SHORT-TERM TRAFFIC VOLUME PREDICTION IN UMTS NETWORKS USING THE KALMAN FILTER ALGORITHM

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ABSTRACT

Accurate traffic volume prediction in Universal Mobile Telecommunication System (UMTS) networks has become increasingly important because of its vital role in determining the Quality of Service (QoS) received by subscribers on these networks. This paper developed a short-term traffic volume prediction model using the Kalman filter algorithm. The model was implemented in MATLAB and validated using traffic volume dataset collected from a real telecommunication network using graphical and r^2 (coefficient of determination) approaches. The results indicate that the model performs very well as the predicted traffic volumes compare very closely with the observed traffic volumes on the graphs. The r^2 approach resulted in r^2 values in the range of 0.87 to 0.99 indicating 87% to 99% accuracy which compare very well with the observed traffic volumes.

KEYWORDS

Traffic volume Prediction, cellular network, UMTS, QoS, Kalman filter

1. INTRODUCTION

Mobile broadband is changing the way the world exchange information. The Universal Mobile Telecommunication System (UMTS) is one of the wide-area wireless networks providing mobile internet access to users. UMTS is made of two main sections namely the access radio network and the core network as shown in figure 1.

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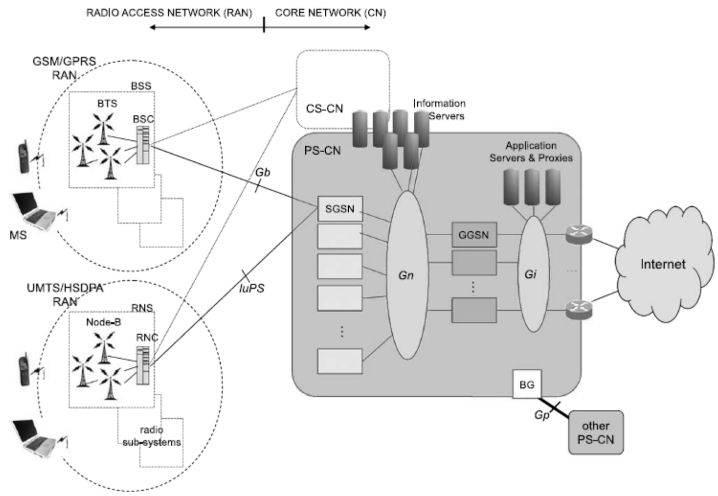

Figure 1: UMTS Architecture (Source: [1])

Efficient operation of a complex UMTS network is a challenging task since it combines wireless cellular paradigm and TCP/IP protocol dynamics. Over a 24 hour period, network traffic volume varies (high, normal, low etc.) and it is imperative to accurately estimate the traffic volume on UMTS networks. Traffic volume prediction problems make it difficult or almost impossible for network operators or planners to anticipate the amount of traffic expected on their networks. When traffic volumes are not estimated accurately, it may lead to network congestions and invariably poor quality of service to network subscribers. Several traffic modeling approaches have been proposed for UMTS networks [**2**]. Most of these techniques make use of the time series methods which are suitable for data that exhibit seasonality. It is, however, known that traffic data show seasonality only in a long term. Short-term traffic volume prediction using time series methods usually impose special requirements on the input data.

The Kalman filter algorithm is developed to produce values that tend to be closer to the true values of the measurements observed over time that contain noise (random variations) and other inaccuracies. The Kalman filter not only works well in practice, but it is theoretically attractive as it is able to minimize the variance of the estimated error**[3]**. It can be described as an optimal linear estimator. Kalman filtering has been applied to many traffic studies such as motorway traffic state estimation **[4]** freeway travel time estimation, freeway Origin to Destination (O-D) demand matrices, and the prediction of traffic volume and travel time **[5]**. In addition to eliminating the need for storing the entire past observed data, the Kalman filter is computationally more efficient than computing the estimate directly from the entire past observed data at each step of the filtering process**[6]**.

The Kalman filter-based model has worked well in the area of transportation and highway engineering. In this paper, we develop a Kalman filter-based model for short-term traffic volume prediction in UMTS networks.

2. THEORETICAL BACKGROUND

In this section we present the theory of Kalman filters and the definition of short-term traffic forecasting.

2.1. The Kalman Filter Theory

The Kalman Filter was named after Rudolf Emil Kalman, born in Budapest, Hungary on May 19, 1930. Its purpose is to use measurements observed over time, containing noise (random variations) and other inaccuracies, and produce values that tend to be closer to the true values of the measurements and their associated calculated values **[7]**. **[8]**, also described the Kalman filter as a set of mathematical equations that provides an efficient computational (recursive) means to estimate the state of a process, in a way that minimizes the mean of the squared error. The Kalman filter addresses the problem of attempting to estimate the state of a discrete-time controlled process**[9]**. The state is represented by two variables:

- $\hat{x}_{k/k}$, the estimate of the state at time k given observations up to and including time k;
- $P_{k/k}$, the error covariance matrix (a measure of the estimated accuracy of the state estimate). Discrete time linear systems are often represented in a state variable format given by a state equation:

$$x_j = ax_{j-1} + bu_j + w_j \quad ----(1)$$

and a measurement equation:

$$z_j = hx_j + v_j \quad ------- \ (2)$$

where the state x_j is a scalar, a and b are constants and the input u_j is a scalar; j represents the time variable. The noise w_j is a white noise source with zero mean and covariance Q that is uncorrelated with the input. Likewise, the noise v_j is a white noise source with zero mean and covariance R that is uncorrelated with the input. The input u_j usually defaults to zero, so it is sometimes omitted. Equations 1 and 2 form the basis of the Kalman filter algorithm. The effects of the noise sources are compensated for by a residual term ($z_k - \hat{z}_k$), where $\hat{z}_k$ is the estimate for the actual measured output z_k. $\hat{x}_k^-$is used to represent the ***a priori*** estimate, which is the initial estimate of the state x_k. The ***a priori*** estimate is used to predict an estimate for the output$\hat{z}_k$, after which the actual measurement z_k is obtained. The difference between z_k and $\hat{z}_k$ (known as the residual, as already stated above) is used to refine the a priori estimate after a gain k (known as the Kalman gain) has been applied to it. The residual is thus used as a correction factor for the a priori estimate [**10**].The *refined a priori estimate* is now known as the ***a posteriori*** estimate of the statex_k, represented as $\hat{x}_k$. This ***a posteriori*** estimate is then fed back into the system to serve as a *previous* estimate of the system state for the next prediction of the Kalman filter [**10**].

2.2.Modeling Traffic Volume

Short-term traffic forecasting can be defined as predicting traffic conditions 20 seconds to several minutes in advance with the hope of employing these forecasts in the design and deployment of telecommunications networks **[5].** Traffic volume is defined as the number of calls that pass through a particular switching or routing device in a telecommunication network in a specified period of time **[5]**. The unit of measurement for traffic volume is Erlang (E). Mathematically, traffic volume and intensity are expressed in equations (3) and (4) respectively.

$$Traffic\ Volume = \sum_{x=1}^{N} xtx \ \ldots\ldots\ldots\ldots\ldots\ldots..(3)$$

Where tx is sum of times during which exactly x out of N devices are held simultaneously within a period T.

$$Traffic\ Intensity = \frac{Traffic\ Volume}{Duration\ of\ the\ specified\ period} \ \ldots\ldots\ldots(4)$$

3. SHORT-TERM TRAFFIC PREDICTION MODEL

Traffic volume prediction problem can be formulated as: given traffic volume history, recorded at discrete time instants, formulate the prediction of traffic volume $\boldsymbol{k}$ time instants from current.

In our proposed solution the traffic volume at any time step is treated as a linear combination of the traffic volumes at previous time steps. This assumption holds for short–term traffic prediction and based on it a Kalman filter-based traffic prediction model is developed for predicting traffic volume in UMTS networks on short-term basis. The short-term basis is chosen because, it allows for certain assumptions as stated below:

(a) For short term forecasting, the state variable transitions may be regarded as a smooth process.
(b) A linear relationship may be assumed between traffic volumes for the current time step and traffic volumes for previous time steps.

From (b) it may be inferred that the traffic volume at any particular time step is a linear combination of the traffic volumes at previous time steps. Assumption (b) is made based on the structure of the Kalman filter equations and also to make it possible to represent the traffic volume accurately.

Let tv_k denote the link traffic volume for the $\boldsymbol{k^{th}}$ time interval to be estimated. Based on the assumption stated in (b) above, there exists the following linear relationship shown in equation (5)

$$tv_k = TV_k\theta_k + \varepsilon_k \quad ------------ (5)$$

Where

$TV_k = [tv_{k-1}, tv_{k-2},...,tv_{k-n}]$, observed traffic volume;
$\theta_k = [\theta_{k-1}, \theta_{k-2},..., \theta_{k-n}]^T$; and
ε_k = noise term.
n = the number of previous traffic volumes taken into account for the computation of the current traffic volume. Column vector $\boldsymbol{\theta_k}$is a collection of coefficients for each corresponding observed traffic volume in the row vector $\mathbf{TV_k}$**[11]**.

4. KALMAN FILTER-BASED ALGORITHM

We present a detailed flowchart of the Kalman filter algorithm in this section of the paper as shown in figure 2. This can easily be translated into a program using any relevant programming language.

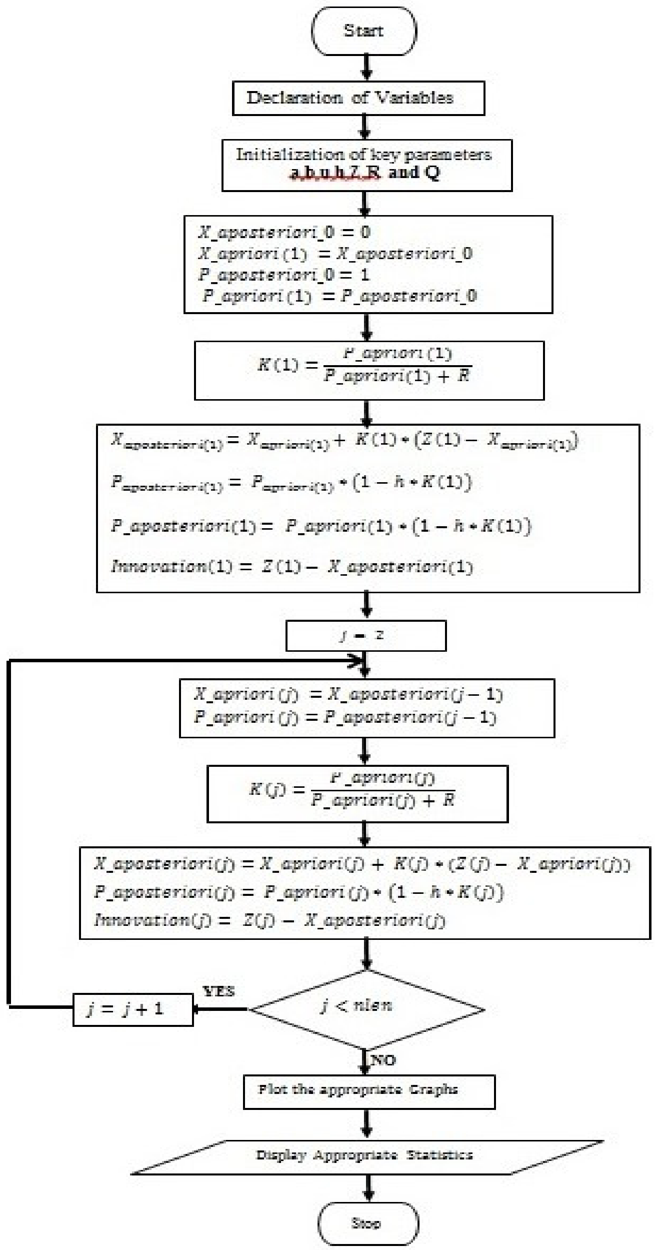

Figure 2: Flowchart for the Kalman filter algorithm

4.1. IMPLEMENTATION AND TESTING

Step 1: Let k = n + 1
Step 2: Initialize $\hat{x}_{k-1}$ and P_{k-1}. Customarily, P_{k-1} is set to be a matrix with very small values. For the purpose of this study, $\hat{x}_{k-1}$ is set to be $[1/n, 1/n, 1/n, ..., 1/n]^T$ and $P_{k-1} = 10^{-2} \cdot \mathbf{I}_{nxn}$.
Step 3: Compute the values of $\hat{x}_k^-$ and P_k^- using the predictor stage equations of the Kalman filter equations.
Step 4: Let $H_k = [tv_{k-1}, ..., tv_{k-n}]$ and $y_k = tv_k$.
Step 5: Compute the Kalman gain K, $\hat{x}_k$, and P_k using the corrector stage equations of the Kalman filter equations.
Step 6: Let $H_{k+1} = [tv_k, ..., tv_{k-(n-1)}]$, and compute the predicted traffic volume as $\widehat{tv}_{k+1} = H_{k+1}\hat{x}_k$
Step 7: Increment k; that is let k = k + 1
Step 8: Repeat steps 3 through to 7.
The Kalman filter-based prediction model developed and implemented is tested using traffic volume data collected from a live UMTS network.

5. RESULTS AND DISCUSSION

Traffic volume data were collected from three operating areas of a telecommunication network operator representing residential, urban/commercial and rural areas. The locations are Nhyiaeso, Adum and Aborfor representing residential, urban/commercial and rural areas respectively, all in the Kumasi metropolis of the Ashanti region of Ghana. Each data set has 25 days of traffic volume data (July 1, 2010 – July 25, 2010). In order to capture effective traffic volume data, the data were collected between the hours of 12:00 am midnight and 11:00pm inclusive, constituting 24 samples of traffic volume data for each day under investigation. Out of these data, an average traffic volume is computed for each day, narrowing down the average traffic volume samples to 25. In order to determine the traffic volume pattern on days of the week basis, 7 average traffic volume samples were also derived from the data sets representing Monday through to Sunday inclusive.

Average traffic volumes of the locations and data sets described above are presented in tables and corresponding graphs in this section of the study. The average traffic volumes for each day for the 25 days are presented here for some sectors of the locations where traffic volume data were collected.

5.1. Model Validation using Direct Graphical Comparison

In this section, we use the direct graphical comparison approach to validate the model by plotting a graph that shows how the observed (Exact), the initially predicted (a Priori) and the updated (a Posteriori) traffic volumes in MATLAB. The observed, initially predicted and the updated traffic volumes are shown in red, blue and green colors respectively on the graphs

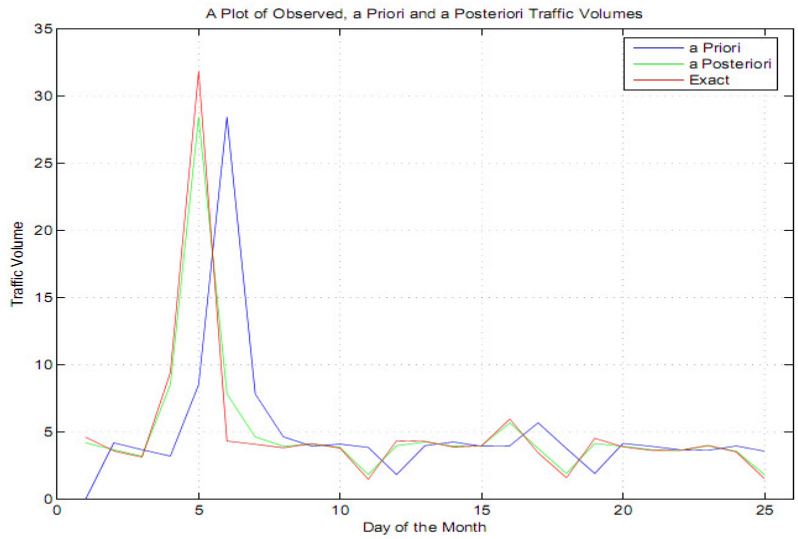

Figure 3. Observed, a Priori and Predicted Traffic Volume for Adum Sector A.

From the plot above, we make the following conclusion: A closer look at the plot indicates that, although the a priori estimate deviates a little bit from the observed traffic volume, the a posteriori estimates however, gives a value that compares creditably with the observed traffic volumes. This indicates that, the initial estimates are corrected using the relevant Kalman equations. We therefore conclude that, the model sufficiently represents a reality based on the graphical display shown in figure 3 above.

Figure 4. Observed, a Priori and Predicted Traffic Volumes for Nhyiaeso Sector A.

Though the a priori traffic volume shown in blue deviates from the exact traffic volume shown in red, the a posteriori traffic volume shown in green gets closer and closer to the observed traffic volume over time. This indicates that, the Kalman filter model's performance gets better as the number of iterations increases. The model's performance can be said to be quite accurate.

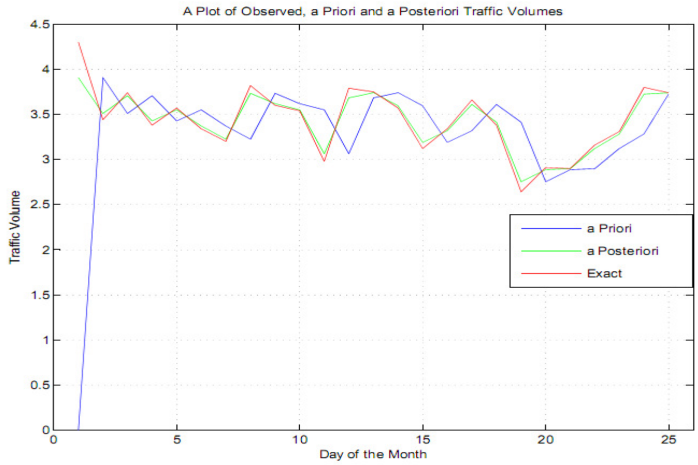

Figure 5: Observed, a Priori and Predicted Traffic Volumes for Aborfor Sector A.

A closer look at the plot shown in figure 5 indicates that, the predicted traffic volume does not deviate so much from the observed or the measured traffic volume. Though the model may need a little adjustment of some parameters to attain perfection, one can conclude that, the model is very reliable for traffic volume prediction in UMTS networks on short term basis.

5.2. Model Validation using the Coefficient of Determination (r^2) Approach

The coefficient of determination denoted R^2 and pronounced R squared, indicates how well data points fit a line or curve. It is a statistic used in the context of statistical models whose main purpose is either the prediction of future outcomes or the testing of hypotheses, on the basis of other related information. It provides a measure of how well observed outcomes are replicated by the model, as the proportion of total variation of outcomes explained by the model **[12]**. R^2 takes on values between 0 and 1. The higher the r^2 value, the more useful the model is. Essentially, r^2 tells us how much better we can do in predicting **[13]**the output from a system under investigation by using the model, than just using the mean as a predictor. In this paper therefore, the r^2 values are computed using the same dataset used for graphical validation to further test the accuracy of the model. The results of the r^2 computation are presented in the tables below for three scenarios.

5.2.1. Scenario 1 ($R = 0.1, P_o = 1, X_0 = 0$ and $Q = 0.5$)

For Scenario 1, we set the covariance of measurement error to 0.1 (i.e. R=0.1), the covariance of estimation error to 1(i.e. $P_0 = 1$), a priori estimate of system's state to 0 (i.e. $X_0= 0$) and the covariance of process error to 0.5(i.e. Q= 0.5).

The table below shows the results obtained from model validation using the r^2 approach under scenario 1.

Table 1: Model Performance for Scenario 1

Location	Mean(μ)	Std(σ)	RMSE	MAPE	r^2
Adum	5.07	5.77	1.02	9.42	0.97
Nhyiaeso	2.36	0.35	0.08	2.17	0.93
Aborfor	3.44	0.37	0.09	1.59	0.91

5.2.2. Scenario 2 (R = 0.05, Po = 0.5, X0 = 0.5 * Z1 and Q = 0.5)

For Scenario 2, we set the covariance of measurement error to 0.05 (i.e. R= 0.05), the covariance of estimation error to 0.5 (i.e. $P_0 = 0.5$), a priori estimate of system's state to half of the first value of the observed traffic volume (i.e. $X_0 = 0.5 * Z1$) and the covariance of process error to 0.5(i.e. Q = 0.5). Z1 is the first value of the observed traffic volume. The table below shows the results obtained from model validation using the r^2 approach under scenario 2.

Table 2: Model Performance for Scenario 2

Location	Mean(μ)	Std(σ)	RMSE	MAPE	r^2
Adum	9.95	4.36	0.49	2.53	0.99
Nhyiaeso	1.91	0.23	0.03	1.14	0.98
Aborfor	2.85	0.29	0.04	0.85	0.97

5.2.3. Scenario 3(R = 0.25, Po = 0.005, X0 = Z1 and Q = 0.5)

For Scenario 3, we set the covariance of measurement error to 0.25 (i.e. R= 0.25), the covariance of estimation error to 0.005 (i.e. $P_0 = 0.005$), the a priori estimate of system's state to the first value of the observed traffic volume (i.e. $X_0 = Z1$) and the covariance of process error to 0.5 (i.e. Q = 0.5). The results obtained from model validation using the r^2 approach under scenario 3 are presented in table 3.

Table 3: Model Performance for Scenario 3

Location	Mean(μ)	Std(σ)	RMSE	MAPE	r^2
Adum	4.88	2.90	0.93	12.05	0.89
Nhyiaeso	2.71	0.35	0.11	2.92	0.87
Aborfor	1.63	0.12	0.04	1.95	0.89

From the tables above, we conclude that the performance of the model is of high accuracy based on the various values produced for r^2 in the tables. The second scenario gives the highest performance index of the model. With the values of r^2 ranging between 0.87 and 0.99 representing 87% to 99% level of accuracy, we can confidently say that the predictive power of the model can be trusted under the above model parameter values.

6. CONCLUSION

This paper investigates modeling and implementation of a Kalman filter-based model for short-term traffic volume prediction in UMTS networks. The Kalman filter-based models were used in traffic volume prediction by many researchers in the field of traffic volume prediction. These researchers used the Kalman filter-based models predominantly in the area of transportation engineering. In this paper, we developed a Kalman filter-based model to suit the characteristics of short-term traffic volume for UMTS networks. The model was then implemented using MATLAB and tested with traffic volume from a real telecommunication network using graphical comparison and r^2 methods of model validation. Future works in this area of research could consider a more rigorous sensitivity analysis of all model parameters as well as the network parameters and measure their impacts on the performance of the model.

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