

DEVELOPING A FUZZY-NEURO TRAVEL DEMAND MODEL (TRIP DISTRIBUTION AND MODE CHOICE)

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ABSTRACT

Various methods are currently used in travel demand modelling (TDM), for example, the Four-Step model, which is widely used and is perhaps the most famous one, Discrete Choice Models, Fuzzy Set Theory and the Neural Network Approach. The emergence of these different methods is due to, for instance, different areas having different problems. Hence, a method successfully applied in one area could be unsuitable for use in others. The literature suggests misused in travel demand modelling process could result in errors up to 60 per cent. The sources of errors are not only from a lack of information related to the parameters that the model tries to estimate but also due to the absence of sharply defined criteria of class membership that can play important roles in human thinking, for which qualitative variables may be better representations. Fuzzy Set Theory is suggested in this study as one approach to tackle the computation of such variables. The Neural Network Approach has a unique ability which, it is claimed, can capture unseen or hidden relationship among the spatial interaction data. A new method, called here the Fuzzy-Neuro approach, is proposed for modelling travel demand, focusing on trip distribution and mode choice, with the expectation that it can improve the accuracy of the resulting models.

KEYWORDS

Travel Demand Model, Fuzzy Set Theory, Neural Network Approach

1 INTRODUCTION

A travel demand model is an important tool for forecasting the impact of the changes in operating characteristics on the usage of the transport networks, either now or in the future. The result is used to enhance the existing service quality through, for example, modifying the use of available services or providing new infrastructure facilities. For the latter purpose, the result is used to plan and evaluate each proposed alternative solution before deciding the best option. In conventional transportation planning practice the model has generally been subdivided into (1) Trip Generation, (2) Trip Distribution, (3) Mode Choice, and (4) Traffic Assignment. This four-step model is the common sequential approach used to develop those models, and is widely used.

The number of trips generated in a specified zone can be estimated using growth-factor, regression or multiple classification analysis, where each of these may also have variants of the modelling techniques. The other three sub-models in the four-step approach also have different techniques for estimation and variation as well (Ortuzar & Willumsen 1994; Taylor, Bonsall & Young 2000). Even though various techniques are available for estimating the travel demand, a modeller should find the one that is most suitable for the analysed area in regard to the quality and nature of existing data, local behaviour, and model output accuracy (Quandt & Baumol 1966).

The accuracy of the model is likely the main question faced by the traffic analyst as well as the decision makers. The increasing contribution of private sector in planning, funding and operating transport projects has also increase the need of finding a robust formal model. Trujillo et al. (2002) suggested there are two type of sources of error in demand forecasting namely (1) Scientific uncertainty, and (2) Strategic manipulation. Each of them could cause error up to 30 and 60 per cent respectively. The first source is mainly dealt with the modelling process such as model structure, quality of data and uncertainty in predicting future value of exogenous variables. Trujillo et al. also suggested that the phenomenon of privatization in transport sector is the main contribution of the second source. The concept of 'optimisation bias' (Skamris & Flyvbjerg 1997; Bain & Polakovic 2005) is a good example of this second source.

The first source of error can be improved by, for instance, improving the model structure, quality of the data and its collection process and method in capturing the uncertainty in the forecasting. Those three components are related each other and become a system. Thus, developing a good model structure supported by a good quality of data and properly counted the uncertainty, can generate a robust model with better output accuracy. A new approach, here called Fuzzy-Neuro, is proposed to achieve it, focusing on the trip distribution and mode choice.

2 LITERATURE REVIEW

2.1 Travel demand forecasting method

Transportation planning and management activities generally require Origin-Destination (O-D) matrices. This is the basis of any transportation planning process. The travel demand condition or pattern can be illustrated by O-D matrices showing the current state and can give good indication for future traffic situation. A gravity model is widely used in developing such

matrix (Ortuzar & Willumsen 1994). Therefore, it is commonly used as a benchmark in comparing the performance of a new approach, see for example the comparative studies conducted by Black (1995), and Mozolin et al. (2000). Another important approach in travel demand analysis is the Logit model, also known as the Discrete Choice model.

In transport systems, the Logit technique is, developed on the basis of random utility theory and also known as behavioural model, the most popular technique in capturing such uncertainty (Carvalho et al. 1998). Doubly constrained Growth-factor/Furness technique is another way of estimating the trips (Interplan 2006). The example of its application is in Padang city, Indonesia. It was used to estimate trip for 2010 (mid term) and 2014 (long term) based on 2005 data. Ortuzar and Willumsen (1994) suggested this method is suitable for short term planning only.

The Logit technique is used in mode choice modelling. It is used to estimate the proportion of trip makers who choose available mode types based on given conditions or utility criteria and widely used in demand modelling. This technique is often used to compare with other techniques, due to its ability in analysing the trip maker behaviour. For example, see Cantarella & de Luca (2005), Hensher & Ton (2000), and Nijkamp et al. (1996). However, the Logit model demands a high level of skill and tends to be complex and expensive. It is also suggested that the predictive ability of this method can drop drastically when the number of alternatives increases (Subba Rao et al. 1998). In addition, some researchers claim that this technique is only able to capture the uncertainty in choice decisions and is unable to capture the impact of imprecision in the data (Dell'Orco, Circella & Sassanelli 2007).

2.2 Discrepancy in demand forecasting

The greatest concern of traffic analysts and decision makers is, perhaps, the accuracy of the estimation of future demand. According to Bain & Polakovic (2005), Skamris & Flyvbjerg (1997), and Trujillo et al. (2002), the forecasted traffic tends to be overestimated. It is above the actual traffic for up to 60 per cent. Increasing involvement of private sector is claimed as the main factor in this 'optimism bias'. Scientific mistakes also can cause a certain amount of error; however, this is commonly within 20-30 per cent. Discrepancy due to scientific errors results from the structure of the model, the quality of the data and the ability of the model to capture the uncertainty of future value of exogenous variables.

The structure of the model can be defined as a function of the indigenous variables that construct the model, categorized as independent and dependent variables, and any exogenous variables used as inputs. The dependent variables represent the value of the estimation generated by the independent variables in a specific function, which represents the relationship of both types of variables. A model is required to be able to capture that relationship. Failure in capturing the relationship can lead to inaccurate estimation.

In order to obtain an accurate result, a model must be supported by a good data set. The data set can be also categorized, such as quantitative (crisp) and qualitative (fuzzy) data. The future value of independent variables could be also in crisp and fuzzy types. Therefore, a model is required to be able to use not only crisp but also fuzzy data. Thus, a model that can properly represent the relationship among the variables and can use both types of data is expected to reduce the errors in its outputs. An approach that can perform that task is required.

2.3 Fuzzy set theory

2.3.1 Basic concept

Fuzzy set theory firstly introduced by Zadeh (1965). It provides a framework in classifying imprecise objects/criteria into a continuum of grades of memberships. The imprecision occurs due to the absence sharply undefined criteria of class membership rather than the presence of random variables and it plays important role in human thinking (Zadeh 1965). This theory is different from probability theory. Both theories can be combined in order to obtain better performance.

In classic set theory, memberships are categorised as binary membership function. There are only two options such as yes or not, true or false, belongs or not belong to a set. The membership function is defined by crispy or precise character and given by the equation below (Teodorovic & Vukadinovic 1998).

$$\mu_A(x) = \begin{cases} 1, & \text{if and only if } x \text{ is member of } A \\ 0, & \text{if and only if } x \text{ is not member of } A \end{cases} \quad (1)$$

Fuzzy set A is represented by order pairs “A = (x, $\mu_A(x)$)”, where $\mu_A(x)$ is the grade of membership of element x in set A. Each element in a fuzzy set is labelled with certain grade of membership. The grade membership has a value from zero to one, i.e. a value from the closed interval [0, 1]. The greater $\mu_A(x)$, the greater the truth of the statement that element x belongs to set A. As fuzzy sets are commonly defined by membership functions, each fuzzy set must comply with the condition below.

$$0 \leq \mu_A(x) \leq 1 \quad \forall x \in X \quad (2)$$

The membership value must be converted to a crisp score before being used in final computation. This process is relatively simple. Various methods are available, such as dominance, maximin, maximax, and conjunctive methods (Hwang & Yoon 1979). Examples of scoring the fuzzy membership are given by studies conducted by Aldian (2003) and Aldian & Taylor (2003).

2.3.2 Application in Travel Demand Modelling

This theory is used in all components of four step model (Teodorovic 1999). The example is, mode choice study located in a middle-sized city in southern Italy by Dell’Orco et al. (2007). They used the Random Utility Theory/Discrete choice model in estimating the proportion of travellers choosing a particular transit/public transport among three alternatives with single a utility criterion, in this case travel time. Travel time is assumed to be a fuzzy criterion representing the users’ uncertainty and vagueness. Thus, the travel time is presented in term of numeric intervals, such as left limit value, central value and right limit value. Hence, the study is considered as a combination of random and fuzzy theories. A method to calculate the unique probability is also presented. Dell’Orco et al. termed this a hybrid approach.

The results were compared to the traditional logit model. The hybrid model generated results which fitted better to the experimental data, with significance levels higher than the logit model. However, there was a difference in the chosen alternative rank. The hybrid model gave

the same rank or order in term of proportion to the observed choice behaviour of the participants, whereas the logit model did not, even though the first/the highest alternative was the same.

Dell'Orco et al. claimed that the different was due to the uncertainty/variability of travellers' choice behaviour which the logit model was unable to capture. Yet, the hybrid model seems to have higher degree of complexity compared to the logit model. Dell'Orco et al. suggested that further research involving problems with more than one attribute is required.

The second study held by Aldian and Taylor (2003) indicated another benefit of fuzzy set theory in transport modelling. The study was about modelling inter-city travel demand/trip production in Central Java, Indonesia. It was a combination of aggregate (direct demand model) and disaggregate model (discrete choice model) with multicriteria attributes. The attributes are then categorized into crisp and fuzzy criteria.

The fuzzy criteria which have been transformed into crisp criteria together with other attributes are used in calculation the proportion of certain trips generated in certain zone within a set of alternatives through the application of multinomial logit model. The results are promising as it gives better estimates than the best traditional trip generation model with higher coefficient of determination (R^2). Examples of another study are given on the Table 2.1.

Table 2.1 Summary of Fuzzy approach application

No.	Author	Application area			
		TG	TD	MC	TA
1	Peeta & Wu (2004)				√
2	Aldian (2003)	√	√		√
3	XU & Chan (1993)		√		
4	Aldian & Taylor (2003)	√			
5	Dell'Orco, Circella & Sassanelly (2007)			√	

2.4 Artificial Neural Network

2.4.1 Basic concept

The neural network approach was firstly developed in the 1960s (Black 1995). It was applied in developing computer-based artificial intelligence system based on neural network activity of the brain. It was no longer used until about next 3 decades in such study due to its weakness, namely the slow response to the modification of inputs despite of its very successful at learning or recognizing pattern. However, Dougherty (1995) found that the neural network approach was used again due to its predictive capability. The application, particularly in transportation studies, was booming in the 1990s.

According to Black (1995) and Zhang et al. (1998), both methods are used in forecasting specified output by minimizing an error term indicated the deviation between input and output through the use of specific training algorithm and random learning rate. Neural network is considered as non-parametric method as it does not presume the form or the distributional attributes of variables used. Due to its ability in solving nonlinear with multivariate problems, it is also termed as a multivariate nonlinear nonparametric statistical method (Zhang, Patuwo & Hu 1998). It is a data-driven self-adaptive method that learns form examples and experiences. Contemporary research is devoted in developing model using neural networks

that can process data in the same way of human brain. One major area of application is forecasting.

This model is then expected to carry out a variety of complex task that are difficult for traditional computational techniques (Teodorovic & Vukadinovic 1998). Neural network, often termed as Artificial Neural Network, has been rapidly used in forecasting area due to its capabilities, such as (1) Powerful pattern classification and pattern recognition, (2) Able to learn and generalize from experience, (3) Able to learn from example, and (4) Able to capture the functional relationships among data even if the underlying relationships are unknown or hard to describe. The last of these capabilities is probably the most important in modelling activity.

Network structure building is the first main concern in using neural network. However, there is no standard rule in the network selection process. It is problem-dependent, heuristic, and trial and error. The configurations of a neural network characterized by several components (Dougherty 1995; Teodorovic & Vukadinovic 1998; Zhang, Patuwo & Hu 1998). It comprises of a set of interconnected neurons/processing elements based on the architecture of biological neural systems. The processing elements receive input signals from the neighbouring nodes/weights. It is then processed locally by specific activation/transfer function and generates output signals. All the activities are operated by designed training algorithm. There are various types of neural network structures. It can be classified by its network structure, presence of feedback and network training.

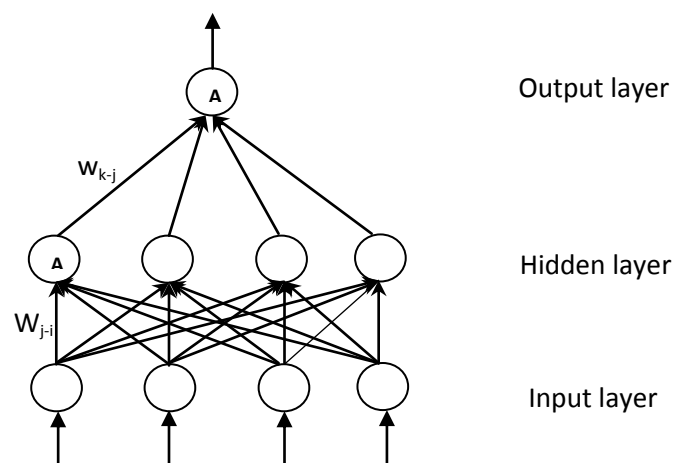


Figure 2.1 A typical feedforward neural network

Source: Zhang et al. (1998)

Even though a standard neural network structure does not exist, the most popular and widely used network is known as Multi-layer Feedforward networks (Black 1995; Dougherty 1995; Zhang, Patuwo & Hu 1998). The structure is depicted on Figure 2.1. There is no set standard for determining the number of layers and nodes, activation function, learning algorithm, data normalization, performance measure, and the proportions of training and testing data set. However, the results of previous studies can be used as guidelines.

For example, the numbers of layers is generally three: input, hidden and output layers. Meanwhile, the numbers of nodes for input and output layers are dependent upon the number of variables assessed in the study. The most popular activation function is sigmoid while Back-Propagation is a widely used example of a learning algorithm. To normalize the data,

linear and simple normalization are the common methods. To measure the performance of the model, most of researchers seem to use Root Mean Squared Error (RMSE) as a matter of convenience (see Table 2.2).

There are several compositions of each data set for training and testing, for examples, 90% vs. 10%, 80% vs. 20% and 70% vs. 30%. Guidance on dividing the data sets into developing and evaluating samples does not seem to exist so far. However, the problem characteristics, data type and the size of the available data are the factors considered in making data division. Dia (2001) used a composition 60%, 10% and 30% for training, testing and validating samples respectively. Carvalho et al. (1998) used 70% vs. 30% as training and testing data sets for mode choice modelling by the neural network approach.

Table 2.2 Summary of Neural Network application

No.	Author	Application area				Network Detail			
		TG	TD	MC	TA	NS	AF	TL	PM
1	Yang et al. (1993)				√	MLF	Sig	BP	NA
2*	Dia (2001)	Speed and Travel Time				MLF	NA	BP	MSE
3*	Fu & Rilett (1995)	Travel time				MLF	Sig	BP	MSE
4	Mozolin, Thill & Lynn (2000)		√			MLF	Sig	BP	AE, RMSE
5*	Yasdi (1999)	Traffic volume				RJN	NA	BP	MSE
6** *	Yin et al. (2002)	Traffic volume				SLF	NA	BP	RMSE
7**	Carvalho (1998)			√		MLF	Sig	BP	RMSE/VSE
8	Zhang et al. (1998)	Review in other area				MLF	Sig	BP	MSE
9*	Ledoux (1997)	Traffic volume and queue				MLF	Sig	BP	RMSE
10	Black (1995)		√			MLF	Sig	BP	RMSE
11	Dougherty (1995)	Review in transport				MLF	Sig	BP	NA
12	Kirby et al. (1997)	Traffic volume				MLF	Sig	BP	AE
13	Gong (1998)		√			HN	NA	NA	Comp
14	Nijkam et al (1996)		√			MLF		BP	ARV
15	Hensher & Ton (2000)			√		MLF	Sig	BP	PST
16	Celikoglu (2003)			√		MLF	Sig	BP	RMSE
17	Palacharla (1999)	Travel time				MLF	NA	BP	SE
18	Chang & Su (1995)	Queue				MLF	NA	BP	PE
19	Cantarella & de Luca (2005)			√		MLF	NA	BP	MSE

Abbreviation definition: *Trip Generation (TG), Trip Distribution (TD), Mode Choice (MC), Trip Assignment (TA), Network Structure (NS), Activation Function (AF), Training Logarithm (TL), Performance Measures (PM), Multi Layer Feedforward (MLF), Hopfield Network (HN), Recurrent Jordan Network (RJN), Sigmoid (Sig), Back-propagation (BP), Mean Square Error (MSE), Absolute Error (AE), Root Mean Square Error (RMSE), Not Available (NA), Prediction Success Table (PST), Average relative Variant (ARV), Percentage Error (PE), Squared Error (SE).*

* = Short-term traffic forecast applications

** = Comparison of Neural Network and Logit model

*** = a combined application of Neural Network and Fuzzy set model

2.4.2 Application in transport travel demand modelling

A review of neural network applications in transport by Dougherty (1995) indicated that more study had been directed to Driver Behavior/Autonomous Vehicles area than others (DA/AV), at least up to 1995. Traffic Forecasting (TF) study was only in fourth position, the same as Freight Operations (FO). However, the current literature review suggests that more attention

is now being given to applications in the Traffic Forecasting area, including Trip Distribution, Mode Choice. There is also more study on long term rather than short term trip estimation (Figures 2.2 and 2.3).

A comparison of logit and artificial neural networks methods in forecasting travel demand was conducted by Carvalho et al. (1998). Using three data sets from disaggregate discrete choice data, two types of neural networks were trained and the results compared to the logit model for all kinds of data sets. The data sets are distinguished by their underlying assumptions.

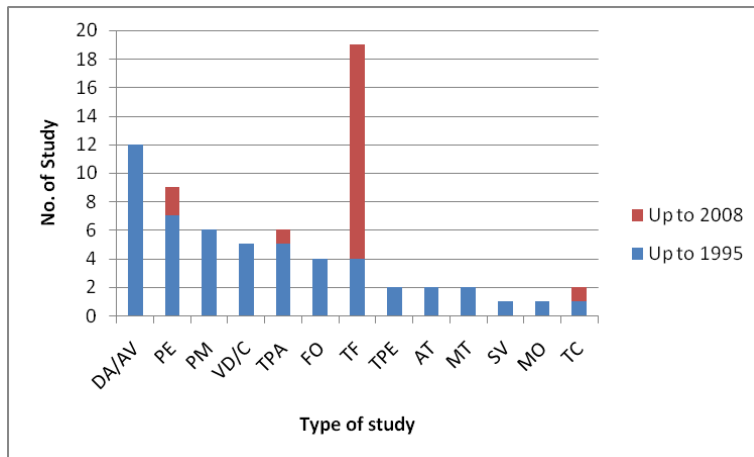


Figure 2.2 Development of Artificial Neural Network application within transport area

The first data set was a synthetic data set, which accommodates the logit approach assumption, the second breached the underlying assumptions (Normal distribution is used instead of Weibull distribution), and the last one was real data. Meanwhile, the first type of neural network model has no hidden layer while the other one uses one hidden layer with various neuron numbers. The study used the ALOGIT package for calibration purposes in logic model and NeuralWorks Professional II plus, a simulation package, to develop and simulate the backpropagation neural networks with different configurations. Measures of fit were based on Mean Square Error (RMSE) and the Variance of Square Error.

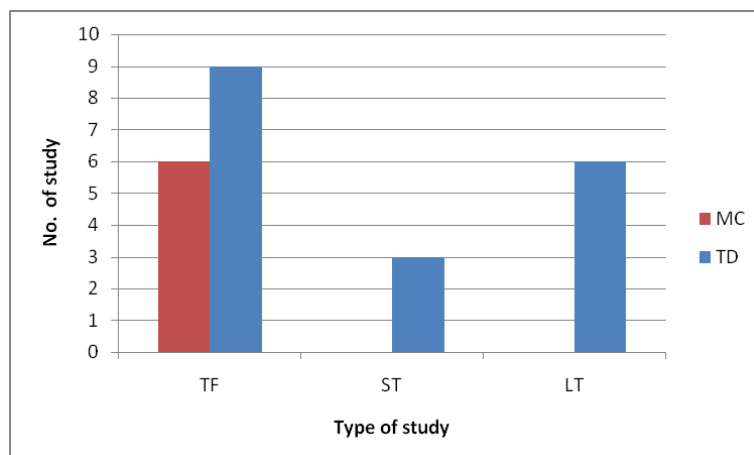


Figure 2.3 Current use of Artificial Neural Network in travel demand model

First comparisons involved the first data set, following by the second and the third data sets. A logit model was compared with three configurations of neural network model. Those configurations were 9-3, 9-3-3, and 9-6-3. The 9-3 configuration means the network had 9 inputs and 3 outputs. The other configurations also have had 9 and 3 inputs and outputs, however, they all had one hidden layer consisting of 3 and 6 neurons respectively.

Results of first comparison indicate that neural networks with no hidden layers produced the same outputs as logit model while the other configurations performed worse than logit results. The assumption embedded in the data set is believed to be the reason for this result. The second comparison had similar results to the former, but the network without a hidden layer had slightly worse performance than logit model. However, the networks with a hidden layer generated different outputs. Hidden layers with 6 and 8 neurons had better results than the logit model. When the hidden layers had 3 and 15 neurons, the performance was poor due to the number of iteration used in the training. Thus it was presumed that the hidden layer improved the measures of fit. The same patterns of outputs were generated by the third comparison.

Other successful studies in using artificial neural networks were conducted by Cantarella & de Luca (Cantarella & de Luca 2005), Nijkamp et al. (1996), and Subba Rao et al. (1998). Those studies all compared neural networks to logit model. Neural network models do not always perform better than logit model; they are sometimes performing equally well or even worse than logit model. This may depend on the configuration of the network. The background knowledge of the researchers may also play a role in determining the relative performance of the models

Finding the best configuration is relatively time consuming as it involves trial and error procedures. However, with the rapid developments in computing systems, this should not be a serious problem. Other problem is 'over fitting'. The model needs to be carefully trained and validated so that over fitting can be prevented. This can be done by stopping the training earlier when the validation error starts to increase.

The Artificial Neural Network approach may also be considered as an optimization method. A study by Celikoglu (2003) demonstrated the application of this method in calibrating the model developed by another method, in this case logit technique. In fact, the training process in finding the best value of weight, learning rate, and network configuration is basically analogous to other calibration methods. It is conducted through an iteration process. The difference is that calibration in a neural network does not provide as a calibration parameter, instead, it generates the best network configuration with weights, learning rate and sometimes momentum value. Table 2.2 provides examples of Artificial Neural Network applications in the transport area.

The application of neural network in demand forecasting is not always successful. One example is the study conducted by Mozolin et al. (2000). The neural network technique was compared with the doubly constrained gravity model in estimating trip distribution. When the majority of former study used the same data set for training, validating and testing, Mozolin et al. used different data sets. The models for both techniques were developed and calibrated (validated) based on 1980 survey and tested on 1990 data set. The neural network models were trained with various node numbers.

The best result was given by network trained by the full first data set with 100000 epochs. The performance is about six per cent lower than gravity model calibrated by using Maximum Likelihood method with negative exponent function of distance decay. Here, it can be assumed that Neural Network model performance is lower than conventional model. The ability of Neural Network to capture the uncertainty in the values of future exogenous variables could be one of the reasons.

2.5 Developing a Hybrid Model

It seems that the neural network method is becoming more commonly used in the forecast area as well as the Fuzzy approach. The neural network tends to have better performance than the conventional models. It can be assumed that both approaches will be adopted by all kinds of discipline and study.

Table 2.3 Summary of hybrid approach application

No.	Author	Application area				Remarks
		TG	TD	MC	TA	
1*	Aldian & Taylor (2003)	√	√		√	* = Fuzzy and discrete choice approach ** = Fuzzy and Four-Step approach *** = Fuzzy and Neural approach
2**	Aldian (2003)	√	√		√	
3*	Dell'Orco et al. (2007)			√		
4***	Yin et al. (2002)	Traffic flow				

Further, the combined models such as discrete choice and fuzzy, and fuzzy and neural network approaches tend to generate better results than if any model is used individually as shown by Aldian & Taylor (2003), Dell'Orco et al (2007), and Yin et al (2002). Based on this, combining two approaches or more could give better results and hence becomes a potential method in travel demand forecasting.

Yin et al. use Neural Network combined with Fuzzy approach. The Fuzzy approach was used in grouping traffic patterns into similar cluster based on its characteristics determined through its degree membership values. The Neural Network approach was used in specifying input and output relationship in the same way as conventional neural network. The hybrid approach was found effective and more accurate than conventional neural network model.

Meanwhile, Yasdi (1999) also used Neural Network in pattern classification and control. Even though the method is not explicitly combined with Fuzzy approach, the study used the knowledge base, which contains verbal information, rule parts and pattern database. Yasdi suggested that the rule part is analogous to the Fuzzy rules. The results are promising as it has good generalization ability. However, there is still lack of study in combining the Neural Network and Fuzzy approaches in travel demand forecasting (Table 2.3). All of these studies indicate the ability of the hybrid approaches to outperform a conventional model. Based on above discussion and this finding, combining Neural Network and Fuzzy approaches in travel demand forecast would potentially perform better than any single conventional model.

3 MODEL STRUCTURES

The attributes or variables considered important in travel demand modelling often present as qualitative forms. For examples are trip length, travel time, road geometry and so forth. The reason for the trip length considered as a fuzzy attribute are (1) Exact distance between O-D is

unknown, and (2) Travellers depart from different points within origin zone to different points within destination zone (Aldian 2003). Travel time is also a fuzzy attribute as it is often labelled with linguistic hedges such as about half an hour (Teodorovic & Vukadinovic 1998). The doubly-constrained Gravity model is widely known and used to model trip distribution when both trip production and trip attraction totals are known. In general, the independent variables are Trip Production in the origin zone (O_i), Trip Attraction in destination zone (D_j) and Travel impedance (c_{ij}) between them. The formula to estimate the flow is given below.

$$T_{ij} = A_i O_i B_j D_j f_{c_{ij}} \tag{3}$$

With the constraints of:

$$\sum_j T_{ij} = O_i \tag{4}$$

And

$$\sum_i T_{ij} = D_j \tag{5}$$

The travel impedance $f(c_{ij})$, is a generalized function of the travel costs with one or more calibration parameters. The best known functions of travel impedance are exponential function ($e^{-\beta c_{ij}}$), power function c_{ij}^{-n} and combination of them ($c_{ij}^{-n} e^{-\beta c_{ij}}$). Trip length (distance) can be used in the deterrence function. To calibrate the model, Hyman’s method is known to be a robust calibration technique (Ortuzar & Willumsen 1994). Here, trip length is assumed as a fuzzy attribute and represented by (\hat{c}_{ij}).

The proposed fuzzy-neuro model structure for trip distribution is illustrated by Figure 3.1.a, which is analogous to the gravity model. There are three input nodes, trip production (X_1), trip attraction (X_2) and trip length (X_3). The output is the trip from specified origin and destination. A similar approach can be used to construct the fuzzy-neuro model for mode choice, by using the logit model instead of gravity structure. The input nodes can be categorized into two types representing the socio-economic characteristics of the individuals and the characteristic of the alternative modes.

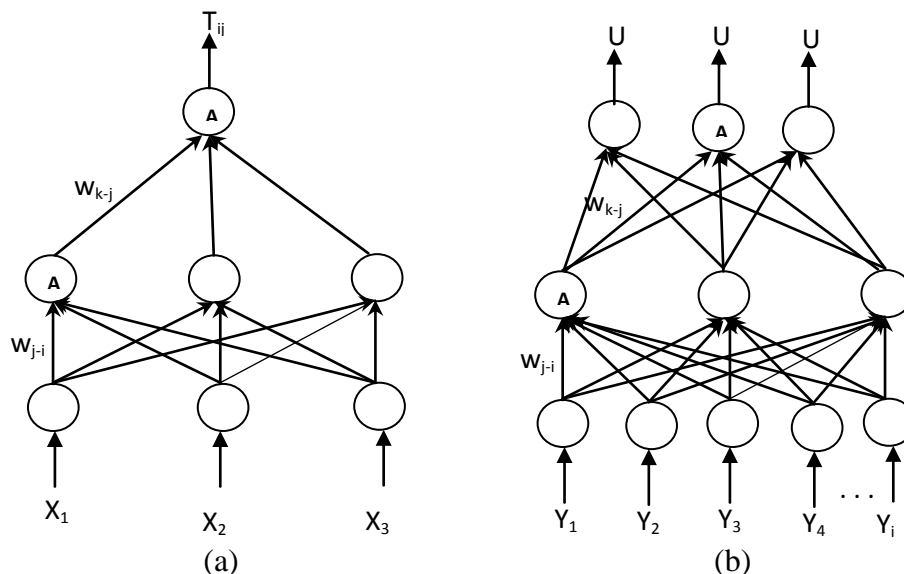


Figure 3.1 Fuzzy-Neuro model structures

The attributes that represent the socio-economic characteristics are, for example, (1) Gender (Y_1), (2) Household income (Y_2), and (3) Household size (Y_3). The attributes for alternative modes could be (1) Walk time (Y_4), (2) Waiting time (Y_5), (3) Journey time by bus (Y_6), (4) Bus fare (Y_7), (5) Journey time by car (Y_8), (6) Expenditure by car (Y_9), and so forth, depends on the variables of interests. The output is the weights assigned for each alternative mode. Some of these attributes are fuzzy, for example, waiting time, travel time and travel cost. Then, their crisp score are also calculated prior to the model training. The structure is illustrated by Figure 3.1.b.

The strength between layers is symbolized by w_{k-j} and w_{j-1} for output-hidden and hidden-input layers respectively. The activation function for nodes in both output and hidden layers (A) could be sigmoid with Back-Propagation algorithm. The number of node in hidden layer could be the same as input nodes or more. All input data are in their crisp form; therefore, the crisp score for fuzzy attributes must be calculated prior to model training.

All data, including output, are suggested to be normalized. To measure the performance of the fuzzy-neuro model, the error can be compared with the gravity, neural network or the fuzzy gravity model output for the trip distribution model. Logit model output is used to measure the mode choice model. The measurement can be done by using Root Mean Square Error (RMSE).

4 CONCLUSIONS

The application of Fuzzy Set Theory and, especially, Artificial Neural Network is significantly increasing in travel demand modelling compared to other study in transport area. Majority of the study suggests that both approaches can improve the well-known techniques such as Gravity models and Discrete Choice models.

Fuzzy set theory can improve the model accuracy by capturing the uncertainty due to the imprecision in the data and is relatively simple to use. Meanwhile, Artificial Neural Networks can be considered as an efficient modelling technique as it develops and calibrate the model at the same times. In addition, it also can represent the spatial relationship better than conventional model. Therefore, this technique could be more reliable and practical than gravity and logit methods. Thus, combining both technique, here called as Fuzzy-Neuro, is expected can improve the ability of Neural Network in forecasting the travel demand and can simplify the model development and calibration.

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