INDIAN JOURNAL OF SCIENCE AND TECHNOLOGY

RESEARCH ARTICLE

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OPEN ACCESS

Received: 11-08-2022

Accepted: 30-10-2022

Published: 21-12-2022

Citation: Sumalatha V, Manohar D, Jayalakshmi C (2022) Hybrid Models in Forecasting Short Term Road Traffic. Indian Journal of Science and Technology 15(47): 2605-2611. https://doi.org/10.17485/IJST/v15i47.1663

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Funding: None

Competing Interests: None

Published By Indian Society for Education and Environment (iSee)

ISSN
Print: 0974-6846
Electronic: 0974-5645

Hybrid Models in Forecasting Short Term Road Traffic

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Abstract

Objectives: To analyze the road traffic in Hyderabad at a selected junction and fit Hybrid model for forecasting the traffic conditions for the next near future also to compare the proposed model with the existing popular models and identifying the best model for forecasting the Hyderabad road traffic. **Methods:** This study considers the data on traffic flow at 6.no. junction in Amberpet, Hyderabad, Telangana state, India. The traffic data has been considered for peak hours in the morning for 8 A.M to 12 Noon, for 6 days. Classical Time series models and recent revolution in time series modelling - Artificial Neural Networks have been applied to develop a forecasting model. Then we combined these models to obtain the Hybrid model for forecasting the road traffic at the selected point. SPSS and Zytun softwares have been used for the analysis. The best fit statistics such as RMSE, MAPE and MAE have been used to identify the best model. **Findings:** Our study indicates the efficacy of the new combinatorial model in acquiring more accurate forecasting as compared to independent models. These results can be considered to monitor traffic signals and explore methods to avoid congestion at that junction. **Novelty:** Though some research has been done in Hyderabad, no work has been done to develop a model for forecasting the Hyderabad road traffic. Our model can give the best forecasts for the Hyderabad road traffic.

Keywords: Multilayer Perceptron; Hybrid model; Exponential smoothing; Artificial Neural Network; Intelligent Transport System

1 Introduction

In recent days, management of road traffic and controlling the congestion has become major problems in Hyderabad city at any busy junction. Hence, short term traffic flow forecasting has gained greater importance in Intelligent Transport System (ITS). Exponential smoothing models have been profitably employed as a popular linear time series forecasting model. Besides, Artificial Neural Networks (ANNs) are being applied to capture the complex relationships with a various pattern as they assist as a flexible and potential computational tool. But, most of these analyses represented mixed results in terms of the efficacy of the ANNs model in comparison with the linear model. In this paper, we propose a Hybrid model, which is distinctive in integrating the advantages of Exponential smoothing models and ANNs in modeling the linear and nonlinear behaviors in the time series data set. An attempt has been made to model and forecast short-term traffic flow at a selected junction in Hyderabad, Telangana state, India.

In the direction of road traffic analysis, some studies have been taken place. Yan H et al,[1] used least square twin support vector regression method for short term traffic flow prediction. Cai,L. et al.,[2] focused on developing a hybrid model for traffic flow forecasting by combining gravitational search algorithm (GSA) and the SVR model. Nadia slimani, et.al,[3] used four methods to forecast daily highway traffic SARIMAX, LSTM, CNN and combined model.[4,5], used deep learning techniques to traffic flow forecasting.

There are many studies aimed at developing a best forecasting model for road traffic in the literature. But from all those studies it is clear that no model would be appropriate for all the regions and under all the circumstances. For every forecasting problem, conditions and characteristics have to be analyzed properly and completely to develop a model. Objective of this study is to develop a model that best forecasts the Hyderabad road traffic at the selected point.

Short term traffic flow forecasting involves predicting the traffic volume in the next time interval usually in the range of 5 minutes to 30 minutes. For this study we have considered 5days traffic data at 6 no. junction, Amberpet, Hyderabad, Telangana state, India. In any junction it is very important to forecast the short term traffic flow to design planning and operations of traffic signals and various traffic strategies. In this paper an attempt was made to develop a short-term traffic flow forecasting model using Hybrid model - combination of Exponential smoothing model and Artificial Neural Network (ANN). Three indicators including the Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and the Mean Absolute Error (MAE) have been used to check the models' performance.

2 Methodology

2.1 Data

The data was taken from the office of Commissionerate, traffic, Hyderabad. The data set used in this study was collected from 6 no. junction, Amberpet, Hyderabad, Telangana state, India. The data was collected for the peak hours in the morning. The data set contains records of number of vehicles passing through the junction from 8 AM to 12 Noon in the intervals of 5 minutes from 08-02-2019 to 13-02-2019. The data was given in the form of video captured by cc TV cameras fixed at the junction. Volume of vehicles was obtained by counting manually. Data extraction was done in the intervals of 5 minutes for 4 directions. 80% of the data has been used for fitting the models and the remaining 20% of the data has been used for testing the adequacy of the model.

Fig 1. Image of CC tv video footage

2.2 Holt-Winters' (HW) method

Seasonal Exponential Smoothing or Holt-Winters method or Method of Winters, is an advanced expansion of the exponential smoothing methodology. It generalizes the procedure to deal with level, trend and seasonality by considering three smoothing parameters α, β, γ and 'm' denotes the observations count in a cycle.

The HW method consists one forecast equation and three smoothing equations- one for the level l_t, one for the trend b_t and one for the seasonal components_t , with smoothing parameters α, β and γ respectively.

Level

$$l_t = \alpha\left(y_t - s_{t-m}\right) + (1-\alpha)\left(l_{t-1} + b_{t-1}\right) \tag{1}$$

Trend

$$b_t = \beta\left(l_t - l_{t-1}\right) + (1-\beta)b_{t-1} \tag{2}$$

Seasonal

$$s_t = \gamma(y_t - l_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m} \tag{3}$$

Forecast

$$\hat{y}_{t+h/t} = l_t + hb_t + s_{t+h-m(k+1)} \tag{4}$$

where $0 \leq \alpha, \beta, \gamma \leq 1$ The seasonal equation picks up differences between the current level and the data at that time in the seasonal cycle. This is then added to a forecast at the same point in the cycle, where k is the integral part of (h-1)/m.

2.3 Artificial Neural Network Method

Neural networks (NN) have broad applicability to real world. Since, neural networks are best for identifying patterns or trends in data, they are well suited for prediction or forecasting needs. Multilayer perceptron (MLP) is most widely used network structure of Artificial Neural Network (ANN)[6]. Multilayer perceptron (MLP) is able to solve non linearly separable problems, a number of neurons connected in layers to build a Multilayer perceptron. Each of the perceptrons is used to identify small linearly separable sections of the inputs. Outputs of the perceptrons are combined into another perceptron to produce the final output. The architecture of the MultiLayer Perceptron includes the neurons are arranged into an input layer an output layer and one or more hidden layers.

MultiLayer Perceptron uses the "back propagation rule" which calculates an error function for each input and back propagates the error from one layer to the previous one. The weights for a particular node are adjusted indirect proportion to the error in the units to which it is connected. An activation function is applied to the weighted sum of the inputs of a neuron to produce the output. In this study we used sigmoid function as activation function. A Sigmoid function is defined as $\frac{1}{1+e^{-x}}$

The MLP learning algorithm using the back propagation rule includes initializing weights (to small random values) and transfer function and then adjust weights by starting from output layer and working backwards. The weight function considered in this paper is

$$W_{ij}(t+1) = W_{ij}(t) + \eta\delta_{pj}O_{pj} \tag{5}$$

where $W_{ij}(t)$ represents the weights from node i to node j at time t, η is a gain term and δ_{pj} is an error term for pattern p on node j (where the sum is over the k nodes in the following layer)

For output layer units:

$$\delta_{pj} = kO_{pj}(1-O_{pj})\ \ (t_{pj} - O_{pj}) \tag{6}$$

For hidden layer units:

$$\delta_{pj} = kO_{pj}(1-O_{pj})\Sigma\delta_{pk}W_{jk} \tag{7}$$

A two step procedure is followed to determine a unit in the output layer

Step1: Using the formula $X_j = \sum_i y_i W_{ij}$ total weighted input X_j is computed. Where y_i is the activity level of the jth unit in the previous layer.

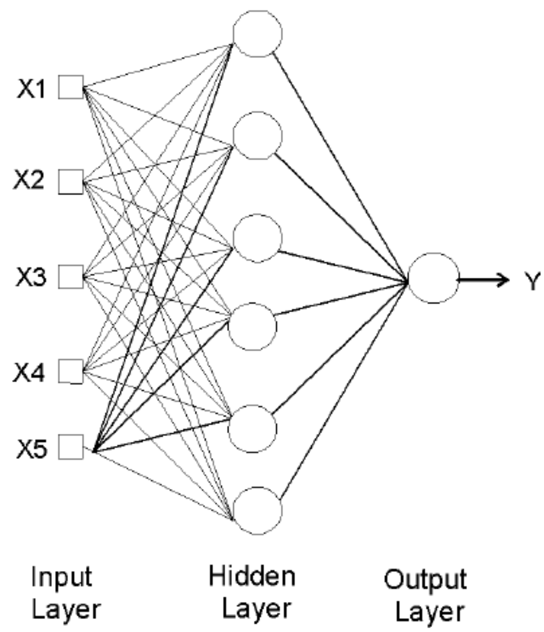

Fig 2. Picture of MultiLayer Perceptron network

Step2: Calculate the activity y_j using sigmoid function of the total weighted input once the activities of all output units have been determined, the network computes the error E

$y_j = \frac{1}{1+e^{-xj}}$

$E = \frac{1}{2}\,\Sigma(y_i\,d_i\,)$

where y_i is the activity level of the jth unit in the top layer and d_j is the desired output of the jth unit.

2.4 Hybrid Model

Linear and non linear models are combined to obtain Hybrid model. Forecasting accuracy can be improved by Hybrid models. Many works have taken place in the light of Hybrid models for solving forecasting problems. Zhang[6] primarily suggested hybrid model by considering ARIMA as a linear model and ANNs as a nonlinear model for forecasting a time series. The mathematical form of combination of linear and nonlinear models given by Zhang[7] is:

$$Y_t = L_t + N_t + e_t \tag{8}$$

where L_t indicates the linear part and N_t indicates the nonlinear part of the model. In this paper, ANN is employed for handling the nonlinear part. Developing the hybrid model is carried in two steps.

1. Obtain the residuals by modeling the linear part

2. Employ a nonlinear model to these residuals for handling with the nonlinear part. This study used Holt Winters model as linear model.

Let a_t be the residual at time point$t$ from the Holt Winters model. i.e.

$$a_t = Y_t - \widehat{L}_t \tag{9}$$

where $\widehat{L}_t$ indicates the forecast at time t from linear model. Next, ANN is employed to model a_t i.e.

$$a_t = f\,(a_{t-1}, a_{t-2} \ldots a_{t-p}) + e_t = \widehat{N}_t + e_t \tag{10}$$

where $f(.)$ is a nonlinear function from ANNs and e_t is the error of this ANNl. Thus, the forecasted values can be obtained from the hybrid HW-ANN model as

$$\widehat{Y}_t = \widehat{L}_t + \widehat{N}_t \tag{11}$$

3 Results and Discussion

The basic Statistical characteristics of the data discussed in 2.1 are presented in Table 1.

Table 1. Statistical characteristics of traffic volume

Statistic	Value
Minimum	487
Maximum	930
Mean	637
Standard deviation	102.424
Skewness	0.4377
Kurtosis	3.77702

3.1 Analysis

To evaluate the performance of the proposed model, three models such as Holt Winters, Artificial Neural Networks and Hybrid HW-ANN models were considered for the data set discussed in 2.1.

3.1.1 Holt Winters Additive model

The parameters of the model were estimated as in the Table 2. The smoothing parameters were obtained as

Table 2. Exponential Smoothing Model Parameters

		Parameter	Estimate
HOLT-WINTERS' Additive model	Level Trend Season	Alpha(α) Beta(β) Gamma(γ)	0.9 0.1 0.1

For this data, level parameter obtained as 0.9, Trend and Seasonal components parameters were estimated as 0.1.

3.1.2 Artificial Neural Network model

In this study, MLP network has been used for the prediction of short term traffic flow. Different Artificial Neural Network (ANN) models have been developed on the data set. In the present study RMSE, MAE values were used to evaluate the performance of the model and predicted results. The specification of all the models has been presented in Table 3. It was observed that model 4 i.e., neural network with 4 hidden neurons has minimum Root Mean Square Error (RMSE), Mean Absolute Error (MAE) values. Hence it is used to forecast the future values.

Table 3. Different Neural Network Models' ERROR, RMSE and MAE Values

Model	Hidden layer	Hidden Neurons	ERROR	RMSE	MAE
M1	1	1	0.47045	34.6948	16.32106
M2	1	2	0.46346	34.4347	15.84144
M3	1	3	0.46236	34.3896	15.77978
M4	1	4	0.46147	34.3539	15.72724

3.1.3 Hybrid HW-ANN model

Firstly, original data is modeled by Holt-Winters model and obtained the residuals and then ANN is fitted to these residuals. Finally, the forecasted values of HW-ANN model can be obtained by summing the forecasted values of Holt-Winters and ANN. The inputs for the ANN at this HW-ANN model for road traffic data are the errors from the Holt-Winters model. By trying the number of neurons in hidden layer from 1 to 4, the results show that 4 neurons in hidden layer is the best model for forecasting the road traffic.

3.2 Discussion

The three models performance was evaluated by the performance evaluation metrics RMSE and MAE. The obtained values of RMSE, MAPE and MAE of the three models are presented in Table 4. The plots of predicted and original values from each model are displayed in Figures 2, 3 and 4.

Table 4. Best Fit Statistics of Three Methods

Method	RMSE	MAPE	MAE
Holt-winters Additive	33.5388	1.953	14.87386
ANN	34.3539	2.4834	15.72724
Hybrid HW-ANN	**31.2706**	1.9062	**13.9786**

From the view point of RMSE, MAPE and MAE the Hybrid HW-ANN method is superior for forecasting the Short term road traffic followed by the individual Holt- Winters method and individual ANN model. In the literature there are studies related to developing linear and non-linear forecasting models separately but our study shows that combined model performs better than that of linear and non-linear models individually. The Figures 2, 3 and 4 represent the agreement between actual and predicted values.

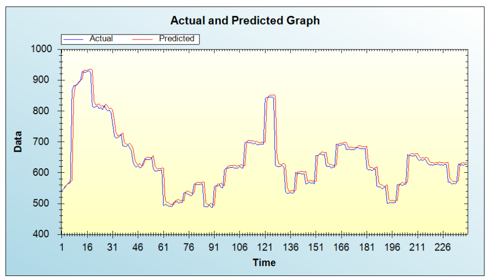

Fig 3. Graph of original and Predicted values by Holt- Winters method

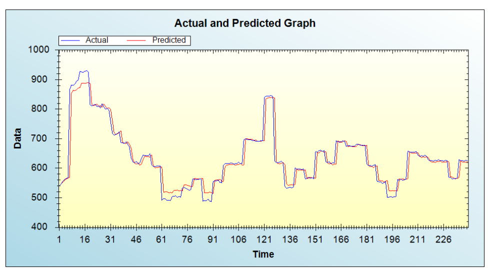

Fig 4. Graph of original and Predicted values by ANN model

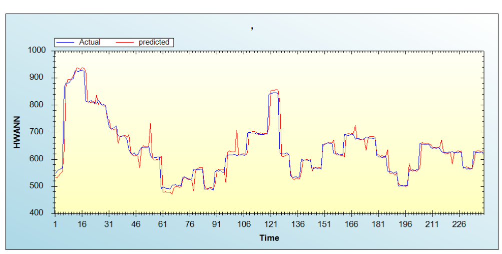

Fig 5. Graph of original and Predicted values by Hybrid HW-ANN model

3.2.1 Adequacy of the best model using testing data

As mentioned earlier 20% of the data has been used to check the adequacy of the best model. Using the best identified Hybrid model, values are predicted for the 20% of the data points for testing the model adequacy and plot of the actual and estimated values is presented below Plot of Actual and Predicted values of Testing data.

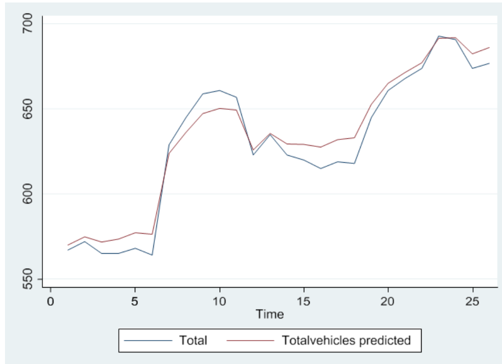

Fig 6. Plot of Actual and Predicted values of Testing data

4 Conclusion

We proposed a Hybrid model comprising Holt Winters model and ANN model for forecasting of Short Term Road Traffic flow in a busy junction (6no. Amberpet) and explored the forecasting capability of the Hybrid model. Generally road traffic has mixed random characteristics which have to be thoroughly analyzed to obtain the valid results. From the fore studies we observed that no model would be ideal for all the forecasting needs. The urban cities like Hyderabad need continuous and perfect updates on traffic. From the analysis we conclude that the Hybrid model performs better than the individual methods, in terms of less error values which imply that Hybrid method can be used as a solution to forecast the Short Term Road Traffic flow at any traffic bottleneck point in Hyderabad.

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