NEURAL NETWORKS FOR TRIP GENERATION MODEL

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Abstract: To estimate the number of trips generated in an area is the first step of the process for transportation planning. A trip generation model expresses the relationship between the socioeconomic factors in an area and the number of trips generated from the area. Up to now, the most common methods for modeling trip generation are the General Linear Regression Model (GLRM) and category analysis.

This paper examines how the neural network model can improve travel demand estimation for trip generation. The efficiency of the proposed neural network model has been compared with a traditional General Linear Regression Model approach, which is commonly used in trip generation model, in terms of prediction accuracy. Some results in this research showed that the neural networks might be efficient tools for transportation planning including trip generation model.

Key Words: Trip generation, Neural Networks, General Linear Regression Model

1. INTRODUCTION

Trip generation which is the first phase in the travel-forecasting process of conventionally applied transportation planning models involves the estimation of the total number of trips entering or leaving a zone as a function of the socioeconomic, locational, and land-use characteristics of the zone.

The model most often used to derive estimates of future trip generation is linear regression which comprises an attempt to construct a linear relationship between existing trip making and the various parameters already identified. However, the imposition of linearity introduces a number of problems in modeling. For example, most surveys have shown that trip-making is not linearly related to socioeconomic parameters such as population, employment, income and car ownership, etc. The use of a linear form in such circumstances represents a basic misspecification.

An alternative method for modeling trip generation is category analysis (Ortúzar and Willumsen, 1994). This method is based on estimating the response (e.g. the number of trip productions per household for a given purpose) as a function of household attributes. Its basic assumption is that trip generation rates are relatively stable over time for certain household stratifications. Another problem of this method remains the need to forecast the number of households in each stratum. In addition, it typically needs a large amount of data for category analysis.

However, Artificial Neural Networks, commonly referred to as Neural Networks, could be applicable for non-linear function approximation and need no assumption of dependent and independent variables. Neural Networks have become one of the most popular techniques for many problems including transportation planning and engineering with their remarkable ability to derive meaning from complicated or imprecise data (Bullock, et al., 1993; Mantri and Bullock, 1995; Mozonlin, et al. 2000).

The objective of this paper is to build trip generation model based on the neural networks. The results from the neural networks will be compared with General Linear Regression Model, which is the most common trip generation model using real data. In this research, the O-D data, which is collected from the freeway tollgates, will be used for the data of trip productions and attractions.

The remainder of this paper is organized as follows. Section 2 presents the basic idea of the application of neural network model for trip generation model. Section 3 describes experiment and shows the results from the experiments. Section 4 offers conclusions.

2. DEVELOPMENT OF NEURAL NETWORKS-BASED TRIP GENERATION

Owing to their self-organizing and adaptive features without a pre-specified functional form representing a physical system, neural networks have become a popular alternative to the traditional model-based approaches in various areas of science and engineering.

There are currently many different types of neural network models (Kim, 1996), and the multilayer feedforward network using Backpropagation is the most popular one, because it is easy to implement and is widely applicable. It has been shown to produce relatively good results in many applications. Backpropagation exhibits following properties that make it good candidates for trip generation:

- It is a universal approximator and can hence model highly complex, strongly non-linear systems.
- It can handle multi-variate systems
- It is useful for dynamic trip generation model since it is suited for real time applications
- More importantly, it is applicable for any value of input and output vectors.

Because of the above reasons, Backpropagation has been used in this research. Figure 1 shows the network architecture of Backpropagation chosen in this research for trip generation model. It consists of three layers: an input layer, a hidden layer, and an output layer. The input represents zonal socioeconomic attributes, which may have an impact on trip generation. In this research, three major factors of population, income (or tax), and car ownership have been considered as the properties of input units. However, in order to compare with the Regression model more precisely, the properties of input unit will be determined after development of the regression model. The output units represent trip production and attraction of each zone. On the figure, *f*( ) denotes activation function - sigmoid function has been used in this paper -, w_{ij} denotes weight vector, which should be determined after training. More importantly, the values for input and output units have been normalized before using them to the network (For more detail in the normalization method, see Kim, 1999a).

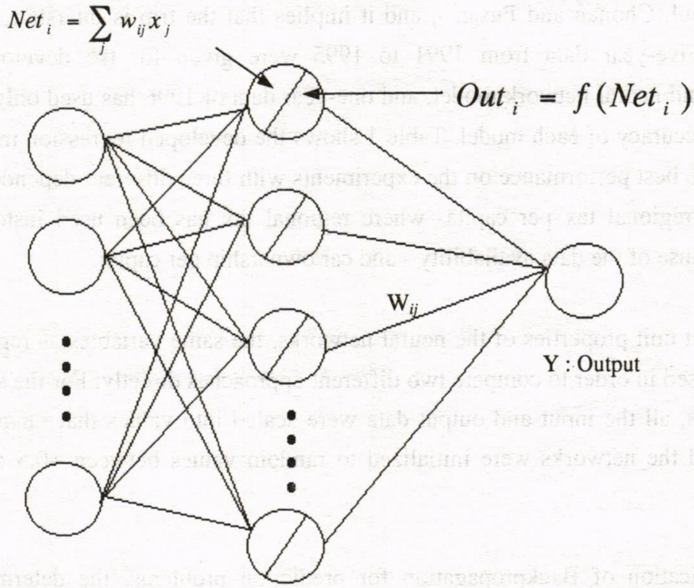

Figure 1. Backpropagation neural network architecture

In Backpropagation, a network topology should be chosen prior to the experiment. In this research, three-layer (one hidden layer) has been used since there has been no improved performance in the two-hidden-layer networks (Kim, 1999b). For the number of hidden neurons, two different architectures have been used according to the number of input units (see section 3). Moreover, this research used an enhanced Backpropagation model (Kim, 1998), BPMP (Backpropagation with Momentum and Prime-offset), since it has been shown the better performance, in terms of computing cost and predictive accuracy, than the standard Backpropagation.

3. EXPERIMENTS AND RESULTS

The experiments in this research were implemented on the three-layer network with one hidden layer. The number of neurons on the hidden layer was given differently according to the number of input units that have been used as dependent variables on the regression models, i.e. 1(input unit)-5(hidden neurons)-1(output unit) and 2(input units)-10(hidden neurons)-1(output unit).

This research used only trips made by vehicle (often called "vehicle trips") for modeling of trip generation. The trip data were obtained from the freeway tollgates in three major cities of Korea - Seoul, Chonan and Pusan -, and it implies that the trip is interstate production and attraction. Five-year data from 1991 to 1995 were given for the development of both regression and neural network model, and one-year data of 1996 has used only for testing the prediction accuracy of each model. Table 1 shows the developed regression models that have produced the best performance on the experiments with three different dependent variables of population, regional tax per capita- where regional tax has been used instead of regional income because of the data availability - and car ownership per capita.

For the input unit properties of the neural networks, the same variables as regression models have been used in order to compare two different approaches directly. For the sake of learning effectiveness, all the input and output data were scaled into values that ranged between 0.1 and 0.9, and the networks were initialized to random values between +0.5 and -0.5 before learning.

In the application of Backpropagation for prediction problems, the determination of the learning stop is very important to achieve the best performance. Normally, cross-validation method has been used to avoid overtraining or undertraining (Haykin, 1994). However, cross-validation method may be useful when a large number of data sets for training are available.

More importantly, the number of epochs and training error can be affected by the number of training data sets. In order to tackle this problem, whole training data sets have been used in this study and only the last year data has been used for the criterion of stopping training, i. e. the learning will be stopped if the prediction error on the last year data among training data sets is increasing.

Table 1. Regression models for trip generation

City	Trip ends	Model
Seoul	Production	$Y = b_0 + b_1 \times Tax$, $b_0 = 1.250e06$, $b_1 = 0.860$, $R^2 = 0.984$, $F = 391.587$
	Attraction	$Y = b_0 + b_1 \times Pop + b_2 \times Tax$, $b_0 = -729675$, $b_1 = 0.178$, $b_2 = 0.883$ $R^2 = 0.957$, $F = 44.612$
Chonan	Production	$Y = b_0 + b_1 \times Car + b_2 \times Pop$, $b_0 = -743357$, $b_1 = 34.04$, $b_2 = 6.893$, $R^2 = 0.954$, $F = 41.38$
	Attraction	$Y = b_0 + b_1 \times Car + b_2 \times Pop$, $b_0 = -281284$, $b_1 = 35.25$, $b_2 = 5.287$, $R^2 = 0.985$, $F = 134.913$
Pusan	Production	$Y = b_0 + b_1 \times Pop + b_2 \times Tax$, $b_0 = -591565$, $b_1 = 0.254$, $b_2 = 0.189$, $R^2 = 0.676$, $F = 4.17$
	Attraction	$Y = b_0 + b_1 \times Car + b_2 \times Pop$, $b_0 = 75099.5$, $b_1 = 0.332$, $b_2 = 0.08135$, $R^2 = 0.811$, $F = 8.565$

Table 2 shows the results of trip generation by two different approaches, regression model and Backpropagation neural network model. The results imply that the Backpropagation may produce the better performance than regression model in trip generation application. In the two cities, the prediction error of the neural networks is very smaller than in the regression model, even though it showed the worse performance in one city.

The input layer represents the major factors, which can have an impact on trip generation while the output layer has one cell representing the estimated trip. Even though restricted input attributes have been used in this research for the purpose of comparing from the regression model, the neural network approach would be much more efficient if many input attributes such as accessibility and land use should be included in the generation model.

Table 2. Performance Comparison between Backpropagation & Regression (vehicles/year)

City	Trip ends	Trips ('96)	Prediction by Backpropagation		Prediction by Regression model	
			Trip	Error(%)	Trip	Error(%)
Seoul	Production	4,966,382	4,965,674	0.01	5,018,700	1.05
	Attraction	4,813,269	4,951,790	2.88	4,956,600	2.98
Chonan	Production	4,128,645	4,123,402	0.13	4,305,000	4.27
	Attraction	4,253,057	4,237,938	0.36	4,336,300	1.96
Pusan	Production	546,017	611,947	12.07	586,990	7.50
	Attraction	581,863	623,523	7.16	608,430	4.57

Moreover, the neural networks would be efficient for a simultaneous model which combines the entire four-step process of trip generation, trip distribution, mode split, and traffic assignment since it normally requires a many variables and non-linear relationship between dependent and independent variables. The further research is needed for finding efficient and reliable neural network models that can substitute for the current trip generation models.

4. CONCLUSION

In this research, the neural network model has been found to be very useful in the application of trip generation. The results from the experiments showed the better performance in terms of prediction accuracy than traditional General Linear Regression Model. Unlike the model-based approach, the neural network approach does not require a predefined functional form. As a result, neural networks would be efficient when we have a large number of variables to be considered and it is too complicate to include them in the model. Moreover, if we deal with a large number of zones, the neural networks would be efficient because of the computational property of massive parallelism.

Even though the neural network model could be a promising method for the trip generation, a problem, which is to decide stopping learning, should be solved. With the heuristic approach as in this research, we may achieve better predictive accuracy. However, this method couldn't be conclusive, and further research will be required to identify whether this method could be applicable on other problems

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