to travel information is typically modelled using data collected from a behavioural survey of congestion (Khattak et al., 1996). For this study in Australia, mail-back questionnaires were distributed to peak-period automobile commuters travelling along a traffic commuting corridor in Brisbane. A total of 490 questionnaires were distributed to drivers on a traffic commuting corridor in Brisbane during the morning and afternoon peak periods. South-west Brisbane was selected as the study corridor because it met a number of criteria including the availability of alternate routes to the CBD area, the availability of public transport and real-time traffic information and variable message signs providing information about traffic delays to the CBD. The mail-back questionnaire had a response rate of 34% (167 questionnaires) comprising a total of 82 pre-tip and 85 en-route questionnaires. This response rate compares favourably with the results obtained from overseas research (Khattak et al., 1996) in which substantial financial incentives were offered to respondents. The format and presentation of the questionnaire is believed to be a key factor in achieving this response rate, considering it was anticipated that it would take 20 minutes to complete each questionnaire.

Detailed results of the survey have been presented in a number of previous publications and are outside the scope of this paper (e.g. the reader is referred to Dia and Panwai (2006) and Dia *et al* (2000) for comprehensive coverage of the survey and its results). For the purposes of this paper, the results in Table 1 are presented as they are necessary for the development of the route choice models. In the survey, respondents were asked to indicate their preferences when presented with hypothetical traffic information by choosing from a set of finite responses which included: “definitely take my usual route”; “probably take an alternative route”; “definitely take best alternative route”; “probably take best alternative route” and “can’t say”. A summary of respondents’ choices is presented in Table 1. These results provide one of the most significant findings from the travel information experiments.

They clearly indicate that prescriptive, predictive and quantitative real-time delay information provided for both the usual and best alternate routes are most effective in influencing respondents to change their routes. Therefore, detailed route choice decision models will be developed and investigated for each of these scenarios.

Table 1: En-route Stated Preferences for Unexpected Congestion (Percent)

Attributes	Qualitative Delay Information (% responses)	Quantitative Real-Time Delay Info. (% responses)	Quantitative R-T Delay on Best Alt. Route (% responses)	Predictive Real-Time Delay Info. (% responses)	Prescriptive Best Alternate Route (% responses)
Definitely take my usual route	11.9	10.1	8	9.2	6.3
Probably take my usual route	28.6	29.1	12	15.8	13.9
Definitely take my best alternate route	32.1	29.1	41.4	40.8	53.2
Probably take my best alternate route	25	24.1	33.3	28.9	22.8
Can't say	2.4	7.6	5.3	5.3	3.8

4 Development of the Neural Network Route Choice Models

4.1 Neural Network Route Choice Modelling Framework

The development of neural network models involves a number of steps which include data pre-processing, selection of input variables, assignment of desired output states, creation of training and validation data sets, selection of neural network architecture (e.g. number of nodes in the hidden layer, number of hidden layers, objective function, learning algorithms and node transfer functions etc), training strategy and selection of key performance indicators to be used for evaluating the performance of the model. The classification process included setting the socio economic attributes in Table 2 as independent variables and the degree of preferences in Table 1 as dependent variables.

4.2 Data for Model Development

The five data sets that were used for model development are shown in Table 3. Each data set comprises respondents' replies to each of the traffic information message types described before (Table 1).

Table 2: Variables Used for Model Development

Input Variable	Category Description	Input Data Set Categorised Value
Work Schedule Flexibility	Flexible	1
	Fixed	2
	Variable	3
Age	Under 18 years	1
	between 18-29 years	2
	between 30-39 years	3
	between 40-49 years	4
	between 50-64 years	5
	over 65 years	6
Gender	Male	1
	Female	2
Income Level	Under 20 thousand $AUD	1
	between 20-40 thousand $AUD	2
	between 40-60 thousand $AUD	3
	between 60-80 thousand $AUD	4
	between 80-100 thousand $AUD	5
	more than 100 thousand $AUD	6
Education Level	High School or less	1
	Vocational or Technical School	2
	Undergraduate Degree	3
	Post Graduate Degree	4
Years at Residence	Under 5 years	1
	between 5-10 years	2
	between 10-15 years	3
	between 15-20 years	4
	more than 20 years	5

Table 3: Data Sets for Model Development

Data Set	Travel Information Message Types	Sample Size
1	Qualitative Delay Information	80
2	Quantitative Real-time Delay Information	74
3	Quantitative Real-time Delay on Best Alternative Route	71
4	Predictive Delay Information	70
5	Prescriptive Best Alternative Route	71

4.3 Selection and Coding of Input and Output Variables

As was mentioned before, drivers' route choice decisions are related to their socio economic characteristics and travel habits. The inputs selected for this study comprised income, education level, age, gender, years at residence (a surrogate for familiarity with road network conditions) and work schedule flexibility. A number of studies (e.g. see Hawas, 2004) also found that these inputs have direct impact on drivers' responses to travel advice. Work schedule flexibility, age and awareness or familiarity with road network conditions are considered factors that impact drivers' aggressiveness and hence may influence their decisions on route choices when provided with real time traffic information (Lai and Wong, 2000). Drivers' willingness to pay for travel information and services is clearly a function of their income and has also been found to be related to age and gender (Ramming, 2002). Having determined the relevant inputs, the neural network architecture can be formulated as shown in Figure 2 where the output of the model represents whether a driver complies or not with the travel information.

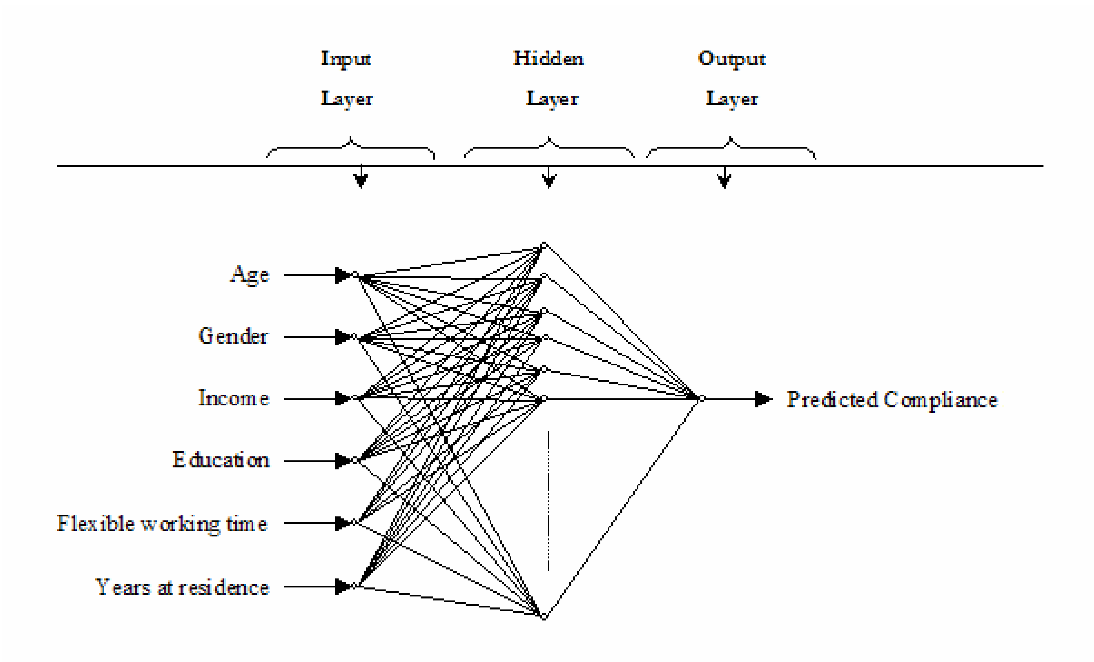

Figure 2: Basic Structure of a Neural Network Route Choice Model

4.4 Drivers' Compliance

Drivers' compliance was captured in the behavioural field survey through the respondents' answers to the different traffic information scenarios. For example, drivers are said to comply with travel information if their response to the specific scenario was "definitely take my best alternate route". Similarly, they are said to ignore the travel advice (or do nothing) if their responses were "definitely take my usual route". For the purpose of model development, these two response or model output categories were coded as 1.0 and 0.0, respectively. Respondents also had two other options to choose from if they were undecided on which route to choose. If the respondent selected either "probably take my usual route" or "probably take my best alternate route", then these two response categories will need to be coded as values between (0,0.5) and (0.5, 1.0) respectively. A number of experiments were conducted where different values e.g. (0.33, 0.67), (0.3, 0.7) and (0.4, 0.6) were coded for these categories but no differences were found in terms of the neural network model performance. The four-point semantic scale of drivers' route choice selected in this study is shown in Table 4 below.

Table 4: Coding of Route Choice Preferences

Strength of Preference	Choice Transformation Scale
Definitely take my usual route	0.00
Probably take my usual route	0.33
Probably take my best alternate route	0.67
Definitely take my best alternate route	1.00

4.5 Selection of Neural Network Architecture

Four neural network architectures are typically used for classification problems (NeuralWare, 2001): Fuzzy ARTMAP, Back Propagation (Logicon Projection Network), Reinforcement Network, and Radial Basis Function Network (RBFN). A brief description of each of these architectures is provided below.

Fuzzy ARTMAP is a general-purpose classification network. It has two fuzzy ART networks (ARTa and ARTb) which are connected by a subsystem referred to as a match tracking system which increases the vigilance of the Fuzzy ART network until a match is made or a new category is formed.

Back-Propagation is a general-purpose network paradigm. Back-prop calculates an error between desired and actual outputs and propagates the error information back to each node in the network. The back-propagated error drives the learning at each node.

Radial Basis Function Networks (RBFN) are general-purpose networks which can be used for a variety of problems including classification, system modelling and prediction. In general, an RBFN is any network which makes use of radially symmetric and radially bounded transfer functions in its hidden ("pattern") layer.

Reinforcement Networks refer to learning schemes which iterate through a number of steps until performance no longer improves. A set of weights is selected in some methodical or semi-random way depending on previously selected and saved weights. Then, the performance of the network is assessed by running the training data through the network and evaluating an objective function.

4.6 Performance Measures

One of the main indicators to evaluate the performance of a neural network classifier is the Classification Rate (CR). This indicator provides a measure of the correctly classified inputs and is best depicted using the classification rate matrix shown in Figure 3 below.

		Desired Output	
		0	**1**
ANN Output	**1**	% Type I Error	% Correctly Classified Compliance Rate
	0	% Correctly Classified Non-Compliance Rate	% Type II Error

Figure 3. Classification Rate Matrix

The columns of the matrix represent the actual or desired results whereas the rows represent the neural network estimates or outputs. The body of the Classification Rate matrix represents the intersection between desired results and actual network predictions. A value of 1.0 for any given cell means that all desired outputs for that category were correctly predicted by the network. Similarly, a value of 0.0 in a cell means that none of the desired outputs were predicted to be a member of that category. A perfect classifier would comprise a value of 1.0 for the correctly classified states and zero for the Type I and Type II errors. Classification rates obtained during the training or model development stage provide a measure of the calibration results while classification rates obtained during testing provide an indication of the generalisation ability and validity of the model. It should be mentioned here that once the ANN has been trained, it can then be applied to predict a driver's compliance with information. The ANN model output is either 1 or 0 (compliance or non-comply, respectively). For cases where the driver is undecided, the output is either be 0 or 1 depending on the drivers' socioeconomic characteristics. A large number of experiments were run to determine the best architecture and set of parameters for the route choice compliance problem. These included 5 different Fuzzy ARTMAP architectures (each with a different mapping layer); 10 different back-propagation and Radial Basis architectures and

12 Reinforcement network models. In total, 185 models with different architectures were developed and tested. The impacts of categorised and normalised data sets were also considered. The models performed better when data was categorised as in Table 2. The best performance model for each architecture is shown in Table 5.

Table 5: Neural Network Best Performance Models Using Categorised Input Data

ATIS Scenario	ANN Architecture	Learning Rule	Transfer Function	Classification Rate (CR) (Percent)
Qualitative Delay Information	Fuzzy ARTMAP (150*)	*N.A.*	*N.A.*	96 #
	Back-Prop	MaxProp	Sine	59
	RBFN	Delta Rule	Sine	96 #
	Reinforcement	Genetic	Perceptron	72
Quantitative Real-time Delay Information	Fuzzy ARTMAP (100*)	*N.A.*	*N.A.*	96 #
	Back-Prop	MaxProp	Sine	73
	RBFN	DBD	Sine	94 +
	Reinforcement	Genetic	Sine	78
Quantitative Real-time Delay on Best Alternative Route	Fuzzy ARTMAP (250*)	*N.A.*	*N.A.*	95 +
	Back-Prop	MaxProp	TanH	61
	RBFN	Delta Rule	Sine	95 #
	Reinforcement	DRS	Perceptron	75
Predictive Delay Information	Fuzzy ARTMAP (50*)	*N.A.*	*N.A.*	96 #
	Back-Prop	Delta Rule	TanH	58
	RBFN	Delta Rule	Sine	92 +
	Reinforcement	Genetic	Sine	74
Prescriptive Best Alternative Route	Fuzzy ARTMAP (250*)	*N.A.*	*N.A.*	97 #
	Back-Prop	DBD	Linear	63
	RBFN	Delta Rule	TanH	94 +
	Reinforcement	Genetic	Linear	78

Remark: * Number of mapping layers (F2 units) for the Fuzzy ARTMAP network,
Best model based on classification rate,
+ Second best model based on classification rate.

The results in Table 5 show the superior performance of the Fuzzy ARTMAP and RBFN architectures over other neural network architectures. These results suggest that prediction errors between the ARTMAP and RBFN models are negligible and that adoption of either model is acceptable for each of the five traffic information scenarios. Closer inspection of the model formulations, however, revealed that the RBFN model had fewer parameters to calibrate than the Fuzzy ARTMAP model and was hence selected as the architecture for implementation in the traffic simulator.

5 Development of the Discrete Choice Models

Discrete choice methods such as multinomial logit models and their variants such as nested logit, mixed logit and multinomial probit have been commonly applied for travel choice decision (e.g. mode choice, route choice, departure time choice). These methods are used to analyse and predict travel decisions. Only binary choice models are explored in this paper (because there are two observed choices in the survey: “comply” and “not comply” with traffic information). For the purpose of comparative evaluation, the same independent and dependent variables were set up for all modelling approaches. Drivers are assumed to comply with travel information if their response to the specific scenario was “definitely take my best alternate route” or “probably take my best alternate route”. Similarly, they are said to do nothing with the travel advice if their responses were “definitely take my usual route” or “probably take my usual route”. The classification process was similar to that reported before for the neural network approach, where the socio-economic attributes (Table 2) were considered the independent variables and the preferences in Table 1 were considered the dependent variables.

5.1 Binary Probit and Logit Choice Compliance Models

Random utility models assume that the decision-maker has a perfect discrimination capability. However, drivers in real-life conditions rarely have complete information and, therefore, uncertainty must be taken into account. Ben-Akiva and Bierlaire (1999) and Manski (1977) identified four different sources of uncertainty: unobserved alternative attributes; unobserved individual characteristics (also called "unobserved taste variations"); measurement errors; and proxy or instrumental variables. The utility is modelled as a random variable in order to reflect the previously described uncertainties. The binary utility choice model is applied when the respondents are presented with two alternatives. The derivation of any binary choice models is conceptually straightforward. The probability that alternative *i* is taken is P(*i*) and the probability that alternative *j* is chosen is 1-P(*i*). The route choice model has two outcomes: "Comply" with the supplied information (probability is 1.0) or "Not Comply" with the displayed information (probability is 0.0). Both Binary Probit and Logit models were investigated in this paper.

5.2 Results of Probit and Logit Models

Tables 6 and 7 present the results for the probit and logit models for all scenarios.

Table 6: Statistical Results: Binary Pobit Model

Variables	Model Coefficient	*t*-ratio	Remark
Qualitative Delay Information			
Age	0.0133	0.099	LRI = 0.0098
Gender	-0.3947	-1.694**	N = 80
Income	0.0018	0.017	P(0) = 0.75
Education	-0.1073	-0.680	P(1) = 0.25
Working Schedule	0.1590	0.633	# CR = 50%
Years in residence	-0.8761	-0.474	
Quantitative Real Time Delay Information			
Age	-0.1137	-0.782	LRI = 0.1569
Gender	-0.9444	-3.231*	N = 74
Income	0.1229	0.951	P(0) = 0.79
Education	0.0551	0.299	P(1) = 0.21
Working Schedule	0.3200	1.131	# CR = 63%
Years in residence	-0.0169	-0.724	
Quantitative Real Time Delay on Best Alternative Route			
Age	-0.3470	-2.189*	LRI = 0.1059
Gender	-0.1072	-0.426	N = 71
Income	0.0824	0.678	P(0) = 0.80
Education	0.0023	-0.013	P(1) = 0.20
Working Schedule	0.2013	0.700	# CR = 53%
Years in residence	-0.0092	-0.425	
Predictive Delay Information			
Age	-0.4211	-2.463*	LRI = 0.0889
Gender	-0.4943	-1.842**	N = 70
Income	0.1188	0.845	P(0) = 0.76
Education	0.2918	1.497	P(1) = 0.24
Working Schedule	0.2573	0.879	# CR = 69%
Years in residence	-0.0283	-1.067	
Prescriptive on Best Alternative Route			
Age	-0.0701	-0.466	LRI = 0.2734
Gender	-1.1287	-3.711*	N = 71
Income	0.1934	1.441	P(0) = 0.73
Education	0.0469	0.249	P(1) = 0.27
Working Schedule	0.4433	1.486	# CR = 73%
Years in residence	-0.0444	-1.713**	

*Significant 5%, P-value (0.01-0.05)
**Significant 10%, P-value (0.05-0.10)
Classification Rate represents the percentage of correctly classified observations.

Table 7: Statistical Results: Binary Logit Model

Variables	Model Coefficient	*t*-ratio	Remark
Qualitative Delay Information			
Age	0.0268	0.118	LRI = 0.0100
Gender	-0.6604	-1.622**	N = 80
Income	0.0045	0.025	P(0) = 0.75
Education	-0.1818	-0.677	P(1) = 0.25
Working Schedule	0.2676	0.632	# CR = 50%
Years in residence	-0.0147	-0.465	
Quantitative Real Time Delay Information			
Age	-0.2261	-0.856	LRI = 0.1637
Gender	-1.7066	-3.060*	N = 74
Income	0.2125	0.951	P(0) = 0.78
Education	0.0877	0.280	P(1) = 0.22
Working Schedule	0.6793	1.300	# CR = 63%
Years in residence	-0.0292	-0.682	
Quantitative Real Time Delay on Best Alternative Route			
Age	-0.6310	-2.172*	LRI = 0.1171
Gender	-0.1567	-0.354	N = 71
Income	0.2451	1.053	P(0) = 0.8
Education	-0.0726	-0.225	P(1) = 0.2
Working Schedule	0.3686	0.733	# CR = 53%
Years in residence	-0.0327	-0.706	
Predictive Delay Information			
Age	-0.7424	-2.412*	LRI = 0.0889
Gender	-0.8797	-1.864**	N = 70
Income	0.2301	0.947	P(0) = 0.76
Education	0.4857	1.430	P(1) = 0.24
Working Schedule	0.5146	0.975	# CR = 69%
Years in residence	-0.0600	-1.137	
Prescriptive on Best Alternative Route			
Age	-0.1560	-0.589	LRI = 0.2745
Gender	-1.9354	-3.437*	N = 71
Income	0.3320	1.409	P(0) = 0.73
Education	0.0921	0.291	P(1) = 0.27
Working Schedule	0.8105	1.530	# CR = 73%
Years in residence	-0.0791	-1.589**	

*Significant at 5%, P-value (0.01-0.05)
**Significant at 10%, P-value (0.05-0.10)
Classification Rate represents the percentage of correctly classified observations.

The two modelling approaches showed slight differences in the *t*-ratio. The Likelihood Ratio Index (*LRI*) was also used to indicate goodness-of-fit of the estimated models (LRI of 1 represents a ‘perfect’ goodness of fit). For the Probit model (Table 6), the results showed that all models had a low goodness-of-fit with the *LRI* values ranging between 0.0098 and 0.2734, which is also reflected in the low CR which ranged between 50 and 73 percent. For the Binary model (Table 7), the results also showed that all models had a low goodness-of-fit with the *LRI* values ranging between 0.01 and 0.2745, which is similarly reflected in the low CR which in this case also ranged between 50 and 73 percent. The effect of gender was negative and significant at the 10% level (for both the Probit and Binary models) indicating that males were very likely to take alternative routes when provided with the qualitative delay information. The same results were found when provided with the quantitative real time delay information. The results also indicate that young drivers had an increased propensity to take an alternative route when provided with quantitative real time delay on best alternative route. In addition, young male drivers were very likely to take alternative routes when provided with predictive delay information. The results reported in Tables 6 and 7 show that male drivers and those with less familiarity of road network conditions had an increased propensity to take an alternative route when provided with the prescriptive information on best alternative routes.

6 Comparative Evaluation of ANN, Probit and Logit Models

Table 8 presents a summary of the results for the different modelling approaches tested in this study. The results show a superior performance in terms of classification rate for the ANN models over the binary Probit and Logit models based on the best performing models in each category. The table also list a number of issues (capabilities or limitations) related to the use of these two modelling approaches in the development of models of driver route choice and compliance with traffic information and interpretation of their results.

Table 8: Comparative Summary of Binary Choice and ANN Models' Capabilities for Modelling Driver Route Choice and Compliance with Traffic Information

Item	Binary Choice Models	ANN Models
Classification Rate	50 – 73 %	95 – 97 %
Model application	Discrete choice estimation models	General purpose prediction and classification models
Estimation method	Maximum likelihood	Back propagation and Radial Basis Function
Number of observations	High impacts on model performance	Good results with imperfect or missing observations
Interpretation of Results	Explicit utility function	Implicit "black box"
Dynamic learning algorithm	N.A.	Yes.

7 Conclusions and Future Research Directions

This study compared the performance of binary choice and ANN models which were developed for modelling driver route choice and compliance with traffic information. The results showed superior performance for the ANN models over the binary choice models in terms of classifying or predicting the categories of drivers most likely to comply (or not comply) with traffic advice. One of the main limitations of the ANN approach, however, is the inability to interpret the ANN results. However, recent studies reported in the literature have shown that combining fuzzy logic and neural networks can address this limitation. The use of neuro-fuzzy systems was found to provide additional benefits by incorporating human decisions when dealing with complex situations. Fuzzy logic is currently being investigated by the authors and is being combined with neural networks to capture the variability of drivers' appraisal of the different route attributes as well as the variability in their perceptions to the various attribute levels. Using this approach, the fuzzy logic will provide a mechanism for representing both precise and imprecise knowledge while neural networks provide the learning capability by using examples of real-life behaviour to calibrate the fuzzy model's parameters. Initial results obtained are encouraging. Furthermore, one important aspect of the modelling framework that was not addressed in this paper is the capability of dynamic learning where the behavioural rules for the route choice decisions are updated in real-time. This issue is also being addressed by the authors using traffic simulation. There is also scope in future research work to validate the performance of these models through detailed route choice field surveys.

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