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Advances in Engineering Software 38 (2007) 71–79
ADVANCES IN ENGINEERING SOFTWARE
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Public transportation trip flow modeling with generalized regression neural networks

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Received 8 March 2006; received in revised form 29 July 2006; accepted 10 August 2006
Available online 22 September 2006

Abstract

Artificial neural networks (ANNs) are one of the recently explored advanced technologies, which show promise in the area of transportation engineering. The presented study comprised the employment of this seldom used ANN method, generalized regression neural network (GRNN), in comparison to both a frequently applied neural network training algorithm, feed-forward back-propagation (FFBP), and a stochastic model of auto-regressive structure for the purpose of forecasting daily trip flows, which is an essential component in demand analysis. The study is carried out under the motivation of knowing that modeling daily trips for available transportation modes will facilitate the arrangement for effective public infrastructure investments and the cited papers in the literature did not make use of and handle any comparison with GRNN method. The ANN predictions are found to be quite close to the observations as reflected in the selected performance criteria. The selected stochastic model performance is quite poor compared with ANN results. It is seen that the GRNN did not provide negative forecasts in contrast to FFBP applications. Besides, the local minima problem faced by FFBP algorithm is not encountered in GRNNs.

Keywords: Trip flow forecasting; Neural networks; Generalized regression neural network

1. Introduction

The urbanization concept is mainly defined by the attributes specifying the quality and the characteristics of life standards that are available for the inhabitants of an urban area. Complexly structured urban transport systems, the crucial attribute for sustainable development on a settlement, require the determination of the level of provided infrastructure. The way managing the infrastructure affects the demand for travel, which can vary by transportation mode, location, and time of day, in turn affects the performance of the transportation system. In the longer term, transport system performance affects land use patterns and this further influences demand. In the short term, both the system performance and the demand patterns produce both benefits and inconveniences for users, residents and businesses. Therefore, it is important to ensure that any infrastructure investment will have beneficial effects on the overall transport system and those affected by it [1]. Because of the infrastructure and the superstructure concept of transportation being generally irreversible, the demand analysis for an investment in a system approach is crucial. By defining the demand for transportation as a potential for traffic flow, the importance of the trips made within a day is being clarified.

Studies considering the daily trip flows in the past, be it time series models [2,3] and Kalman filtering models [4], were employed to forecast traffic volume. Due to the stochastic nature of traffic flow and the strongly non-linear characteristics of traffic dynamics, methods of soft computing have received much attention since early 90s and

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doi:10.1016/j.advengsoft.2006.08.003

considered as alternatives for the traditional statistical models. Among these methods the neural network (NN) approaches have been commonly applied in a number of areas of transport [5]. Including the studies of traffic volume forecasting [6,7], short-term traffic flow prediction [8–11], macroscopic modeling of freeway traffic [12], hybrid models of NNs [13,14], and NN applications in mode choice modeling (summarized in [15]), diverse kinds of NNs have been proposed in the literature.

The artificial neural network (ANN) approach, which is a non-linear black box model, seems to be a useful alternative for modeling the complex time series. In the majority of the above-mentioned cited papers, feed-forward back-propagation method (FFBP) was employed to train the neural networks. The performance of feed-forward back-propagation neural networks (FFBPNNs) was found superior to conventional statistical and stochastic methods in continuous flow series forecasting. However the FFBP algorithm has some drawbacks. It is very sensitive to the selected initial weight values and may provide performances differing from each other significantly. Another problem faced during the application of FFBP algorithm is the local minima issue. During the training stage the networks are sometimes trapped by the local error minima preventing them to reach the global minimum. Methods used in the literature to overcome local minima problem as training a number of networks starting with different initial weights, the on-line training mode to help the network to escape local minima, inclusion of the addition of random noise, employment of second order (Newton algorithm, Levenberg–Marquardt algorithm), global optimization method or other global methods (stochastic gradient algorithms, simulated annealing) are summarized in the literature [16]. In the review study of the ASCE Task Committee other ANN methods such as conjugate gradient algorithms, radial basis function, cascade correlation algorithm and recurrent neural networks are briefly explained [17].

For knowing that modeling daily person trips for available transportation modes will facilitate the arrangement for effective public infrastructure investments and the above-mentioned papers did not make use of and handle any comparison with GRNN method, we model daily person trips made by public transit mode by means of two ANN methods, FFBPNN and generalized regression neural network (GRNN), used as forecasting tools in comparison to an auto-regressive model throughout this study.

The article consists of four sections. After the introduction, ANN concept and utilized methods of ANNs, FFBPNN and GRNN, are explained briefly in Section 2. Data analysis, network preparations, and prediction results are presented in Section 3. The paper ends with a discussion of the findings and possible future extensions in Section 4.

2. Neural networks and used methods

In this section, theoretical basis of the utilized neural NN methods are summarized in brief.

2.1. Neural network theory

In the neural network model, the neuron is the basic component. As shown in Fig. 1, a multilayer perceptron structure is a fully interconnected set of layers of neurons. Each neuron ($N_{i\ldots j}$) of a layer is connected to each neuron of the next layer so that only forward transmission through the network is possible, from the input layer to the output layer through the hidden layers.

In this structure, the output Y_i of each neuron of the nth layer is defined by a differentiable non-linear function F as shown with Eq. (1).

$$Y_i = F\left(\sum_j w_{ij} y_i\right) \tag{1}$$

where F is the non-linear activation function, w_{ij} are the weights of the connection between the neuron N_j and N_i, y_i is the output of the neuron of the $(n-1)$th layer. For each input vector presented into the network, the set of connection weights between the different neurons determines the response of the network in the output layer. Partial specifications of the problem (i.e. input–output pairs) allow the measurement of output error of the network and the adjustment of its behavior. An iterative algorithm does the adjustment during training phase of the neural network. During the training phase, a selected set of training patterns is presented to the network. When the error between the network output and the desired output is minimized, the network can be used in a testing phase with test pattern vectors. At this stage, the neural network is described by the optimal weight configuration, which means that theoretically ensures the output error minimization. The average system error or the mean squared error (MSE), E, for all input patterns is shown with Eq. (2).

$$E = \frac{1}{2N}\sum_{n=1}^{N}\sum_{i=1}^{m}(d_{ni} - y_{ni})^2 \tag{2}$$

Here d_{ni} is the system output value for the nth pattern, y_{ni} is the neural network output value for the nth pattern, and N and m are the total numbers of the inputs and outputs respectively.

As the form of the mapping F a priori is not known, an approximation is sought. The development of ANNs offers

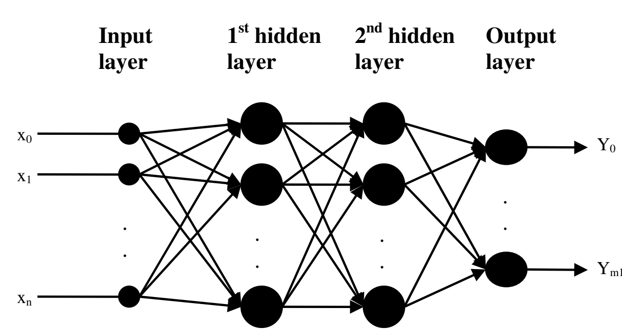

Fig. 1. Configuration of a feed-forward multilayer perceptron.