Analysis of Approaches to Short Term Passenger Volume Prediction in Public Transport

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ABSTRACT
Public Transport systems form an integral part in development of city. The development of the city can be correlated to the proportion of its population adopting public transport as its primary mode of transport. For organizations, which provide public transport services in a city, it will be beneficial to have real-time intelligent scheduling and dispatching system. To have a functional intelligent scheduling system, it is necessary to build a passenger flow prediction system, which predicts the flow of passengers based on historical data and environmental conditions. This paper presents various approaches for transit passenger volume prediction, merits and demerits of each.

Keywords
forecasting, grey model, interactive multiple model, neural networks, public transport, support vector machines

1. INTRODUCTION
To solve the transport problems faced by most major cities in the world, it is necessary to improve the public transport systems. The major reason, which keeps a person from adopting public transport is ill and irregular frequency of buses, which leads to degraded availability. An intelligent scheduling and dispatching mechanism will help in improving availability.

The manual dispatch of buses doesn't consider the potential increase or decrease in demand due to various factors. Prediction of passenger volume based on historical data and other environmental factors would provide a solution to this problem. This would also help organizations to serve commuters in a better way.

The passenger count is a dynamic variable, real time prediction of such value would help in intelligently dispatching public transport services. The forecasting can be done in any of the two ways: long term forecasting and short term forecasting. Short term forecasting is also called as real-time forecasting because it can predict the passenger volume for shorter intervals of time, which can range from a few minutes to days or weeks, whereas long term forecasting predicts the passenger volume over a longer period, which can range from months to years. Considering the scenario for public transport, long term forecasting would not be an appropriate choice for real-time scheduling and dispatching. A short-term approach for passenger volume prediction would surely help in intelligent scheduling and dispatching of buses.

Factors to be considered for short- term forecasting [1]:

1. Time intervals being forecasted
2. The passenger flow just before the time for which forecasting has to be done
3. Weather conditions in an area at the time for which forecasting is to be done
4. Road traffic situations

This paper provides a comprehensive study of various approaches for passenger flow prediction and also examines strengths and weaknesses of each.

2. NEURAL NETWORKS
2.1 Why NN?
- Self-learning
- Self-configurable and Self-healing (has the ability to perceive that it is not operating correctly and, without human intervention, make the necessary adjustments to restore itself to normal operation.)
- Robust and Fault tolerant
- Strong computation power

2.2 Data Collection
Passenger flow volume be collected via vehicle devices such as infrared scanning, image processing, gravity sensor or video recognition technique.

2.3 Neural network model
The neural network is composed of three layers: The Input layer, Hidden layer and Output layer. The input vector is formulated as a Ik=(I1,I2,I3,I4,I5,I6), in which I1,I2,I3

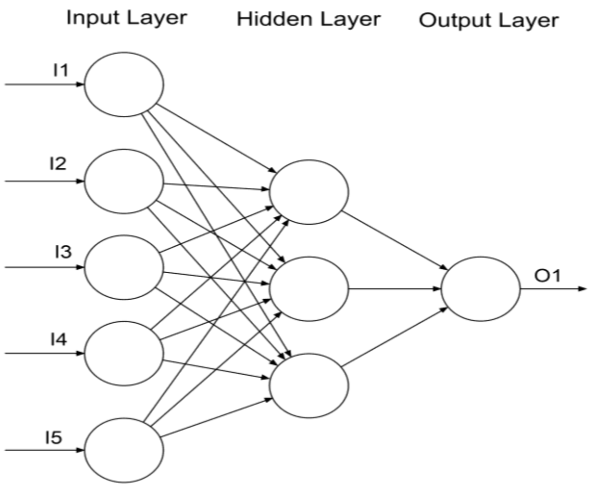

Fig 1. Neural network model structure

represents 3 represent the volume of passenger flow occurring within three time intervals prior to the forecasting moment, and I4, I5, I6 denote the weather variable, forecasting date and forecasting time, respectively. The corresponding output vector is defined as Ok=O1 referring to the volume of bus route passenger flow at the forecasting moment.

The number of artificial neurons in the Hidden Layer is currently suggested by equations of: (1) L =Nm / (n + m), (2) L = (nm) 0.5, where L is the number of artificial neurons in the Hidden Layer, n & m refer to the number of artificial neurons in the Input Layer and Output Layer respectively and N is equal to the sample capacity. Calculation by equation 1 will end in excessive number of artificial neurons when large sample base is present.

2.4 Calculations

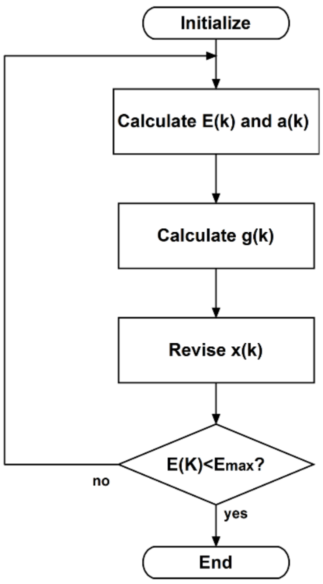

Fig 2. Neural networks flow diagram

In the neural network as illustrated in Figure 2, let k be the iterative times, and the strength (weights) of the connections, threshold and change are expressed in the following equation:

x (k +1)= x(k) – ag(k) (1)

Where x(k) denotes the vector of the strength of connections or vector of the threshold between layers when iterative scenario k occurs. The function of g(k) =aE(k)/ ax(k) expresses the output error under the occurrence of iterative scenario k against the gradient vector of each weight or threshold, with a negative sign representing the opposite direction of the gradient, i.e. The steepest descent direction of the gradient. E(k), represents the Error Function in the network output upon the occurrence of iterative scenario k.

$$E(k) = E[e^2(k)] \approx \frac{1}{nS^2}\sum_{j=1}^{n}\sum_{t=1}^{S^2}(t_j^2 - a_j^2(k))^2$$
(2)

$$a_i^2 = f^2\left\{\sum_{j=1}^{S^2}\left[\omega_{i,j}^2(k)a_i^1(k) + b_i^2(k)\right]\right\}$$

$$= f^2\left\{\sum_{j=1}^{S^2}[w_{i,j}^2(k)f^1(\sum_{j=1}^{S^1}\left(iw_{i,j}^1(k)p_i + ib_i^1(k)\right) + b_i^2(k)]\right\}$$

(3)

The gradient of the total error surface when iterative scenario k occurs can be derived from equation g(k) =aE(k)/ax(k) based on both function (2) and the transfer functions at each layer. The gradient g(k) thus obtained is then substituted into equation (1). Successive modification can be made on the weights and threshold so as to direct the total error to gradually diminish until the required error allowance is reached.

The storage of well-trained neural network can be applied to real-time forecasting of bus route passenger flow.

Neural network based real-time forecasting method of bus route passenger having advantages like self-healing, self-learning, ease in model establishment, capacity to deal with stochastic problems. Despite these tremendous advantages, one main drawback of this method is channel to obtain input data as a result of which no relevant calculation or analysis is undertaken due to lack of practical data.

3. SUPPORT VECTOR MACHINES

Basically SVM is based on principle of regression, its foundation algorithms are

a) Insensitive Function

b) Kernel Function

Achieves the objective of increasing dimensions.Kernel functions are divided into four categories

a) linearity

b) multi classification

c) radial basis function

d) sigmoid kernel function

Radial basis function is the most used function for classification and regression forecasting

Radial basis function is always depicted, as follows:

K(x,xi) = exp[- g* (x - xi)2] (1)

Radial basis kernel function could resolve the linearly non separable case, which maps low dimensional input space to higher dimensional feature space by nonlinear transformation.

3.1 Principle of Evaluation Model of Public Transport Competitiveness Based on SVM [2]

The evaluation model of public transport competitiveness based on SVM, which uses series of evaluation indices, takes advantages of expert's knowledge and experience, excludes the effect of subjective factors through learning and training by SVM and provides support for decision makers. Generally, the principle and process of SVM forecasting algorithm of public transport competitiveness can be described as follows, firstly transform the input space to a higher space through non-linear transformation defined by integral operator kernel functions and then seek the Optimal Hyperplane in this space [3,4]. Suppose there are m (M>2) competitiveness factors of public transport, and the number of competitiveness indices needed is n (n>0), so a map exists from m dimension to n dimension. If define m as the input number and n as the output number of of SVM, then in the m dimensional space R, m has a bounded subset A, and there is a map from n dimensional space Rn to a bounded subset F(A) [5], as follows:

$$F : A \in Rm \to Rn\ ,\ Y=F(X) \qquad (2)$$

In regards to training set A={X,Y}, a optimized approximate map G could be found out through learning, making

$$Yj = G(Xi)(I=1,2,....,m) \qquad (3)$$

This example can be seen as the application of SVM in regression problems.

3.2 Evaluation Model of Public Transport Competitiveness Based on SVM [2]

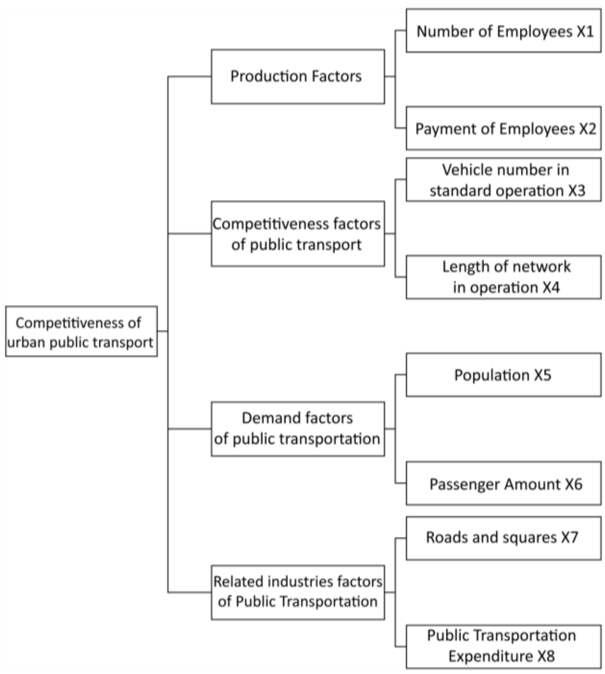

Fig 3. Indexes of Urban Public Transport competitiveness

(1) Indexes of production factors (PF) In this aspect, number of employees (NOE) X1 and payment (PT) of employees X2 are selected. The number and payment of employees can reflect the competitiveness of an industry horizontally compared to other industries. People's effect is the most significant in all the production factors, thus number and payment of employees can fully reflect this standard [2].

(2) Indexes of public transportation competitiveness factors (CF) Vehicle number (VN) in standard operation X3 and length of network (LON) in operation X4 are selected as the indexes, as these two indexes are the standards of facility index and infrastructure index, which could best reflect the competitiveness of public transportation [2].

(3) Indexes of demand factors (DF) of public transportation Here the population (POP) X5 and total passenger amount (PA) X6 are selected, as the residents are the main service objects of public transportation and also the potential customers of public transport, so population can directly reflect this index. Meanwhile, total passenger amount reflects the actual requirement of public transport [2].

(4) Indexes of related and supporting industries (RSI) As the most direct indexes of related and supporting industries to the public transportation competitiveness, roads and squares (RAS) X7 and public transportation expenditure (PTE) X8 are selected [2].

4. GREY MODEL

A grey box model combines a partial theoretical structure with data to complete the model. Dr. Julong Deng developed Grey theory in 1980s [16]. The theory develops a model based on uncertain discrete data and find a rule. Thus, developed models and rules are used to forecast and make decisions. In the theory's terminology white refers to the complete information, black refers to the information that is scanty or insufficient and grey refers to the information that is incomplete. The system with such incomplete information is a Grey system. Normally, a differential equation is built based on given data. Then, the random information in data is weakened and contained information is strengthened by accumulated generation. The general form of a grey model is GM (n, h), where n is progression of grey differential equation and h is the number of the variable [17].

Following are the steps to set up GM (1,1) model for forecasting:

Let the initial data be as following,

$$X(0)= (x(0)(1), x(0)(2),...,x(0)(n)) \qquad (1)$$

2. Now, X(0) is processed by 1-AGO (accumulating generation operator), following equation can be obtained

$$X(1) = (x(1)(1), x(1)(2),..., x(1)(n)) \qquad (2)$$

Where,

$$x(1)(k)= \sum_{i=1}^{k} x(0)(i),\ k=1,2,...,n$$

3. Now, X(1) can establish whitenization function show as

$$\frac{d}{dt}x(1) + ax(1) = b \qquad (3)$$

4. a ,b are elements of parameters vector â, that is

$$\hat{a}=[a, b]^T \qquad (4)$$

The equation (3) can be expressed in matrix form:

$$Y(n) + \mathcal{E}(y) = B.\hat{a} \qquad (5)$$

where B is repeated additive matrix and Y(n) is a constant vector

5. Finding the parameter â using least square, then

$\hat{a} = [a\ b]^T = [B^T B]^{-1} B^T Y_n$ (6)

6. The value of differential equation in whitenization format:

$\hat{x}^{(1)}(k+1) = (x^{(0)}(1) - b/a) e^{(-ak)}$ (7)

k=1,2,…,n

7. The simulation value of $X^{(1)}$ is calculated by the following formula:

$\hat{X}^{(1)} = (x^{(1)}(1), x^{(1)}(2), ..., x^{(1)}(n))$ (8)

The simulation value of $X^{(0)}$ by IAGO (Inverse accumulating generation operator):

$\hat{X}^{(0)} = (x^{(0)}(1), x^{(0)}(2), ..., x^{(0)}(n))$

$\hat{x}^{(0)}(k) = (x^{(1)}(k) - x^{(1)}(k-1))$ (9)

Parameter a : is developing coefficient , reflects development trend of $\hat{X}^{(0)}$ and

$\hat{X}^{(1)}$.

Parameter b: is grey action factor, comes from background data and reflects variety relation of data.

Jaio-Young-lan and Sun Bing-zhen used three grey prediction models viz. GM(1,1) model, Dynamic GM(1,1) model and altered version of residual GM(1,1) to predict cargo transportation and passage volume [12]. Also, application of Grey prediction theory by Wang Jing-hui in Zhuzhou railway station obtained high precision results [13]. In 2003, Chaug-Ing Hsu and Su-Miao suggested applying grey topological forecasting to model airline passenger data and also proposed a system combining grey theory and Markov-Chain model to predict passenger volume based on economic cycle [14].

In 2012 Hai-jun et al. took into account monthly fluctuation regulator into account along with grey model which was not done before [15]. They predicted railway station annual passage flow based on GM(1,1) model and monthly passage flow based on monthly professional coefficient method. They predicted of data from 2005 to 2010 with relative error varying from 1.4% to 4.5%. The calculations in this method are easy and provide results in short time. Even though they considered new factors not all possible factors are considered and hence there is a scope to improve accuracy by analysing forecasting factors.

5. INTERACTIVE MULTIPLE MODEL

Traditional methods for forecasting Passenger Flow focus on long term prediction [7-9]. As a result, reliable forecasting of short term passenger demand based on historical data has some importance. An IMM filter algorithm combines the prediction of multiple Time Series models, in order to create a hybrid method for short-term passenger flow forecasting [6]

5.1 Objectives

1. Analysis of historical data for stationarity, periodicity and volatility on different time scales.
2. Development of prediction models which capture data characteristics to predict daily, weekly and 15 minute time series
3. Dynamic combination of prediction models to produce hybrid output by applying IMM algorithm.

Various models can be used for forecasting the passenger flow viz.

1. Statistical (ARIMA, SARIMA, ARIMA-GARCH)
2. Non parametric (NN, SVM)

Statistical models such as SARIMA and ARIMA-SARCH have proven to be useful for short term passenger flow forecasting [10-11].

IMM algorithm combines the results from multiple time series models, which reduces the error rate caused by a standalone model [6]. The accuracy of this hybrid model depends upon the precision of the input models, hence it is necessary to ensure accuracy of the input models

5.2 Steps for IMM approach

1. Construction of three time series models. (Weekly, Daily, 15 min)
2. Individual forecasting of each time series based on correlation and heteroscedastic analysis
3. Calibration based on past performance of the algorithm
4. Combinations of predictions using IMM algorithm

5.3 Algorithm

1. Calculate mixed state and covariance at time t based on the time
2. Filter estimations for each model using Kalman filter algorithm.
3. Update probability for each model.
4. Provide hybrid output at time t by combining updated estimations at time t (IMM)

The detailed IMM algorithm is elaborated in Xue, Sun, and Chain [6].

As IMM approach is hybrid approach, which combines the results from multiple models, hence, the error rate is far more reduced as compared to error rate of single model. The only drawback is that, the models which are given as Input to IMM algorithm, must be accurate in themselves, otherwise the errors would be carried forward to the hybrid output.

6. CONCLUSION

Passenger flow prediction is at the heart of intelligent real time scheduling of transport system. With introduction of new and innovative approaches in algorithms and advancement in engineering technology, the accuracy of prediction is improving. Different techniques consider different factors for prediction and have their own merits. There is still a scope of improvement with respect to time taken, accuracy and easiness of the prediction. A more effective and functional approach is needed to make such a system practically realizable.

Each approach described above has its own merits and demerits. Neural network based has many advantages over statistical approaches, such as self-healing, self-learning, ease while dealing with stochastic problems, but deciding the input parameters for neural network based models is a difficult process. Grey Model works well even if limited data is available, and has a significant accuracy for long term forecasting. IMM model works best for short term prediction. It combines multiple statistical models and chooses the best one or combination of multiple models for prediction. It gives a good throughput, provided that the input models have high accuracy, which is not the case always.

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