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Research Article

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Trip Distribution Modeling Using Neural Network and Direct Demand Model

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Keywords

Travel demand,
Direct demand model,
Neural network.

Abstract

The transportation system as one of the main elements of providing services in cities is of particular importance in urban management, and therefore high budgets are spent annually in this sector. In this regard, the management of this system takes various measures to apply the costs optimally and improve the transportation system's performance. Since these costs must be applied fairly in the sectors with the highest demand, an accurate estimate of travel demand should be available. In this study, using direct demand and neural network models, a travel demand forecasting model between the provinces of Iran has been compared and investigated. In other words, the second stage of the four basic stages of the travel demand, i.e., the trip distribution in the direct model, obtained a regression coefficient of 0.41, and for the neural network model, this value was 0.70, which shows that the neural network model is a far better model for trip distribution.

1. Introduction

The travel demand has complex characteristics that are caused by two major factors. One of the factors is the origin of this demand from the existing demand for goods and services, and the other is the existence of many choices that the travel demand is inevitable [1]. The process of forecasting is a part of the overall process of production management and planning. Correct forecasting helps to respond to future changes and needs faster and correctly. In matters related to transportation, the basis of work is always based on future demand, and planning often proceeds in the direction of providing the necessary facilities to respond to this demand. On the other hand, the aforementioned demand can only be achieved by forecasting the situation and changes in the future [2, 3]. In the history of transportation planning, these models have been mostly used for intercity trips. Direct models combine different aspects of travel decision-making (including trip generation, trip distribution, and route choice) and show them in the form of a model. In fact, in these models, the calculation of route choice is done only by using trips between specific pairs of origin and destination [4, 5]. Similar to the four-stage models, the output of these models is the forecasting of the traffic volume in the future. An important advantage of direct models is that they can examine many related factors without the need for extensive statistics [6]. The Kraft model is one of the models for the direct estimation of travel demand by transportation mode. The importance of these models comes from the fact that they do not have a specific approach to intracity or intercity travel and have a general approach to travel demand. However, these models were first developed by the System Analysis and Research Company of SAARC for an intercity project [7].

Kim et al. proposed a neural network-based combined model for trip generation, distribution, and modal spilt. The experimental results showed that the proposed direct demand model using the neural network model is an attractive

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proposition, particularly in areas where we have to deal with a large number of zones to determine future trips [8]. Rasouli and Nikraz estimated the distribution of the journey to work trips in the city of Mandurah in WA using generalized regression neural network (GRNN) and gravity model models. This study also tried to estimate the trip distribution based on land uses. The modeling analysis indicated that the GRNN modeling could provide slightly better results than the gravity model with a higher correlation coefficient and less root mean square error and could be improved if the size of the training data set is increased [9]. In the study of Guler, a travel demand modeling framework was developed to calculate the transportation demand in the Marmaray corridor of Turkey. In addition, a model including empirical modeling methods was developed for the highways to estimate the origin and destination matrices. The developed model was used to estimate freight and passenger transportation between Istanbul and other Turkish provinces. The estimated transportation demand results were used to calculate the required train numbers on a daily basis through the Marmaray corridor, and some suggestions were put forward to increase the capacity of this corridor [10]. Xu et al. proposed a sequence learning model that can predict future taxi requests in each area of a city based on the recent demand and other relevant information. They used one of the best sequence learning methods, long short-term memory that has a gating mechanism to store the relevant information for future use. They evaluated the method on a data set of taxi requests in New York City by dividing the city into small areas and predicting the demand in each area. They showed that this approach outperforms other prediction methods, such as feed-forward neural networks. In addition, they indicated how adding other relevant information, such as weather, time, and drop-offs, affects the results [11]. Yan et al. applied machine learning methods for direct demand modeling of ridesourcing services in Chicago. They used the random forest to estimate a zone-to-zone (census tract) direct demand model for ridesourcing services. Results indicated that compared to the traditional multiplicative models, the random forest model had a better model fit and achieved much higher predictive accuracy. They found that socioeconomic and demographic variables collectively contributed the most (about 50%) to the predictive power of the random forest model. Travel impedance, the built-environment characteristics, and the transit-supply-related variables were also indispensable in ridesourcing demand prediction [5]. Alsaleh and Farooq developed trip production and distribution models for on-demand transit (ODT) services at the dissemination areas (DA) level in Belleville, Canada, using four machine learning algorithms. The results showed that the land-use type was the most important variable in the trip production model. On the other hand, the demographic characteristics of the trip destination were the most important variables in the trip distribution model. Moreover, the results revealed that higher trip distribution levels are expected between dissemination areas with commercial/industrial land-use types and dissemination areas with high-density residential land-use [12].

Many intelligent transportation system services use vehicle location and time information to help manage traffic congestion and, in the case of public transportation, improve service reliability. Time and location data can be obtained in a variety of ways, including probe vehicles, embedded road sensors, electronic toll collections (ETC), automatic vehicle location (AVL), etc. As part of advanced public transportation systems, many transit agencies deploy AVL. Another public transportation system that could benefit from this technology is the vehicle sharing system (i.e., vehicle sharing, station vehicles). In particular, shared vehicle systems with multiple shared stations must closely manage their fleets to avoid vehicle distribution problems at their stations. In this paper, an attempt was made to describe a route prediction and arrival time estimation method implemented with a real-world multi-station vehicle sharing system (VSS). Each vehicle has an AVL system, generating position and time data that can be used at the system level for estimation. This is slightly different from bus arrival estimation techniques because the routes are not known in advance. The developed algorithm is tested against real routes and arrival times and provides encouraging results. It was found that if the frequency of position/time data increases, the estimation method can be improved [13-15]. Research in the field of artificial intelligence systems is using artificial neural networks (ANN) as a framework in which to investigate many traffic and transportation problems [16, 17]. One of the advantages of ANN is its use in model correlation and error correction to represent a problem [18]. This is in contrast to the rule of maximization of stochastic means in discrete choice modeling. ANN represents a complete set of human understanding of a particular problem by artificial neural networks [19-21]. The claim of ANN is that it can solve the problem of forecasting and modeling travel demand. Therefore, the use of such tools in the study of individual travel behaviors provides an opportunity to consider the extent to which representational frameworks exist that complement or replace discrete choice methods. In this study, by comparing the prediction ability of neural network models in the field of commuting route choice, an attempt was made to examine the competence of neural networks.

2. Methodology

2.1. Case Study

In this study, the data of the 2020 statistical yearbook of passenger transportation as well as the census data of the employment population, the number of households, services, and income were used. Travel data is the number of interprovincial travels, and obtaining the distribution of the number of trips is the goal of the study.

2.2. Method

The transportation system as one of the main elements of providing services in cities is of special importance in urban management, and therefore large budgets are spent annually in this sector. In this regard, the management of this system takes various measures in order to optimize costs and improve the performance of the transportation system. Considering that the most important influencing factor in the performance of this system is its users, in other words, system passengers, many of these measures are based on predicting the traffic behavior of system users, which takes place in the form of different transportation models. Direct models combine different aspects of travel decision-making, including trip generation, trip distribution, and route choice, and show them in the form of a model.

The travel demand is determined according to the mode of transportation based on the following characteristics: service level characteristics provided by the desired mode of transportation, service level characteristics provided by other modes of transportation, characteristics that describe the potential of an area to attract travel, and characteristics that describe the potential of an area to produce travel. Based on these four assumptions, Kraft presented Eq. (1) in such a way that its parameters express a more specific concept [7]:

$$Distribution = a \times employO^{b} \times employD^{c} \times popO^{d} \times popD^{g} \quad (1)$$

where employO is employed population in the origin province, employD is employed population in the destination province, popO is population in the origin province, and popD is population in destination province.

The selection of the model and the number of neurons as well as the type of function play an important role in the process of neural network prediction. In this study, multilayer perceptron (MLP) was used, and according to Figure 1, the TrainLM training function provided 2 internal layers, in which the hyperbolic sigmoid tangent function was used in the first layer, and the purelin linear function was applied in the second layer. In the performance section, the mean squared error (MSE) function and 6 neurons were used in the hidden layer. Figure 1 shows the process and functions for different layers. In this figure, as can be seen, the data is entered, and in the first layer, it is weighted by w1 and placed in the hyperbolic sigmoid tangent function, and then it enters the second stage and is weighted by w2, and the final output of the model is obtained.

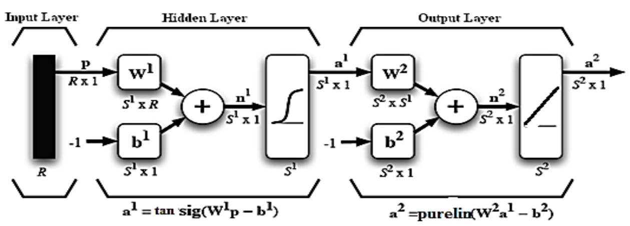

Figure 1. The neural network model and its functions

3. Results

3.1. Modeling With Direct Demand Method

Figure 2 shows the transferred passengers according to the origin province and the months in 2020. In the first half of the year, the share of intercity travels was higher. In month 4, this reached its lowest level in the whole year. In the second half, intercity travels were more uniform. In month 6, the largest volume of travels was possible, which may be related to recreational travels in this month.

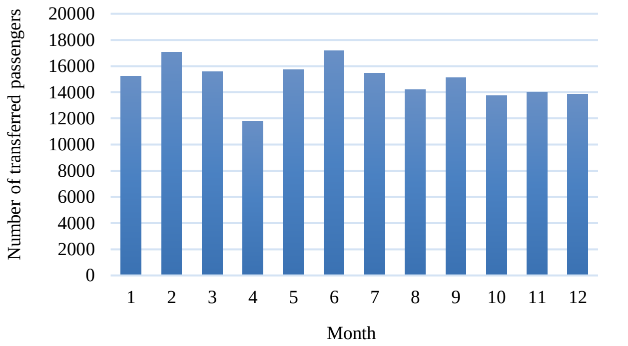

Figure 2. Transferred passengers according to the months in 2020

The direct model is defined as a model in which the route choice calculations are made using only trips between specific pairs of origin and destination. Similar to the four-stage models, the output of these models is the prediction of the passenger volume in the future. The important advantage of direct models is that they can examine many related factors without the need for extensive statistics.

The coefficients of the constructed model are shown in Table 1 and are presented in Eq. (2).

Table 1. Estimation of the coefficients of the distribution model

Coefficient	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
a	1.134E-08	.000	-4.021E-08	6.288E-08
b	2.934	.890	1.187	4.681
c	1.900	.712	.502	3.298
d	-1.899	.916	-3.697	-.102
g	-.980	.736	-2.424	.464

$$Distribution = 1.13 \times 10^{-8} \times employO^{2.93} \times employD^{1.9} \times popO^{-1.89} \times popD^{-0.98} \quad (2)$$

Table 2 shows the error value and parameters of the model. The coefficient of determination (R^2) was 0.39, and R-value was 0.41.

Table 2. Error value and parameters of distribution model

Source	Sum of Squares	df	Mean Squares
Regression	24191181.10	5	4838236.221
Residual	27215794.90	925	29422.481
Uncorrected Total	51406976.00	930	
Corrected Total	44678883.09	929	

3.2. Modeling With Neural Network Method

Figure 3 shows the structure of the neural network model for the distribution model. Also, in Figure 4, there are four diagrams of the target data for training, test, validation, and all data. In each diagram, the regression line represents the fit between the best results of the network output and the target data, where the target data is the number of travels between the provinces of the country.

The closer the R-value is to one, the more correlation there is between the outputs of the neural network and the target data, which was reported 0.7. The accumulation of data on the regression line is relatively good, which shows the efficiency of the network, indicating the appropriate ability of the neural network for prediction. The linear equation in the y axis of all four graphs is the regression line relationship.

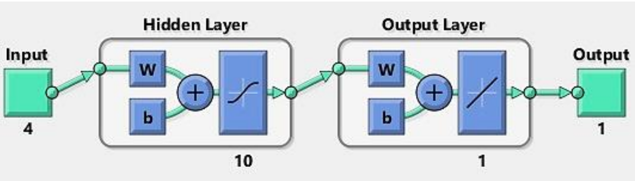

Figure 3. The neural network model architecture

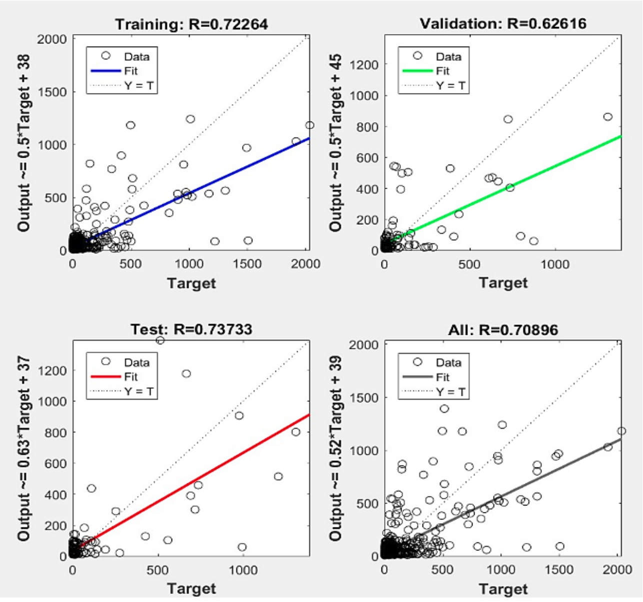

Figure 4. The prediction power of neural network model

4. Conclusion

The direct demand modeling approach has advantages over some other modeling approaches, the most important of which is that it can be developed to a large extent using existing data, as the model explains the influence of various factors, affects people's choice of travel, and it can have an important contribution in the decision-making process. But compared to the neural network, this model has less accuracy, so the accuracy of the neural model is about twice that of the direct demand model.

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