International Journal of Scientific & Engineering Research Volume 4, Issue 5, May-2013
ISSN 2229-5518

OD Matrix Estimation from Link Counts Using Artificial Neural Network

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Abstract— The estimation of origin-destination (OD) matrix is the most important part of any transportation planning problem. The conventional estimation techniques based on surveys are soon becoming outdated as they are time consuming and are highly expensive. In the case of a developing country, such changes occur at a very fast rate, and constant updating of the OD matrix by the conventional methods becomes almost impossible. The easily available data which represents the travel pattern is the link counts. This can be used for the estimation of the OD matrix. Considering the highly dynamic, large scale, complex and uncertain nature of many transportation systems,Artificial Neural Networks (ANN) are recently considered as an efficient tool in solving numerous transportation problems. Attempts are made here to make use of the potential of the ANN for OD matrix estimation. The link selection procedure used for the model is the K and L link selection method. A model is developed based on the certain assumptions and constrains of the estimation problem. The developed model is applied on two hypothetical networks and the resulting OD matrix is statistically compared to the target OD matrix. Based on the results obtained, the developed model fits fairly well.

Index Terms— Artificial Neural Networks (ANN), Link Counts, Link Selection, Network Assognment, OD Matrix Estimation, Transportation Planning, Travel Demand.

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1 INTRODUCTION

ORIGIN–Destination (OD) travel information is necessary in transportation planning of any urban area. The knowledge about trip flows is usually organised in the form of two dimensional matrices called the OD matrices whose cell values represent the travel demand between each given origin (row) and destination (column) zone. One of the most crucial requirements for the transportation planning is to arrive at the traffic pattern between various zones through OD matrix estimation.

In developing countries, changes in the land-use and economic state of affairs require momentous transportation planning. Traditional four stage process of estimating OD matrix is through a large scale sampled surveys. But in situations of financial constraints these surveys become impossible to conduct. And by the time the survey data are collected and processed, the O-D data obtained becomes obsolete. The estimation of OD flows from traffic counts can be considered as the inverse process to that of assignment.

2 ARTIFICIAL NEURAL NETWORKS AS AN OPTIMISATION TOOL

Artificial Neural Networks (ANNs) are a functional abstraction of the biologic neural structures of the central nervous system. They are powerful pattern recognizers and classifiers. They operate as black box, model-free, and adaptive tools to capture and learn significant structures in data. Their computing abilities have been proven in the fields of prediction and estimation, pattern recognition, and optimization. They are suitable particularly for problems too complex to be modelled and solved by classical mathematics and traditional procedures.

There is no technique in trip distribution that is universally applicable, so attempts to develop alternative ways are always needed. This includes the adoption of approaches from other disciplines. Neural Networks are one of them and are proposed as an alternative method. ANN is characterized by its important properties, such as learning algorithm, activation function, number of layers, number of nodes inside each layer, and learning rate. The neural networks provide superior levels of performance when compared with unconstrained conventional models.

3 ESTIMATION OF OD MATRICES FROM LINK COUNTS

Traffic counts contain information concerning trip activities, which could be used to estimate or at least update OD matrices. Measurement of link volume can be made relatively inexpensively, and when automatic traffic counters are used, very little manual labour is required. Several methods have been developed so far for the estimation of OD matrices from traffic volume on selected links in a network.

3.1 Gravity Based Models

The Gravity Model assumes that each trip interchange value is based on the levels of productions and attractions at the trip origin and destination, and on a factor that represents the special separation of each OD pair. In these models the entries of the OD matrix are assumed to be functions of the traffic counts, measure of travel cost or impedance and other parameters.

3.2 Entropy Maximisation and Information Minimisation Models

In these models, the probability of a particular trip distribution occurring is assumed to be proportional to the number of states or entropy (disorder) of the system. The OD matrix which can arise in the greatest number of ways or in other words, the one with which the maximum entropy is associated is estimated as the most likely trip matrix.

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International Journal of Scientific & Engineering Research Volume 4, Issue 5, May-2013
ISSN 2229-5518

The information available in the traffic counts in the links is insufficient to determine a complete trip matrix. In the information minimisation approach, the trip matrix that adds as little information as possible to the knowledge contained in the traffic counts is estimated

3.3 Statistical Models

These models attempt to estimate the trip tables directly from the prior information based on statistical techniques. Traffic volumes and target OD matrix are assumed to be generated by some probability distributions. An estimate of the OD matrix is obtained by estimating the parameters of the probability distributions. The commonly used generalised least square based method is an example of a statistical model.

3.4 Equilibrium Models

This approach uses mathematical programming techniques associated with the equilibrium traffic assignment methods to estimate a trip matrix in a congested network. This approach is based on the traffic assignment following Wardrop's first criterion, which states that the traffic distributes itself on alternate paths in such a way that no driver could save his travel time or travel cost by changing over to alternate paths.

3.5 Gradient Based Solution Techniques

In this technique, the target OD matrix is taken as an initial solution to the OD matrix estimation problem. The target OD matrix is adjusted or changed to reproduce the traffic counts by iteratively calculating directions based on the gradient of the objective function.

3.6 Multi Objective Programming Model

In this model, the objective programming formulation for the estimation problem is interrupted as a problem that has two types of objectives – one of which is to satisfy the traffic counts constrains and the other to search for a solution as close as possible to the target OD matrix.

4 PROBLEM DEFINITION

The important criterion in the estimation of OD matrix using traffic counts is the assignment technique used. Availability of multiple routes with unequal travel costs between any pair of zones increases the complexity of the OD estimation problem. Given observed link volumes, V_a, on a set of the links, a ϵA, and traffic proportions, p_{ij}, the OD matrix can be determined by solving (1)

$$V_a = \sum_{i=1}^{n}\sum_{i=1}^{n} p_{ii}^{a} T_{ii} \tag{1}$$

Where, Tij is the total trips from zone I to zone j in a network of n zones. The equation system is normally under specified. There are many more elements in the OD matrix than the number of links on which the traffic counts are collected. Thus prior information and/or assumptions about the travel behaviour are needed in order to find a unique OD matrix. The important prior information required for the training of the neural network is the target OD matrix. The distance between the target OD and the estimated OD is minimised subject to flow constrains.

The problem for the estimation of OD matrix can be defined as in (2)

$$\min f\left(t_{ij}\right) = \left(\sum_1^n (t_{ij}^e - t_{ij}^t) + \sum_1^m (v_a^e - v_a^t)\right) \tag{2}$$

Subject to the constrains t_{ij} and v_a are greater than zero. In (2) superscript e and t are the estimated and target values for trips t_{ij} and link volume v_a for a study area of n zones with m links of known volume.

The assumptions made are – 1. The traffic is assigned onto the network by all or nothing assignment. 2. The intra-zonal trips are neglected. 3. The links are prioritised based on their importance in the network. From the prioritised links the links covering at least forty percent of the OD pairs are assumed to be known.

5 SELECTION OF LINKS

In real life situation it is not possible to collect volumes from all the links in the network. Also, the link volumes on all the links may not be independent, giving rise to linearly dependent set of equations. So the link volumes are collected on selected links. The amount of information supplied by volume counts on different links will be different. Thus, selection of appropriate links for collecting volume counts considerably affects the accuracy of the estimated OD matrix. The links are to be selected in such a way that maximum information regarding the trip matrix is obtained from the minimum number of link volume counts.

The experimental study was done using the K and L link selection technique. The procedure is based on two indices called K and L indices. The L index is defined as the volume carried by each link per unit OD interchange carried by it. The link with the highest L index is chosen as the first link for taking volume count. The K index for the rest of the links is calculated by multiplying the L index to the number of additional OD interchanges covered by selecting that link. The link with the highest K index is selected as the next highest link. The K index is calculated after selecting each link. The procedure is continued to obtain the links in their order of importance in the network

6 LEVENBERG-MARQUARDT ALGORITHM

In mathematics and computing the Levenberg-Marquardt (LM) algorithm, also known as the Damped Least-Squares method, provides a numerical solution to the problem of minimizing a function, generally nonlinear, over a space of parameters of the function. These minimization problems arise especially in least squares curve fitting and nonlinear programming. The algorithm interpolates between the Gauss-Newton algorithm and the method of gradient descent. The LM algorithm is more robust than the Gauss-Newton, which means that in many cases it finds a solution even if it starts very far off the final minimum. For well-behaved functions and reasonable starting parameters, the LM algorithm tends to be a bit slower than the Gauss-Newton algorithm. The LM algorithm can also be viewed as Gauss-Newton using a trust region approach. The LM algorithm is a very popular curve-fitting algorithm used in many software applications for solving generic curve-fitting problems.

The LM algorithm is used for training the neural networks. This algorithm was chosen as it was clear from the literature that it performs better for the estimation of the OD matrix than the other algorithms available for the training of the neural networks. It is the fastest back-propagation algorithm in the neural networks, and is highly recommended as a first-choice supervised algorithm, although it does require more memory than other algorithms.

Like the quasi-Newton methods, the LM algorithm was designed to approach second-order training speed without having to compute the Hessian matrix. When the performance function has the form of a sum of squares (as is typical in training feed-forward networks), then the Hessian matrix, H can be approximated as in (4)

$$H = J^T J \tag{4}$$

International Journal of Scientific & Engineering Research Volume 4, Issue 5, May-2013
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The gradient, *g* can be computed as in (5)

$$g = J^T e \quad (5)$$

Where, J is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and e is a vector of network errors. The Jacobian matrix can be computed through a standard back-propagation technique which is much less complex than computing the Hessian matrix.

The LM algorithm uses this approximation to the Hessian matrix in the (6) in a Newton-like update

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e \quad (6)$$

When the scalar μ is zero, this is just Newton's method, using the approximate Hessian matrix. When μ is large, this becomes gradient descent with a small step size. Newton's method is faster and more accurate near an error minimum, so the aim is to shift towards Newton's method as quickly as possible. Thus, μ is decreased after each successful step (reduction in performance function) and is increased only when a tentative step would increase the performance function. In this way, the performance function is always reduced at each iteration of the algorithm.

For the neural networks, back-propogation is used to calculate the Jacobian Jx of performance with respect to the weight and bias variables x.

The adaptive value μ is increased by a specified value until the change above results in a reduced performance value. The change is then made to the network and μ is decreased by specified values. When μ is large the algorithm becomes steepest descent, while for small μ the algorithm becomes Gauss-Newton. The LM algorithm can be considered a trust-region modification to Gauss-Newton.

7 ESTIMATION PROBLEM

7.1 Shortest Path Estimation

The shortest path between the various centroids is found using Dijkstra algorithm. It is a graph search algorithm that solves the single-source shortest path problem for a graph with non-negative edge path cost/distance, producing a shortest path tree. This algorithm is often used in routing and as a subroutine in other graph algorithms.

7.2 Selection of Links

The links in the network are prioritised as per the K and L link selection procedure. On applying the link selection procedure, the links of the network based on their order of importance in the network is obtained. The number of OD pairs covered by each link is found out and number of links of top priority which covers around 40% of the OD pairs is assumed to have known volumes.

7.3 Training the Neural Network

As a computation technique based on iterative processes, the neural network model estimates the outputs by minimizing the deviation between model outputs and the target values. This process is called training or learning.

The neural network is a two layer network consisting of one layer of input neurons, two layers of hidden neurons and one layer of output neurons. The transfer function used is the log-sigmoid function. For training the neural network LM algorithm is used. The performance of the neural network is measured using MSE (Mean Squared Error).

8 STUDY NETWORKS

Two hypothetical networks were selected for the study.

The network is shown in figure 1. The network consists of 6 centroids connected with 18 unidirectional links.

The network is shown in figure 2. The network consists of 15 centroids and 43 nodes connected with 102 unidirectional links.

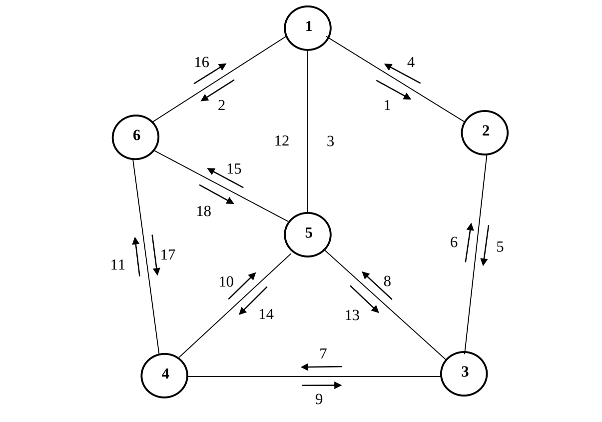

Fig. 1. Hypothetical Network 1 used in the study

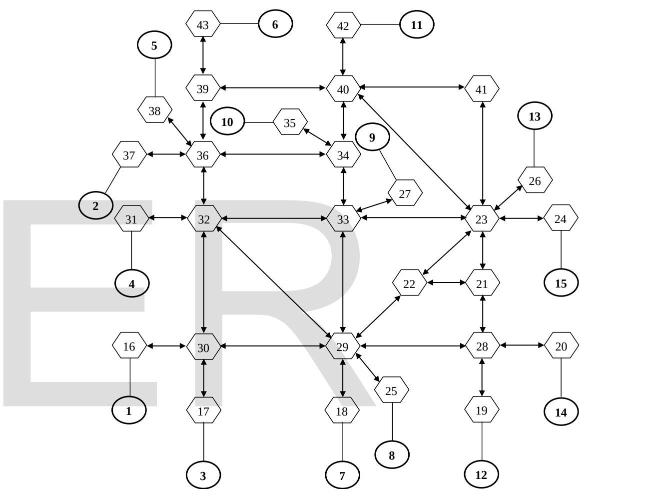

Fig. 2. Hypothetical Network 2 used in the study

TABLE 1
RMSE AND R-SQUARED VALUES

Network	*Output Type*	*Number of Samples*	*RMSE Value*	*R-sq Value*
Network 1	t_{ij}	36	1.55	0.993
	P_i	6	3.11	0.957
	A_j	6	3.21	0.988
	V_a	18	2.00	0.996
Network 2	t_{ij}	225	8.23	0.992
	P_i	15	22.75	0.976
	A_j	15	31.30	0.998
	V_a	102	9.00	0.998

9 ANALYSIS OF RESULTS

The developed model was tested on the selected hypothetical study networks. The resulting OD matrix and the link volumes were compared based ion statistical techniques. The values obtained for both the study

International Journal of Scientific & Engineering Research Volume 4, Issue 5, May-2013
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networks are shown in Table 1.

8 CONCLUSION

The results analysed for the estimation of OD matrix on hypothetical networks selected from the literature show that the developed neural network model fits good in the analysed scenarios. The experiments on the hypothetical networks were subject to several assumptions and constrains. The model can be used for other scenarios having characteristics similar to the scenario for which the model was developed. The use of artificial neural network for the estimation of OD matrix from link volumes needs to be studied and experimented to a greater extent to fully utilise the potential of the artificial neural networks.

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