

Wavelet - Bayesian Hierarchical Short-Term Traffic Volume Model for Non-Critical Junctions

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ABSTRACT (203 words)

In ITS (Intelligent Transportation System) equipped urban transportation systems non-critical junctions are often ignored in short-term traffic condition prediction algorithms as the traffic data collection systems in these junctions are not adequate. The paper proposes a short-term traffic volume model based on a combination of discrete wavelet transform (DWT) and Bayesian hierarchical methodology (BHM) applicable to non-critical junctions lacking continuous data collection systems. Unlike typical short-term traffic condition forecasting algorithms, large traffic flow datasets including information on current traffic scenarios are not required for the proposed model. In this model, a non-functional representation of the daily 'trend' of urban traffic flow observations is achieved using DWT while the fluctuations in the traffic flow in addition to the variations represented by the 'trend' are modeled as a stochastic process using BHM. The time-varying variance (within day) of these fluctuations over the 'trend' in urban traffic flow observations at a signalized intersection has been estimated in the model. The effectiveness and the accuracy of the model have been compared with a conventional short-term traffic flow forecasting time-series model based on Holt-Winters Exponential Smoothing (HWES) technique. Both the models are applied at two signalized intersections at the city-centre of Dublin and their performances have been discussed.

INTRODUCTION

The major existing Urban Traffic Control Systems (UTCS) (like, SCATS and SCOOTs) collect traffic condition related data for real-time monitoring and operational purposes. In an Intelligent Transportation Systems (ITS) equipped transport network one of the important uses of traffic data collection is continuous forecasting of traffic conditions in near (short-term) future based on the current traffic conditions. A significant amount of research has been conducted to improve the real-time applicability of short-term forecasting techniques in relation to ITS. Extensive review on this subject is available from the studies of Van Arem (1) and Vlahogianni (2). The well known short-term forecasting techniques include non-parametric regressions [e.g. (3)], neural networks [e.g. (4)], linear and non-linear regression, historical average algorithms (such as, moving average technique or exponential smoothing technique) [e.g.(5)] and, ARIMA time-series models [e.g. (6),(7)].

The existing short-term traffic forecasting algorithms require large datasets from historical observations and are heavily dependent on data from recent past available through continuous monitoring of traffic conditions. However, due to financial and operational constraints, generally the continuous collection of traffic condition related data is limited to the critical junctions in an urban transportation network. Hence, for non-critical urban signalised junctions where data related to traffic conditions (e.g. volume, speed or density) are not collected regularly or for junctions where the data collection system (inductive loop-detector or video imaging system) is out of service for a considerable period of time, the existing short-term traffic forecasting algorithms cannot be applied due to unavailability of data on real time traffic conditions. This paper develops a random process model to simulate short-term traffic flow time-series datasets that can be used in such situations. The proposed model is formulated based on a combination of discrete wavelet transform (DWT) (8) and Bayesian hierarchical methodology (BHM).

In short-term traffic flow forecasting algorithms, DWT has been mainly used by researchers as a de-noising technique in wavelet pre-processing of traffic flow observations for increasing the accuracy of the algorithms (9). Chen et al. (10) combined the wavelet transform with a Markov model to forecast traffic volume. In traffic pattern modeling, varied studies on optimized aggregation level (11), data reduction (12) and mesoscopic-wavelet model (13) have been carried out. In WA based traffic flow modelling, DWT using multi-resolution analysis (MRA) technique has the potential to decompose the fluctuations in the traffic flow observations at different or multiple time-scales (within a day). This feature of the MRA has been used in the proposed model to capture the 'approximate' variation of the traffic flow observations at a time-scale of the order of a day, smoothing out the short-term fluctuations, leading to the 'trend' of the traffic flow time-series dataset. The non-functional 'trend' obtained by this proposed technique has two distinct advantages over the trends obtained using most of the existing short-term traffic flow forecasting time-series models. Firstly, the function-free form of the trend has better flexibility in accommodating the variations as compared to the trends in functional forms associated with most of the existing time-series models. Secondly, the DWT technique is a computationally efficient method to calculate the trend. Once the 'trend' has been modeled, the random fluctuations over the 'trend' in traffic flow observations may be considered as an additive random process. The characterization of these random fluctuations is carried out following a Bayesian statistical approach.

The use of Bayesian statistics is quite recent in the field of traffic flow modelling and research on Bayesian networks (14), hierarchical regression models (15) and Bayesian SARIMA models (16) are only a few studies reported till date. The residuals derived for the time-series traffic flow observations have been modelled by the BHM. The advantage of using BHM is that the randomness is represented by a parametric statistical model with parameters stochastic in nature. This can account for the variation of the statistical variance of the traffic flow observations in a day (depending on the time of the day), the variance itself being treated as a random variable.

The effectiveness and accuracy of the proposed traffic flow model is compared with a well-known short-term traffic flow forecasting algorithm based on Holt-Winters exponential smoothing (HWES) technique. The relative performances of the two models have been compared by considering two signalized junctions at the city centre of Dublin. For the sake of comparison, the junctions had to be chosen such that data collection system and recent data were available for the applying the HWES technique. However, the proposed wavelet-Bayesian hierarchical model is independent of the availability of recent data and can be useful for application at non-critical urban signalised junctions even in the absence of a continuous data collection system.

TREND+BHM (TBHM) MODEL

Non-Functional Trend Model

Multi-Resolution Analysis

The WA technique provides a time-frequency/time-scale representation of any signal/time-series data. The time-series is decomposed using DWT into linear combination of shifted and scaled versions of the original (or *mother*) wavelet basis function. MRA uses a computationally efficient technique by which different frequencies/scales of a signal are split at different resolutions to evaluate the DWT coefficients.

The DWT (8) of a signal $X(t)$ generates a collection of coefficients

$$\left\{ \begin{array}{l} c_j(k) = \langle X, \varphi_{j,k}(t) \rangle \\ d_j(k) = \langle X, \psi_{j,k}(t) \rangle \end{array} \right\} j, k \in Z \quad \text{where, } Z=1,2,3\dots \quad (1)$$

where $\langle *, * \rangle$ denotes inner product, t is time, $\{d_j(k)\}$ are the detail coefficients at level j ($j = 1, 2, \dots, J$) and $\{c_j(k)\}$ are the approximate coefficients at level J . The signal X to be analyzed is integral-transformed using a set of basis functions

$$\psi_{jk}(t) = 2^{-j/2} \psi(2^{-j}t - k) \quad (2)$$

The set of bases in Eq. (2) is constructed from the mother-wavelet $\psi(t)$ by a time-shift operation (k) and a dilation operation (j). The function $\varphi_{jk}(t)$ is a low-pass filter which can separate the low frequency component of the signal. Thus DWT decomposes a signal into a large time-scale (low frequency) approximation and a collection of details at different smaller time-scales (higher frequencies).

The original signal can be reconstructed back from the decomposed approximation and the detail components.

$$X(t) = A_J(t) + \sum_{j \leq J} D_j(t) \quad (3)$$

where, $A_J(t)$ is the reconstruction of the approximation coefficients c_j at level J and $D_j(t)$ is the reconstruction obtained from the detail coefficients d_j at level j . In the reconstructed approximation (A_J) and in the reconstructed details obtained at each stage/level ($D_1, D_2 \dots D_J$) the numbers of data points remain the same as the original dataset.

Trend Model

The 'trend' of a time-series data can loosely be defined as the 'long-term' change of the mean level of the data (17). In the daily trend model of the traffic flow observations from an urban signalized intersection, the word 'long-term' indicates stability over time on a daily basis. In this study, MRA is used to develop a representative daily trend model underlying the traffic flow observations over a day (18).

In this study, DWT associated with the basis *Daubechies' 4* (db4) is used to decompose the signal (time-series traffic flow observations) into different time-scales. Initially, the original signal is decomposed into approximation coefficients c_1 (low frequency/fluctuations or variability) and detail coefficients d_1 (high frequency/fluctuations or variability). The approximation coefficients c_1 (relative low frequency components) are again decomposed to approximation coefficients c_2 and detail coefficients d_2 at the next level. This procedure is repeated for further decompositions. The aim of repeating the decomposition procedure is to find an optimum approximation level for extracting the trend in the data. The optimum approximation level is the one in which the reconstructed approximation coefficients, A_m (m is the optimum approximation level), are the optimal smoothed estimate of the traffic flow data which can truly represent the traffic flow pattern on an average day. This is essentially an averaging or smoothing technique in a statistical sense and is computationally similar to denoising technique in signal processing. The local variation in traffic flow observations due to signal control in the urban arterials is considered as fluctuations to be smoothed (for the mathematical treatment) in this methodology. The traffic flow pattern at any particular approach at any intersection in an urban transport network is similar for the weekdays. However, there can be some day-to-day variability due to other factors like, the day of the week, accidents or recurrent congestion in some other part of the transport network etc. These factors are uncontrollable and cannot be modeled as such. So, to obtain a 'regular trend over an average day', the A_m values over some regular days (approximately, 20 days in this study) are to be averaged.

The residuals are obtained by subtracting the 'regular trend over an average day' from the original traffic volume observations. The 'non-functional trend model' forms the skeleton of a background model for simulating traffic flow at an urban intersection. The subsequent modeling of the residuals helps to establish a tight simulation interval over the 'trend'.

Bayesian Hierarchical Residual Model

The Bayesian hierarchical (BH) model (19) is a parametric statistical model with a tree-like structure based on the dependencies of the variables. The parameters of the model at each stage are represented by other parametric statistical models at the next stage.

In this study, the variance of the residuals is assumed to be dependent on time and has to be modeled accordingly using another parametric statistical model. If \mathbf{R} is the vector of the residuals averaged over 20 days, then in a normal hierarchical model,

$$\mathbf{R}_t \sim N(m, \sigma_t^2) \quad t = 1, 2, \dots, T \quad (4)$$

where, m is the sample mean of the residuals and σ_t is the standard deviation of the residuals for each time instant denoted by a subscript t . The vectors m , σ and \mathbf{R} are both of dimension $\{T \times 1\}$ where T is the number of time intervals or time instants in a day (for 5 minute aggregate traffic flow observations as used in this study, $T = 288$). The variance σ^2 , of the residual dataset \mathbf{R} changes with the time of the day. To model this time varying variability of the variance, the following parametric distribution is proposed.

$$\sigma \sim \text{LN}(\log(y), \tau^2) \quad (5)$$

As σ is always positive, a lognormal distribution is taken in equation 5 to ensure that all σ_t lie within $(0, \infty)$. The lognormal distribution for each σ_t is centered at y_t with standard deviation of τ . The variances of the high resolution components (sum of level 1, 2 and 3 reconstructed from detail coefficients) from traffic flow observations over multiple days (say, 20 days in this study) calculated over each hour of a day are considered as the initial estimates of the standard deviation of the residual (y_t) for that hour of the day. The values of the vector \mathbf{y} of dimension $\{T \times 1\}$ are constant and site specific. At the next stage of the tree-structure of the BH model the variance τ^2 of the lognormal distribution is assumed to follow a uniform distribution, within a range $(0, k)$

$$\tau \sim U(0, k) \quad k < \infty \quad (6)$$

where, k is an arbitrary constant signifying the maximum limit of the values of τ . The exact value of k does not influence the estimation process. In this study, the equations 4, 5 and 6 define the BH model for the residuals. In the model, the unknown parameters to be estimated are $\sigma(\sigma_1, \sigma_2, \dots, \sigma_{288})$ and τ . These unknown parameters are represented by a vector

$$\xi = (\tau, \sigma_1, \sigma_2, \dots, \sigma_{288})^T \quad \text{and are estimated by the Bayesian estimation technique (19). For the Bayesian inference, the posterior probability density function of the normal hierarchical model is}$$

$$p(\xi | \mathbf{R}, \mathbf{t}) = p(\tau) L(\sigma | \mathbf{R}, \mathbf{t}) L(\tau | \sigma, \mathbf{t}) \quad (7)$$

where, $p(\xi | \mathbf{R}, \mathbf{t})$ is the posterior density function of ξ ; $L(\sigma | \mathbf{R}, \mathbf{t})$ is the likelihood function of σ and $L(\tau | \sigma, \mathbf{t})$ is the likelihood function of τ ; $p(\tau)$ is the prior probability density function of parameter τ . As \mathbf{R} is assumed to follow a normal distribution, the likelihood function of σ given \mathbf{R} and the time instant vector \mathbf{t} (unit time interval = 5 minute) is

$$L(\sigma | \mathbf{R}, \mathbf{t}) = \prod_{t=1}^T \frac{1}{\sqrt{2\pi\sigma_t^2}} \exp\left(-\frac{R_t^2}{2\sigma_t^2}\right) \quad (8)$$

Similarly, the likelihood function of τ given $\boldsymbol{\sigma}$, \mathbf{y} and \mathbf{t} is,

$$L(\tau|\boldsymbol{\sigma}, \mathbf{t}) = \prod_{i=1}^T \frac{1}{\sigma_i \tau \sqrt{2\pi}} \exp\left[-\frac{(\log \sigma_i - \log y_i)^2}{2\tau^2}\right] \quad (9)$$

$p(\tau)$ is equal to a constant as the prior probability density function of τ is assumed as flat on the range $(0, \infty)$. Hence, the posterior density from equation 7 is

$$p(\boldsymbol{\xi}|\mathbf{R}, \mathbf{t}) \propto \prod_{i=1}^T \frac{1}{\sigma_i} \exp\left(-\frac{R_i^2}{2\sigma_i^2}\right) \prod_{i=1}^T \frac{1}{\sigma_i \tau} \exp\left[-\frac{(\log \sigma_i - \log y_i)^2}{2\tau^2}\right] \quad (10)$$

which yields,

$$p(\boldsymbol{\xi}|\mathbf{R}, \mathbf{t}) \propto \left(\frac{1}{\tau^T}\right) \prod_{i=1}^T \frac{1}{\sigma_i^2} \exp\left(-\frac{R_i^2}{2\sigma_i^2} - \frac{(\log \sigma_i - \log y_i)^2}{2\tau^2}\right) \quad (11)$$

$$\int_0^\infty \dots \int_0^\infty \int_0^\infty \left(\frac{1}{\tau^T}\right) \prod_{i=1}^T \frac{1}{\sigma_i^2} \exp\left(-\frac{R_i^2}{2\sigma_i^2} - \frac{(\log \sigma_i - \log y_i)^2}{2\tau^2}\right) d\tau d\sigma_1 \dots d\sigma_T \quad (12)$$

By integrating out the other unknown parameters except for the one whose distribution is to be estimated, the 'marginal distributions' of each of the unknown parameters can be determined from the integral in equation 12. The computation of the marginal distributions of the unknown parameters in $\boldsymbol{\xi}$ involves evaluation of a multiple integral with problems of high dimensionality. In this paper, *Markov Chain Monte Carlo* (MCMC) method, a particular iterative variation of the Monte Carlo simulation techniques, is used to simulate the marginal probability distributions of the unknown parameters. There are two popular MCMC algorithms, (i) Gibbs sampler (20) and (ii) Metropolis-Hastings algorithm (21), (22).

In the MCMC method, to simulate the marginal probability distributions for the unknown parameters in the vector $\boldsymbol{\xi}(\tau, \sigma_1, \sigma_2, \dots, \sigma_T)$, given an initial condition $(\tau^{(0)}, \sigma_1^{(0)}, \sigma_2^{(0)}, \dots, \sigma_T^{(0)})$ the following 289 steps are to be iterated (i denotes the number of iteration):

1. Sample τ^{i+1} from $p(\tau^{i+1} | \sigma_1^{(i)}, \sigma_2^{(i)}, \dots, \sigma_T^{(i)}, \mathbf{y}_i, \mathbf{t})$ using Gibbs sampler technique
2. Sample σ_1^{i+1} using Metropolis Hastings technique
- ⋮
289. Sample σ_T^{i+1} using Metropolis Hastings technique

The initial conditions $(\tau^{(0)}, \sigma_1^{(0)}, \sigma_2^{(0)}, \dots, \sigma_T^{(0)})$ are as follows,

$$\begin{cases} \boldsymbol{\sigma}^{(0)} = |\mathbf{y} - 0.5| \\ \tau^{(0)} \sim \text{Inverse-gamma}\left[0.5(T-1), 0.5\left(\sum_{i=1}^T (\log \sigma_i^{(0)} - \log y_i)^2\right)\right]^{-1} \end{cases} \quad (13)$$

The steps 1 to 289 are repeated for 10000 times to simulate 10000 values for all the unknown parameters.

HWES MODEL

The HWES technique is a generalized version of the exponential smoothing technique for dealing with the variations in trend and seasonality in time-series data. In HWES, the weights associated with the observations are reduced from two directions, viz. seasonally and historically. The equations for the 'additive' HWES model are:

- Updating the level index L_t (Overall Smoothing),

$$L_t = \alpha(y_t/S_{t-s}) + (1-\alpha)(L_{t-1} + b_{t-1}) \quad (14)$$

- Updating the trend index b_t (Trend Smoothing),

$$b_t = \beta(L_t - L_{t-1}) + (1-\alpha)(L_{t-1} + b_{t-1}) \quad (15)$$

- Updating the seasonal index S_t (Seasonal Smoothing),

$$S_t = \gamma(y_t/L_t) + (1-\gamma)S_{t-s} \quad (16)$$

Using these three indices, the equation for forecast, F_{t+m} for the additive model is,

$$F_{t+m} = L_t + mb_t + S_{t-s+m} \quad (17)$$

where, m is number of periods ahead. At any time point t , L_t stands for the smoothed observation, and y_t stands for the original observation; α , β and γ are the level, trend and seasonal smoothing parameters respectively and s is the number of periods in a seasonal cycle. The constants, α , β and γ are estimated by minimizing the MSE using any non-linear optimization technique. HWES being particularly good in modeling data with seasonality is suitable for modeling univariate traffic volume observations from an urban signalized intersection (7).

ILLUSTRATIVE EXAMPLES

As illustrative examples, univariate short-term traffic volume data are simulated and predicted for two representative junctions (TCS 183 and TCS 439) at the city-centre of Dublin on 12th and 13th July 2005 using the proposed TBHM model and the conventional HWES model respectively. The model fitting techniques and the comparison of the accuracies of both the models are discussed in this section.

Traffic Flow Observations

The univariate traffic flow time-series observations, used for modeling, are obtained from the inductive loop-detectors embedded in the streets of the junctions TCS 183 (critical junction) and TCS 439 (non-critical junction) as a part of the urban traffic control (UTC) data collection system of the city of Dublin. A map of the junctions is given in figure 1. In junction

TCS 183, the traffic volume passing through Tara Street, measured on the loop-detectors numbered 1, 2, 3, 4, and in junction TCS 439 the traffic volume passing through Townsend Street, measured on the loop-detectors numbered 1, 2, 3, are used in describing and evaluating the proposed traffic volume model. The data used for modeling was recorded from 15th June 2005 midnight to 13th July 2005 midnight

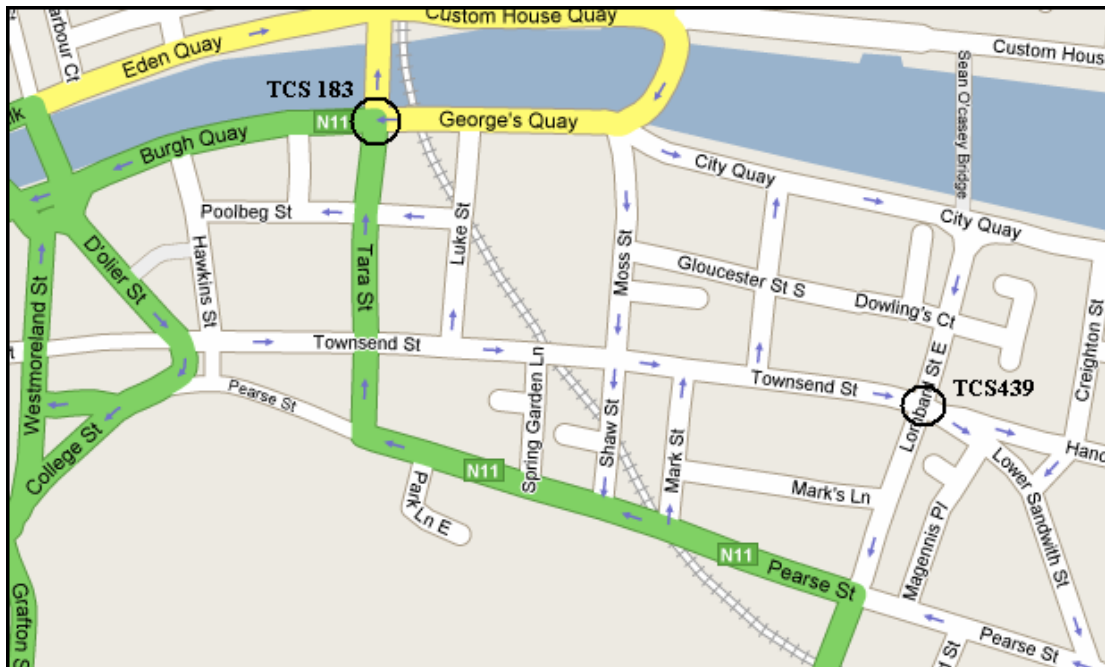


Figure 1 Diagram of the Junction TCS 183 and TCS 439

In short-term traffic flow forecasting models data aggregate intervals from 3 min. to 30 min. are used based on the forecasting algorithms. In view of the wavelet analysis techniques to be applied on the traffic volume observation a 5 min. data aggregation interval is chosen for this paper. In case of an urban transport network, the weekend travel dynamics is inherently different from the travel dynamics in the weekdays. In this study, the modeling is essentially carried out on the data observed during weekdays. A plot of the traffic flow data from both the junctions in vehicles per hour (vph) against time is shown in figure 2.

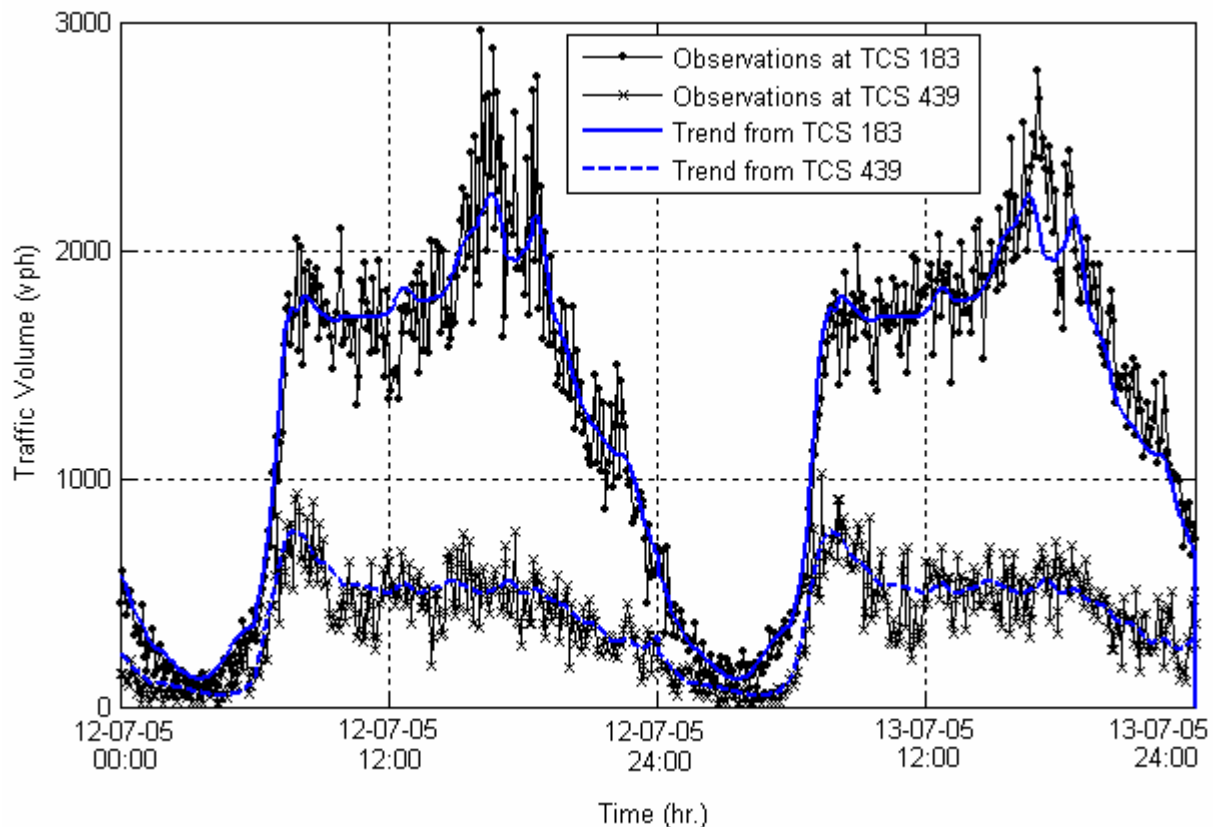


Figure 2 Trend and Traffic Flow Observations from Junctions TCS 183 and TCS 439

Fitting TBHM Model

This proposed wavelet based methodology of finding ‘regular trend over an average day’ is applied to univariate traffic flow observations obtained collectively over each 5 minute interval from the loop detectors at the intersections TCS 183 and TCS 439 at the city-center of Dublin. A plot of the traffic flow observations from the chosen sites on 12-07-2005 is given in figure 2.

The traffic flow observations over twenty days i.e. four weeks (as weekends are not included), in the month of June-July from the two chosen sites are decomposed into three levels of resolution using MRA with *Daubechies’ 4* wavelet basis function. The three different levels represent the three different time scales. The wavelet coefficients for approximations and details are then reconstructed at all three levels (Figure 3). For the purpose of modeling, the reconstructed values of the approximation and detail coefficients are used in this study. At each level, during decomposition the high frequency part of the data is separated from the low resolution or the low frequency part. The low frequency part at level three is quite smooth (Figure 3) and can be used as a representative of the overall trend over a day in the traffic data. Hence, the third level is considered as the optimum level of decomposition to obtain optimum smoothed estimates of the times-series data.

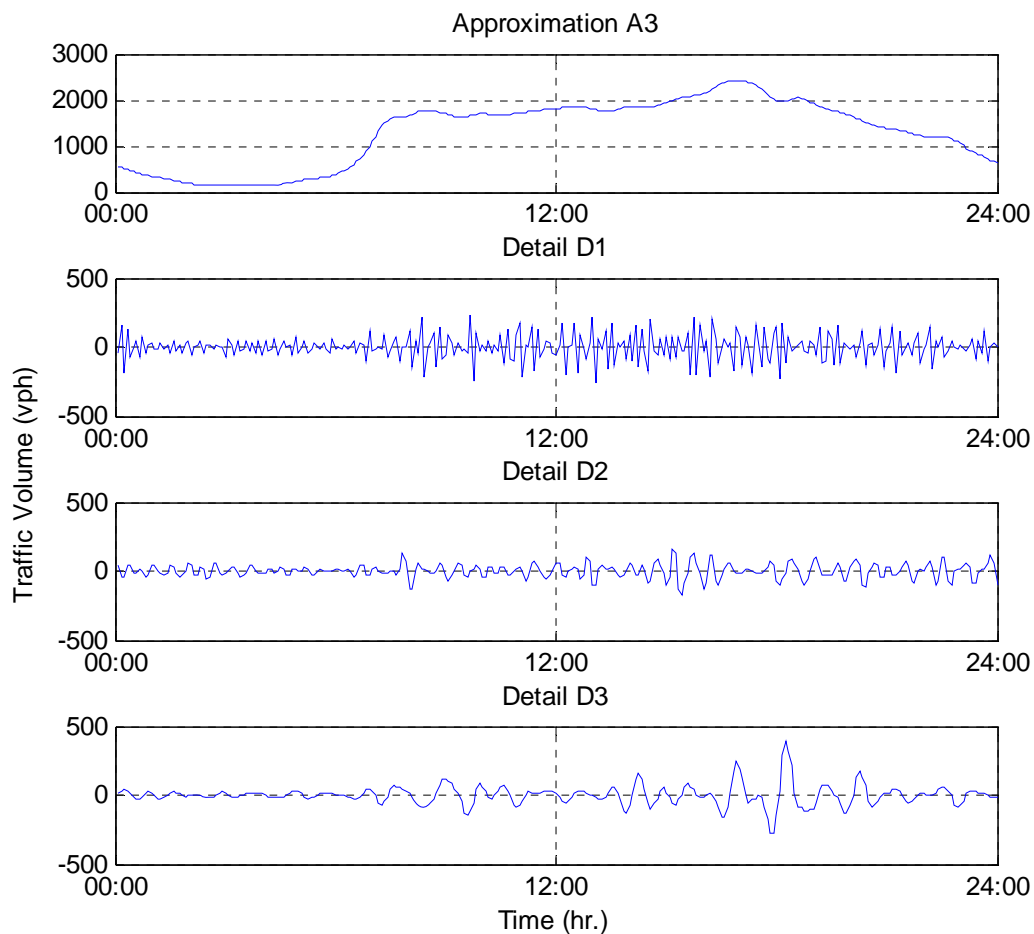


Figure 3 Reconstructed Approximation Coefficients at Level 3 and Reconstructed Details Coefficients at Level 1, 2, 3 on 12-07-05 from TCS 183

To model the representative trend for the two chosen approach lanes at the two chosen intersections, an average over 20 days of the reconstructed flow using level 3 approximations is considered. The selection of the average coefficients helps to reduce the effect of certain abrupt daily changes (introducing the effect of smoothing). In figure 2, the 'regular trend over an average day' is plotted in dotted lines over the traffic flow observations over 12th July, 2005 from junctions TCS 183 and TCS 439. It can be observed from the graphs that the computed trend provides a very good approximation of the traffic volume on any arbitrary day.

The residuals are obtained by subtracting the 'regular trend over an average day' from the original observations. A plot of the residuals for both junctions TCS 183 and TCS 439 on 12-07-2005 is given in figure 4. From figure 4, it can be observed that the spread of the residuals vary with time as assumed in the BHM model.

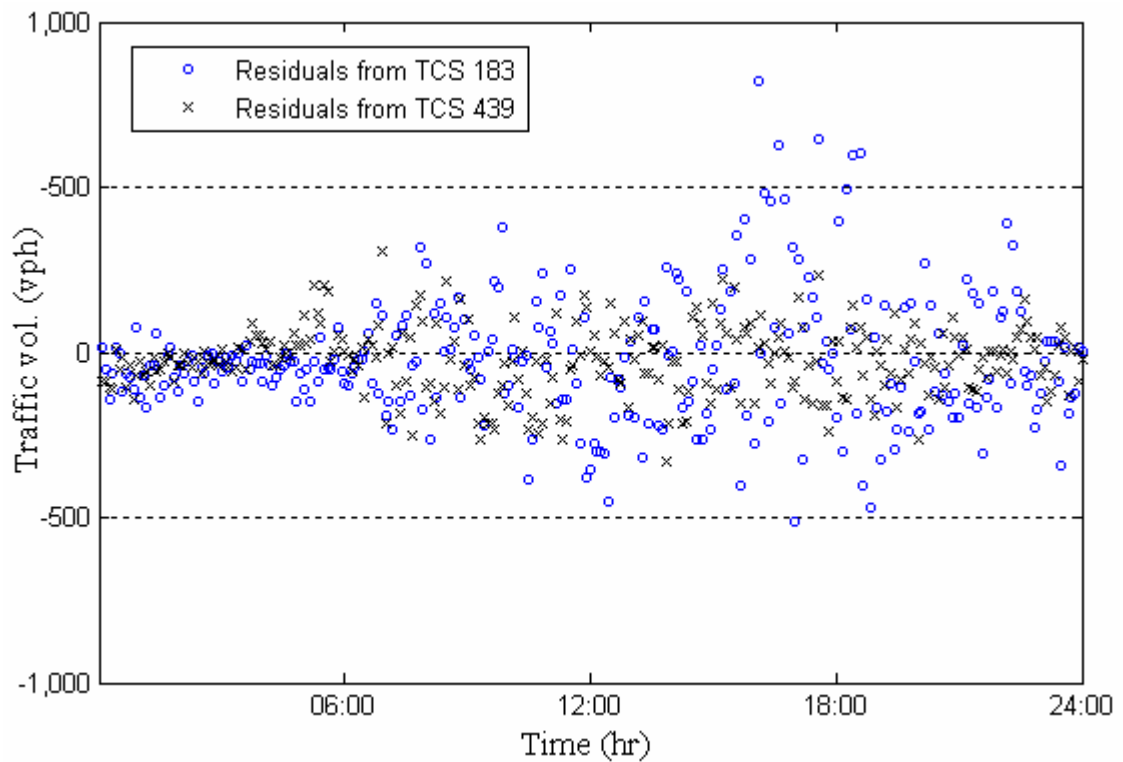


Figure 4 Dot Plot of Residuals on 12-07-2005

The simulated values of σ for traffic volume for the two junctions are plotted in a graph in figure 5. The sample standard deviation of the residuals derived after subtracting the trend from the traffic volume observations on 12-07-2005 for the two junctions are shown as horizontal lines in the figure.

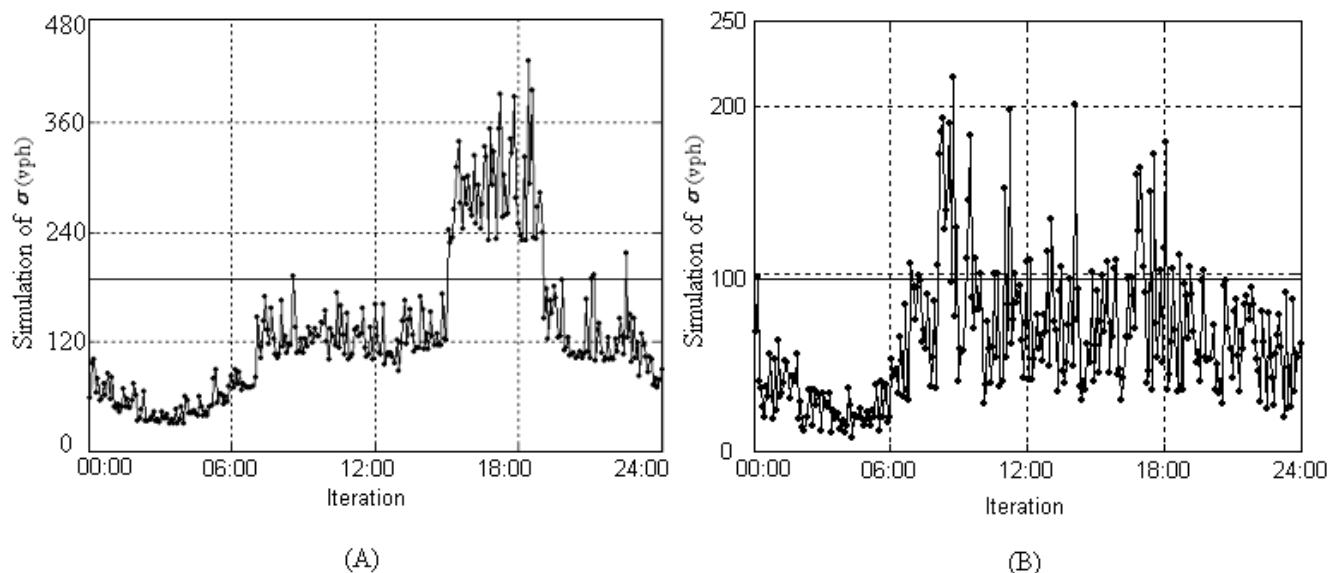


Figure 5 Simulations of Values of σ for TCS 183 (A) and TCS 439(B).

The estimates of σ obtained from the BH model change with the time of the day. The estimates during the peak hours are higher than the estimated values of σ_i during the rest of the day and the estimates of σ during the early hours in the morning are the least. The nature of the variability of the variance of the residual conforms to the spread of the residual data points in figure 4. To illustrate the effectiveness of the BH model of the residuals a 95% confidence interval is constructed on the regular average trend. The original 5 minute traffic flow observations from intersections TCS 183 and TCS 439 on 12th and 13th July 2005 are plotted along with the simulated 95% confidence limit in figure 6(A) and 6(B). The error estimates of the TBHM model for both junctions are given in Table 1.

	Mean of Observations (12-07-05) (vph)	Mean of Observations (13-07-05) (vph)	MAPE from TBHM Model (12-07-05)	MAPE from TBHM Model (13-07-05)	MAPE from HWES Model (12-07-05)	MAPE from HWES Model (13-07-05)
TCS 183	1300.83	1253.9	19.99%	12.83%	21.75%	23.07%
TCS 439	374.7	362.8	27.55%	28.73%	35.27%	38.08%

TABLE 1. Error Estimates of TBHM and HWES Models

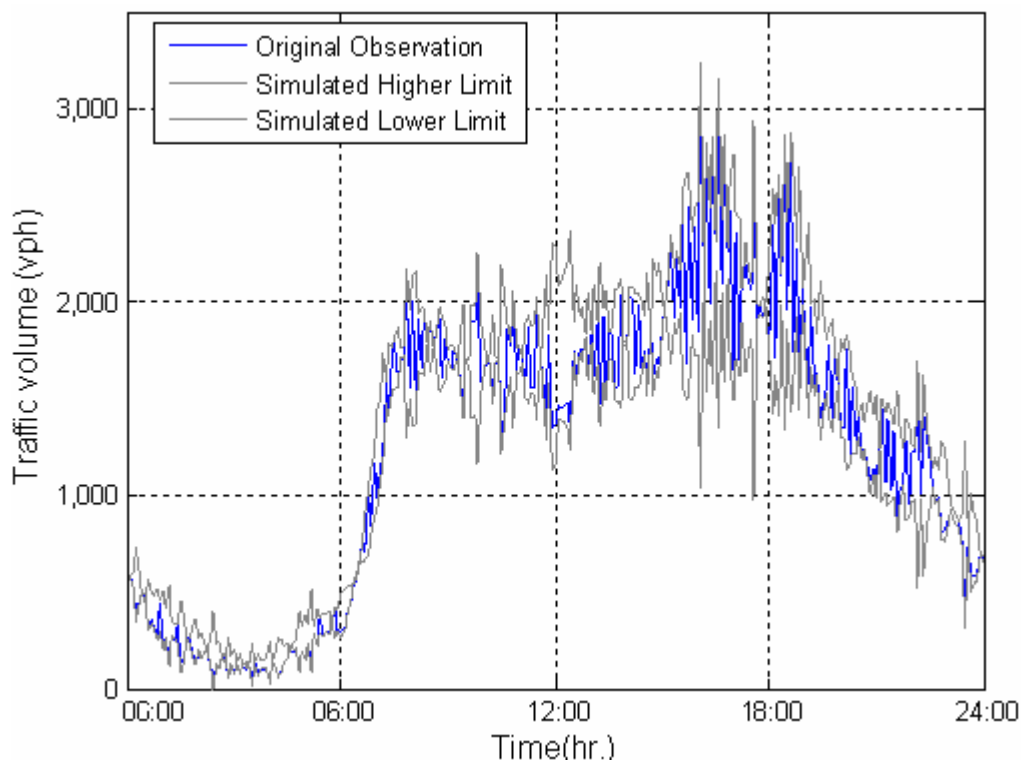


Figure 6(A) Simulated and Original Traffic Volumes on 12-07-2005 at TCS 183

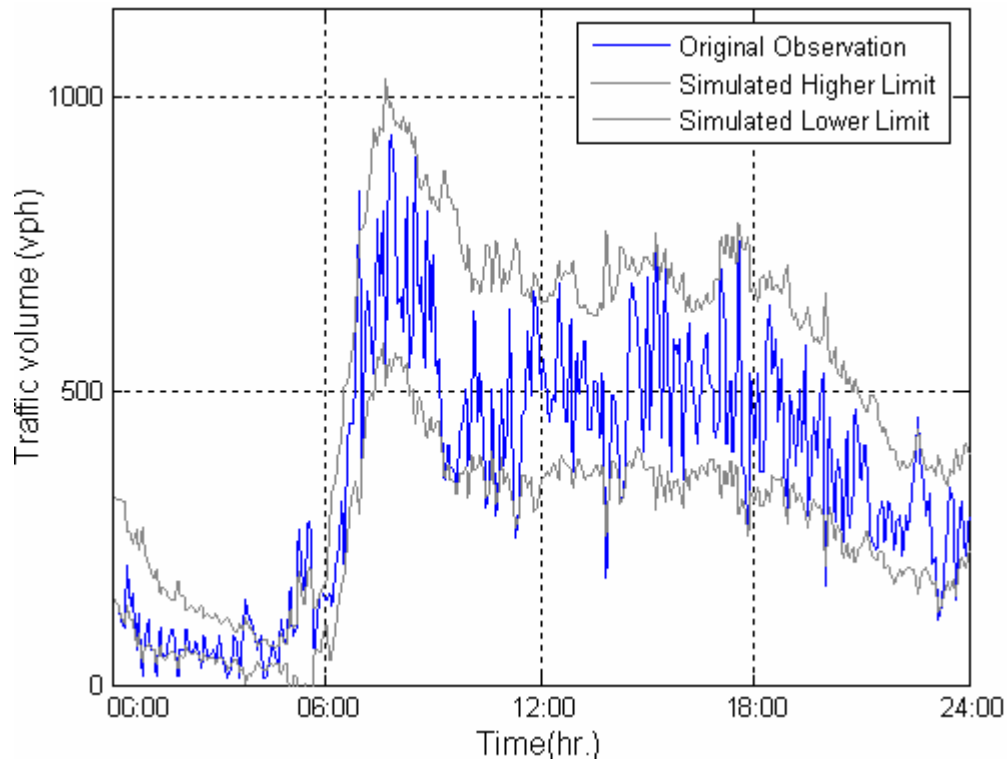


Figure 6(B) Simulated and Original Traffic Volumes on 12-07-2005 at TCS 439

Fitting HWES Model

Using the HWES model as described previously, short-term traffic volume forecasts are generated for 12th and 13th July, 2005.

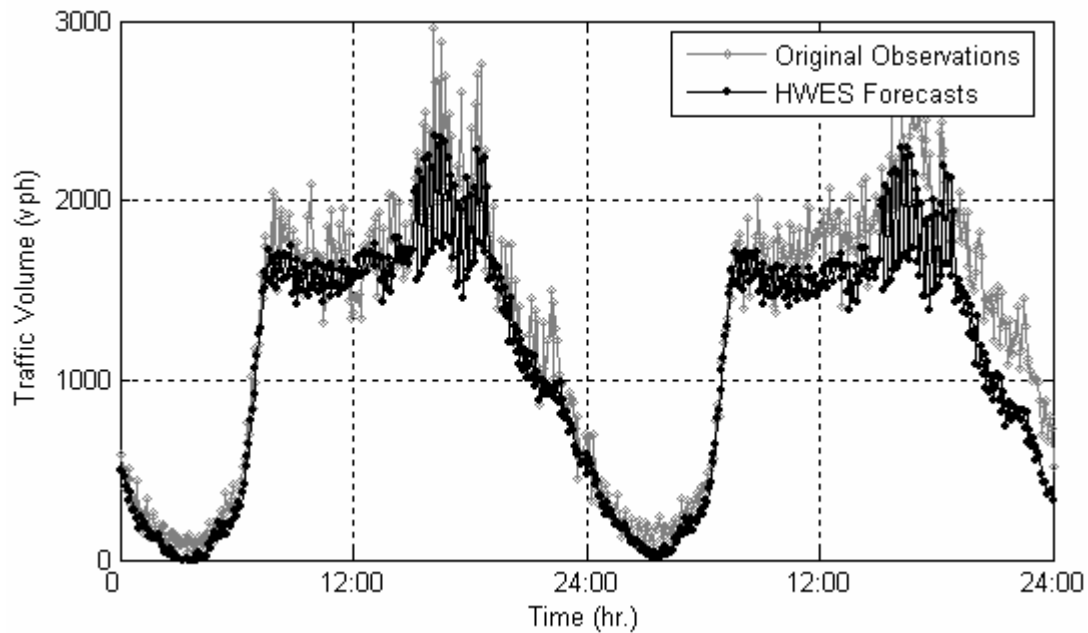


Figure 7(A) Forecasts from HWES model on 12th and 13th July from TCS 183

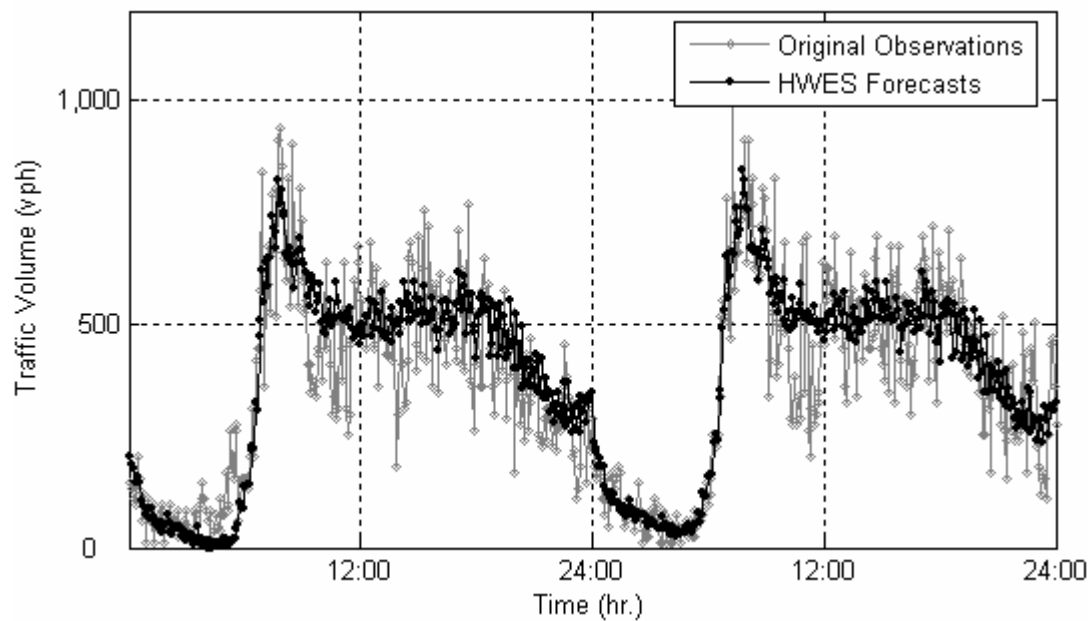


Figure 7(B) Forecasts from HWES model on 12th and 13th July from TCS 439

The initial values of the smoothing parameters are taken as, $\alpha = 0.05$, $\beta = 0.02$, $\delta = 0.03$ for modeling the original traffic flow data. The optimum values of the smoothing parameters are found out by minimizing the mean absolute percentage error (MAPE). The forecasts from the HWES along with the original observations are plotted in figure 7(A) and 7(B). The prediction accuracy of the forecasts obtained using the HWES model for junctions TCS 183 and TCS 439 are discussed in Table 1.

Comparison of Results

The results from the proposed TBHM model and the conventional HWES model are compared based on their accuracy (quantitative) and effectiveness (graphical). The quantitative comparison of accuracy has been done by comparing the error estimates from both the models (Table 1) and the proposed TBHM model has been proved to be superior to the HWES model. Based on MAPE values, it can be concluded that the 'non functional average trend' model is a reasonably accurate and inexpensive method of modeling short-term traffic flow data for urban signalized intersections.

The effectiveness of the two models are judged by comparing the variation in the traffic volume prediction intervals from the HWES model and the TBHM model (for 12th and 13th July 2005) for both junctions TCS 183 and TCS 439 in figures 8(A) and 8(B).

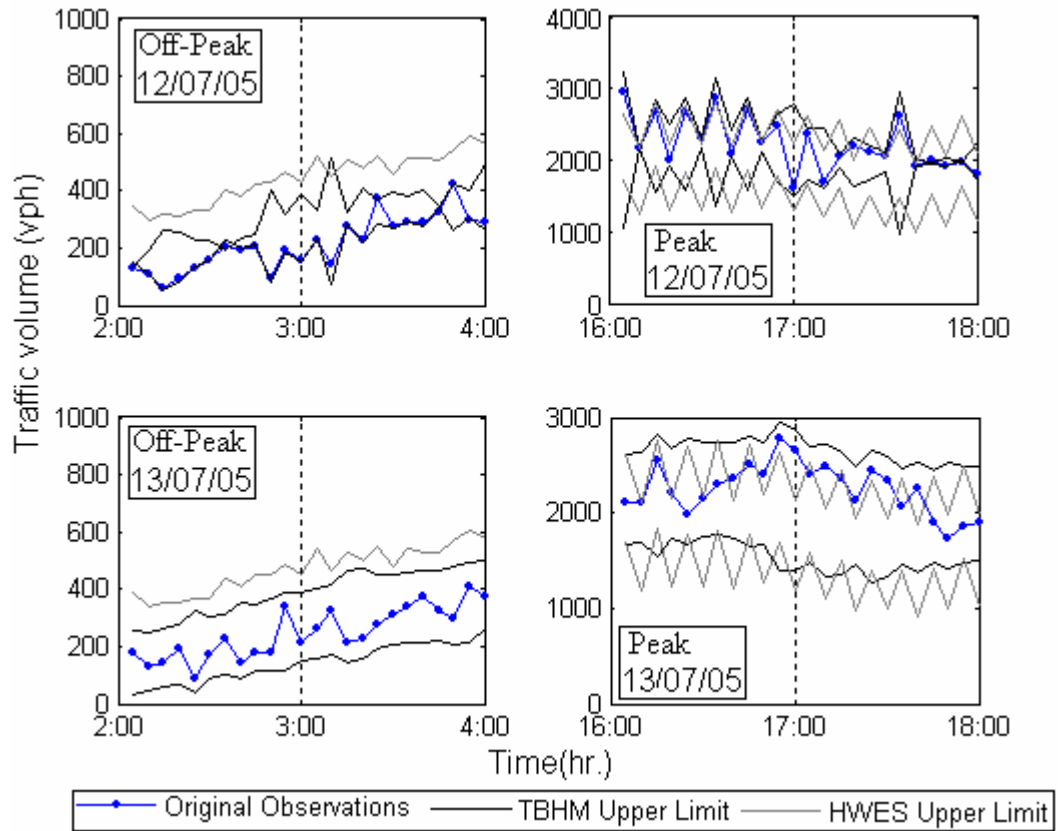


Figure8(A) Simulation and Prediction Interval from TBHM and HWES models for Traffic Volume at Junction TCS 183

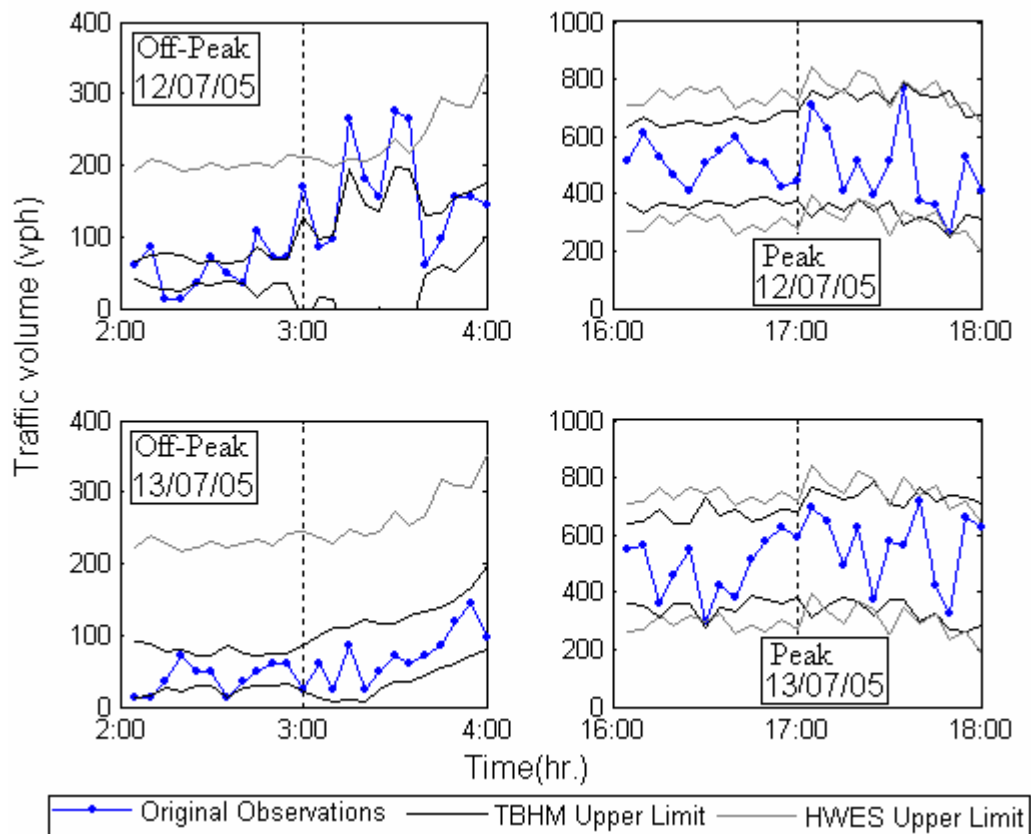


Figure8(B) Simulation and Prediction Interval from TBHM and HWES models for Traffic Volume at Junction TCS 439

It can be observed from the graphs that the simulation range obtained from the TBHM model varies with the time of the day (wider at peak hours and narrower at off-peak hours) unlike the seemingly constant prediction interval from the HWES model for traffic flow observations for both the junctions. In all the off-peak hour graphs the HWES model fails to give any satisfactory lower limit of prediction. Both models give higher error estimates when traffic volumes are lower than 300 vph.

CONCLUSIONS

A novel formulation of a hybrid model (TBHM) using a combination of the DWT technique and the BH model to simulate daily short-term traffic flow time-series dataset at urban signalized intersections has been proposed in this paper. One of the major contributions of the model is in developing a wavelet-based 'non-functional trend' by isolating the low resolution component from the high resolution components of a univariate traffic volume time-series dataset. The proposed wavelet-based modeling of the trend is more flexible being not limited to any functional forms and is computationally inexpensive. In addition, the subsequent Bayesian hierarchical residual model can represent the time-varying statistical variance of the high resolution components of the univariate traffic flow time-series dataset. The consideration of this inherent property (time-varying variance) of the short-term traffic volume observations in the

proposed model reflects more realistically the real life behavior of traffic in an urban transportation network.

The proposed TBHM model can simulate a short-term traffic volume range over a day reasonably accurately without using any observations from current and/or recent past unlike all other existing short-term traffic flow forecasting algorithms. Examples involving two urban signalized intersections in Dublin illustrate that the TBHM model is more effective with a time-varying prediction interval is more effective than the well-known short-term traffic flow forecasting HWES model.

A useful application of the proposed TBHM model can be for modeling traffic flow observations at non-critical junctions as well as critical junctions when the data collection systems for the same is not functioning for a considerable period of time leading to lack or absence of data from recent past. The proposed model can be effective in such scenarios where the existing short-term traffic forecasting models may not be applicable at all.

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