A Model Based Scheme for Real Time Estimation of Traffic Density

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Abstract—**Rapid urbanization and growth of private vehicle ownership have led to severe traffic congestion on most of the urban roads in India. The use of advanced technology applications such as Intelligent Transportation Systems (ITS) is one of the recent and cost-effective ways to manage traffic congestion. Providing travelers with real time information on traffic congestion is an important component of ITS. Real time estimation and prediction of traffic density is essential for traffic congestion management through ITS. Because of the practical difficulty of measuring density directly from field, it is usually estimated from other parameters that can be readily measured using available location based sensors. To achieve this, it is necessary to develop adequate macroscopic models of sufficient accuracy to process these location based information into spatial information such as traffic density in real time. Traffic flow is highly stochastic in nature that necessitates the need for incorporating the uncertainty associated with the traffic flow phenomena while modeling it. Since none of the deterministic models are able to describe the uncertainties associated with traffic flow phenomena, model based approaches using techniques such as Kalman filtering or extended Kalman filtering are more suitable for accurate real time traffic state estimation. Also, as this method requires only minimal data for implementation, it is advantageous at places like India where no historic data base is available. A macroscopic model based approach is presented for the real time estimation of traffic density. A lumped parameter macroscopic traffic flow model has been proposed and the estimation scheme is built using the Extended Kalman Filter (EKF). The effects due to heterogeneity and limited lane discipline in the traffic stream of India were taken care of. The proposed scheme was corroborated using data measured from a road stretch in Chennai and the performance was found to be satisfactory.**

Keywords—Traffic flow modeling; Intelligent Transportation Sysems; traffic density; model based estimation; Kalman filter.

I. INTRODUCTION AND BACKGROUND

Traffic congestion on urban roads is becoming a serious problem to transportation engineers all over the world. As against the traditional way of adding more capacity, one of the cost-effective ways to manage traffic congestion is by utilizing the existing facility more efficiently through operational means. A relatively recent approach in achieving this is with the help of advanced technology applications, which are commonly known as Intelligent Transportation Systems (ITS). One of the most popular ITS applications is to provide real time information to travelers regarding traffic congestion through Advanced Traveler Information Systems (ATIS). Accurate traffic information is crucial for the development of reliable ATIS [1]. The number of vehicles occupying a given length of roadway (known as traffic density) is one of the main traffic parameters that can directly be used as a measure of the level of congestion. Thus, accurate estimation of traffic density in real time is important for managing and controlling traffic congestion through ITS applications. However, a direct measurement of this spatial parameter, density, for real time ITS application is not economical as it needs techniques such as aerial photography. Because of this practical difficulty, traffic density is usually estimated from other parameters that can be readily measured from field using available location based sensors. One of the basic requirements for achieving this is the availability of sufficiently accurate mathematical models to process these location based information into traffic density in real time.

One approach for such a modeling is the use of microscopic models, which are complex and computationally intensive and hence not normally preferable for real time applications. The other option of macroscopic traffic flow models is appropriate for such applications where computational effort is crucial. Existing macroscopic models simulate homogeneous traffic, and are not applicable to the vehicle heterogeneity seen on the Indian road. Only limited research has been done on this topic in India.

As deterministic models alone are not sufficient for accurate estimation of traffic variables in real time, model based estimation schemes using techniques such as Kalman filter are more appropriate [2]. Such macroscopic model based schemes are more popular now a days [3-8]. These schemes have the ability to account for the uncertainty associated with the traffic flow phenomena, which is of more relevance under traffic conditions such as in India where the randomness associated with traffic is high. Another advantage of this approach is that in order to estimate state variables at a given instant of time, one needs only the estimate from the previous instant of time and the measured data collected during that instant of time. Thus, unlike data or pattern driven methods, the data measured during all the previous instants of time need not be stored, which is advantageous in places where the system is being implemented and hence a database is not available, such as under Indian conditions.

A macroscopic model based approach is presented in this study for the real time estimation of traffic density. A lumped parameter macroscopic traffic was developed based on the conservation of vehicles equation and empirically developed traffic stream models. Using this model and based on extended Kalman filter, the model based estimation scheme was designed. Traffic density and flow passing the exit section were considered as the state variables and flow entering through the main road and through the side roads were used as inputs to the scheme. The output variable was the flow passing the exit section and was used for correcting the a priori estimates given by the model equations. Using data collected from the three sections along the study stretch, the proposed scheme was implemented and corroborated. Heterogeneity was incorporated at an aggregate level by expressing the heterogeneous traffic into a homogeneous equivalent using standard static Passenger Car Units (PCU). The results showed that the proposed scheme is performing well.

II. MODEL FORMULATION

The lumped parameter approach was followed in formulating the governing equations of the variables for characterizing the traffic system. A brief introduction on the lumped parameter approach and details on formulation of the governing equations of the proposed model, based on the lumped parameter approach are given in the following sections.

A. *The Lumped Parameter Approach*

In a lumped parameter approach [9], the physical system under study is divided into lumps or segments and within each segment, the aggregate characteristics such as velocity, pressure, density etc., may vary with time, but are assumed to be uniform over the segment. The lumped parameter approach results in the governing equations of the model being ordinary differential equations (in the continuous time domain) and ordinary difference equations (in the discrete time domain). This approach has been widely used in formulating models of dynamic systems from various fields including fluid systems [10-12], mechanical systems [13, 14] and electric systems [15, 16].

When the lumped parameter approach is applied to roadways, within a small section of roadway, the spatial variation of traffic variables (such as density, speed, etc.) is neglected and it is assumed that the variables depend only on time. A reasonable section length for this assumption to hold good may be around 1-1.5 km, which is the usual spacing between automated data collection sensors. The section length (L) in this study was also selected in this range. To apply this procedure to longer roadways, the section can be divided into sub-sections of lengths in this range.

B. *Governing Equations*

Consider a typical road segment as shown in Figure 1. The number of vehicles inside the section per unit length (density, ρ) which is a spatial parameter difficult to measure from field, and the flow rate at which the vehicles are exiting from the section (q_{ex}) were considered as the macroscopic state variables to describe the state of traffic inside this section.

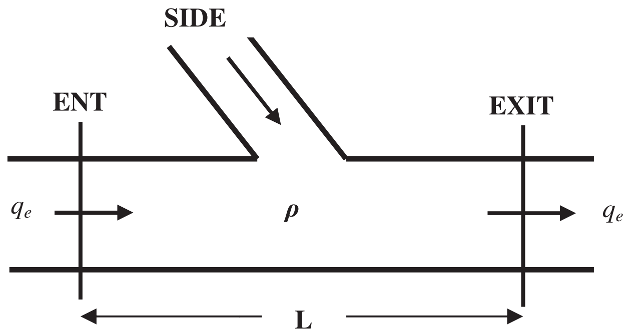

Figure 1 Schematic diagram of a typical road section

The governing equation for density was formulated based on the conservation of vehicles inside the section (Figure 1) as follows.

Let $N(k)$ denote the number of vehicles inside the section at the k^{th} instant of time. Then, the conservation of vehicles inside the section for a time step of h can be represented as

$$N(k+1) = N(k) + h\left(q_{en}(k) - q_{ex}(k) + q_{side}(k)\right), \quad (1)$$

where, $q_{en}(k)$ is the flow rate at which vehicles are entering into the section, $q_{ex}(k)$ is the flow rate at which vehicles are exiting from the section and $q_{side}(k)$ is the net flow rate at which the vehicles are entering into the section from the side road in the time interval (k, $k+1$).

Dividing Equation 1 by the length of the section (L) results in

$$\rho(k+1) = \rho(k) + \frac{h}{L}\left(q_{en}(k) - q_{ex}(k) + q_{side}(k)\right), \quad (2)$$

where, $\rho(k+1)$ denotes the density inside the section at the $(k+1)^{th}$ instant of time. Thus, Equation 2 governs the time evolution of traffic density.

The second governing equation of the model is a dynamic flow equation formulated by incorporating the appropriate flow-density relationship developed for the specific traffic under study. The best fitting two regime steady state flow-density relationship derived was incorporated. The dynamic equation was obtained with the motive of minimizing the error (e) between the flow values estimated using this steady state flow-density relation $q(\rho)$ and the observed flow values q_{ex}, i.e., $e := q(\rho) - q_{ex}$. The time evolution of this error was hypothesized to behave as governed by

$$\frac{de}{dt} = -a.e(t), \tag{3}$$

where, the parameter a is selected to be positive. This equation is a linear homogeneous ordinary differential equation (ODE) and it is well known that its unique solution is $e(t) = e(0)\exp(-at)$, [17], where $e(0)$ is the initial error (can be either positive or negative), which will converge to zero with time. Although, there may be other choices for describing the time evolution of the error function, an exponentially decaying error function (an exponential function is a very commonly used function in many phenomenological studies) has been chosen in this study since its performance will be comparably good to any alternate choice. This approach is applied in other studies involving the dynamical systems approach [18, 19].

Substituting $e = q(\rho) - q_{ex}$ in Equation 3 and re-arranging resulted in

$$\frac{d(q(\rho))}{d\rho}.\frac{d\rho}{dt} - \frac{dq_{ex}}{dt} = -a.\left(q(\rho) - q_{ex}\right) \tag{4}$$

Discretizing Equation 4 using a time step h resulted in

$$\frac{d(q(\rho))}{d\rho}.\frac{\left(\rho(k+1) - \rho(k)\right)}{h} - \frac{\left(q_{ex}(k+1) - q_{ex}(k)\right)}{h} = -a.\left(q(\rho) - q_{ex}\right) \tag{5}$$

By putting $\frac{\rho(k+1) - \rho(k)}{h} = \frac{1}{L}\left(q_{en}(k) - q_{ex}(k) + q_{side}(k)\right)$ from Equation 2, the dynamic equation for flow passing the exit section (that is, the equation governing the evolution of q_{ex}) was obtained as

$$q_{ex}(k+1) = q_{ex}(k) + ah\left(q(\rho) - q_{ex}(k)\right) + \frac{h}{L}\frac{d\left(q(\rho)\right)}{d\rho}\left(q_{en}(k) - q_{ex}(k) + q_{side}(k)\right). \tag{6}$$

Thus, the complete model was represented by Equations 2 and 6. These equations are the general model equations applicable for any roadway section. Now, the site specific flow density relationship $q(\rho)$ developed empirically (the base work of this can be found at [20] and was incorporated in Equation (6). A brief description of the developed flow density relations (stream model) and the details on incorporating these in Equation (6) is provided below.

A study stretch was identified along an urban arterial in Chennai (Figure 2 shows a schematic diagram of the study stretch) between two locations A and C based on suitability to data collection. The study stretch was a six lane roadway with three lanes in one direction. For the present study only one direction of traffic was considered.

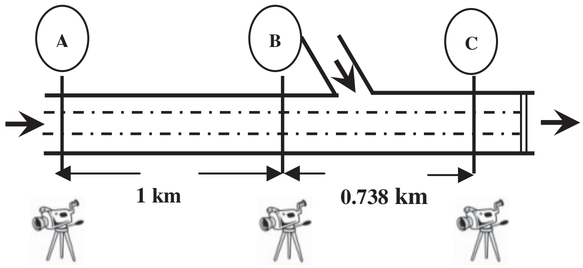

Figure 2 Schematic diagram showing the study stretch.

Data were collected from locations A, B and C using videographic technique covering both peak and off-peak periods. Video recordings were analyzed in the laboratory to extract traffic parameters namely, volume and occupancy of different vehicle groups at every one minute intervals. The traffic volumes in terms of vehicle counts in every one minute were converted into per hour flow values. Density values were calculated from occupancy values extracted from videos using the relation connecting density and occupancy [21]. Based on this data, the best fitting stream model was derived empirically. To take into account the lack of lane discipline, the roadway was analyzed without considering the lanes, and heterogeneity of traffic was incorporated by converting the data into standard PCU equivalent values [22]. A two-regime stream model (which assumes separate relationships for representing the behavior of traffic under free-flow and congested regimes) was found to be best fitting and the functional forms of the best fitting two-regime flow density relations were obtained as

$$\left.\begin{aligned} q &= 53.86\rho.\exp\left(-0.5\left(\frac{\rho}{172}\right)^2\right) \quad for \quad 0 \le \rho \le 149, \\ q &= 12.146\rho\left(\frac{602}{\rho} - 1\right) \quad for \quad 149 \le \rho \le 602, \end{aligned}\right\} \tag{7}$$

where density ρ is in *PCU/km* and flow q is in *PCU/hr*.

Incorporating Equation 7 in Equation 6, the governing equation for exit flow is obtained as

$$q_{ex}(k+1) = q_{ex}(k) + ah\left\{53.86.\rho(k).\exp\left[-0.5\left(\frac{\rho(k)}{172}\right)^2\right] - q_{ex}(k)\right\} + \frac{53.86\,h}{L}.\exp\left[-0.5\left(\frac{\rho(k)}{172}\right)^2\right]\left[1 - \left(\frac{\rho(k)}{172}\right)^2\right].\left(q_{en}(k) - q_{ex}(k) + q_{side}(k)\right)$$
$$for \quad 0 \le \rho(k) \le 149 \tag{8}$$

$$q_{ex}(k+1) = q_{ex}(k) + ah\left[12.146.\rho(k)\left(\frac{602}{\rho(k)} - 1\right) - q_{ex}(k)\right] - \frac{12.146\,h}{L}\left(q_{en}(k) - q_{ex}(k) + q_{side}(k)\right) \; for \;\; 149 \le \rho(k) \le 602 \quad (9)$$

Thus, the complete model was represented by Equations 2, 8 and 9. In this model, the generic governing equations derived using the conservation of vehicles and the hypothesis regarding the evolution of the error *e*, will hold for any road segment. However, the specific equations for the evolution of error obtained from developed steady state flow-density relation (traffic stream model) are site specific. This is due to the site specific nature of traffic stream models [23]. Thus, though the generic equations are transferable, the site specific steam model is transferable only to sections with similar characteristics. In other cases, the section specific stream model should be known or developed and need to be used in the generic governing equations for good performance.

Next, the estimation scheme development using the Kalman filtering technique is detailed.

III. DESIGN OF MODEL BASED ESTIMATION SCHEME

The model based estimation has been developed by using the above models and Kalman fitering technique. The Kalman filter [24] is a popular tool for recursive estimation of variables that characterize a system (these variables are usually referred to as 'state variables'). The Kalman filter is used when the governing equations of the system are linear. When the governing equations are non-linear, an 'Extended Kalman Filter' (EKF) [25, 26] is commonly used. Since the model equations are non-linear in the present study, extended Kalman filter was used as detailed below.

. The EKF linearizes the governing equations at each time step about the estimate obtained from the previous time step. Consider a non-linear system whose model is given by

$$\mathbf{x}_{k+1} = \mathbf{f}\,(\mathbf{x}_k, \mathbf{u}_k, \mathbf{w}_{\mathbf{1}k}), \quad (10)$$

$$\mathbf{z}_k = \mathbf{g}(\mathbf{x}_k, \mathbf{v}_{\mathbf{1}k}), \quad (11)$$

where **f** represents the non-linear function that relates the state at time step k to the state at time step $k+1$. Similarly **g** is the non-linear function that relates the state to the measurement. The above equations can be linearized using Taylor's Series expansion to result in

$$\mathbf{x}_{k+1} = \tilde{\mathbf{x}}_{k+1} + \mathbf{A_1}\left(\mathbf{x}_k - \hat{\mathbf{x}}_k^{+}\right) + \mathbf{W}\mathbf{w}_{1k}, \quad (12)$$

$$\mathbf{z}_k = \tilde{\mathbf{z}}_k + \mathbf{H}_1\left(\mathbf{x}_k - \tilde{\mathbf{x}}_k\right) + \mathbf{V}\mathbf{v}_{\mathbf{1}k} \quad (13)$$

where, $\tilde{\mathbf{x}}$ and $\tilde{\mathbf{z}}$ are the approximate state and measurement variables without considering the process disturbance and measurement noise as indicated by equations

$$\tilde{\mathbf{x}}_{k+1} = \mathbf{f}\left(\hat{\mathbf{x}}_k^{+}, \mathbf{u}_k, 0\right) \quad (14)$$

$$\tilde{\mathbf{z}}_k = \mathbf{g}\left(\tilde{\mathbf{x}}_k, 0\right) \quad (15)$$

where $\mathbf{A_1}$ is the matrix of the partial derivative of **f** with respect to **x**, **W** is the matrix of the partial derivative of **f** with respect to $\mathbf{w_1}$, $\mathbf{H_1}$ is the matrix of the partial derivative of ***g*** with respect to **x** and **V** is the matrix of the partial derivative of ***g*** with respect to $\mathbf{v_1}$.

Now the following recursive algorithm is used to obtain the estimate of the state variables:

1. The a priori estimate in the $(k+1)^{th}$ interval of time is obtained through

$$\hat{\mathbf{x}}_{k+1}^{-} = \mathbf{f}\left(\hat{\mathbf{x}}_k^{\,+}, \mathbf{u}_k\right).$$

2. The a priori error covariance in the $(k+1)^{th}$ interval of time is obtained through

$$\mathbf{P}_{k+1}^{-} = \mathbf{A_1}\mathbf{P}_k^{+}\mathbf{A_1}^T + \mathbf{W}\mathbf{Q}\mathbf{W}^T.$$

3. The Kalman gain $\mathbf{K}_{k+1}$ is calculated through

$$\mathbf{K}_{K+1} = \mathbf{P}_{k+1}^{-}\mathbf{H}_1^{\,T}\left[\mathbf{H}_1\mathbf{P}_{k+1}^{-}\mathbf{H}_1^{\,T} + \mathbf{V}\mathbf{R}\mathbf{V}^T\right]^{-1}.$$

4. Then, the a posteriori state estimate is calculated through

$$\hat{\mathbf{x}}_{k+1}^{+} = \hat{\mathbf{x}}_{k+1}^{-} + \mathbf{K}_{k+1}\left(\mathbf{z}_{k+1} - \mathbf{g}\left(\hat{\mathbf{x}}_{k+1}^{-}\right)\right).$$

5. Finally, the a posteriori error covariance is obtained through

$$\mathbf{P}_{k+1}^{+} = \left[\mathbf{I} - \mathbf{K}_{k+1}\mathbf{H}_1\right]\mathbf{P}_{k+1}^{-}.$$

In the present study the density of vehicles (ρ) expressed in *PCU/km* and the rates at which vehicles are exiting from the section (q_{ex}) in *PCU/hr* were taken as the state variables of interest. The output variable was taken as the measured values of q_{ex}. The rates at which vehicles enter into the section from upstream and from the side road in *PCU/hr* were provided as inputs to the estimation scheme. Here the parameters **x**, **u**, **z** and $\mathbf{H_1}$ were obtained as

$$\mathbf{x} = \begin{bmatrix} \rho \\ q_{ex} \end{bmatrix}, \quad \mathbf{u} = \begin{bmatrix} q_{en} \\ q_{side} \end{bmatrix}, \quad \mathbf{z} = q_{ex}, \quad \mathbf{H_1} = [0\ 1]$$

The parameters **W** and **V** were assumed as

$$\mathbf{W} = \begin{bmatrix} h & 0 \\ 0 & h \end{bmatrix}, \mathbf{V} = 1.$$

In the free-flow regime the quantity **f,** the non-linear function relating the state **x** at $(k+1)^{th}$ instant to the k^{th} instant and $\mathbf{A_1}$, the matrix of partial derivative of **f** with respect to the state **x** were obtained as

$$\mathbf{f}=\begin{bmatrix} \rho(k)+\dfrac{h}{L}\left(q_{en}(k)-q_{ex}(k)+q_{side}(k)\right) \\ q_{ex}(k)+ah\left(53.86.\rho(k).\exp\left(-0.5\left(\dfrac{\rho(k)}{172}\right)^2\right)-q_{ex}(k)\right)+ \\ \dfrac{53.86*h}{L}.\exp\left(-0.5\left(\dfrac{\rho(k)}{172}\right)^2\right)\left(q_{en}(k)-q_{ex}(k)+q_{side}(k)\right) \end{bmatrix},$$

$$\mathbf{A_1}=\begin{bmatrix} 1 & -\dfrac{h}{L} \\ 53.86.\exp\left(-0.5\left(\dfrac{\rho(k)}{172}\right)^2\right)* \begin{pmatrix} a\left(1-\left(\dfrac{\rho(k)}{172}\right)^2\right)+ \\ \dfrac{\left(q_{en}(k)-q_{ex}(k)+q_{side}(k)\right)}{L*172^2} \\ \left(\left(\dfrac{\rho(k)}{172}\right)^2-\left(\rho(k)+1\right)\right) \end{pmatrix} & \begin{pmatrix} 1-ah-53.86*h* \\ \exp\left(-0.5\left(\dfrac{\rho(k)}{172}\right)^2\right)\left(1-\dfrac{\rho(k)}{172^2}\right) \end{pmatrix} \end{bmatrix},$$

In a similar way in congested regime the these papameters

were obtained as

$$\mathbf{f}=\begin{bmatrix} \rho(k)+\dfrac{h}{L}\left(q_{en}(k)-q_{ex}(k)+q_{side}(k)\right) \\ q_{ex}(k)+ah\left(12.146\rho(k)\left(\dfrac{602}{\rho(k)}-1\right)-q_{ex}(k)\right)- \\ \dfrac{12.146*h}{L}\left(q_{en}(k)-q_{ex}(k)+q_{side}(k)\right) \end{bmatrix},$$

$$\mathbf{A_1}=\begin{bmatrix} 1 & -\dfrac{h}{L} \\ -12.146ah & 1-ah+\dfrac{12.146h}{L} \end{bmatrix},$$

The traffic variables required for the implementation of the proposed scheme include flow through the entry and exit points and side roads of the study stretches. All these data were collected from selected sections along the study stretch as detailed in the following section.

IV. DATA COLLECTION AND EXTRACTION

Three sections of roadway AB, BC and AC as shown in Figure 2 were selected for the implementation and corroboration of the model based estimation scheme. The main criteria for the selection of the study sections was the presence of pedestrian foot-over bridges at the entry and exit points which would serve as vantage points for the video data collection. The sections AB and BC have lengths of 1km and 0.738 km. A longer section was also considered between A and C having a length of 1.738 km. Video data were collected at the entry and exit points of the selected sections of roadway and the corresponding data from side road were collected manually. Both the cameras were made to record simultaneously at the entry and exit points. An aerial picture of the study sections at the start of video recording was taken to get a measure of the initial number of vehicles inside the sections. The details of the data collection namely, the dates of data collection, the study stretch chosen and time duration of data collection are enumerated in Table 1.

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Table 1 Details of Data Collection

Section	No.	Date	Duration (Minutes)	Peak/Off Peak
AB (L=1 km)	1	28 July2009	61	Peak
	2	30 June2010	160	Off Peak
	3	03 December 2010	120	Off Peak
BC (L=0.738 km)	4	29 December 2008	53	Peak
	5	02 January 2009	54	Peak
	6	12 September 2009	56	Peak
	7	03 December 2010	117	Off Peak
AC (L=1.738 km)	8	23 September 2010	124	Off Peak
	9	03 December 2010	117	Off Peak

Video data collected at the entry and exit points of the selected sections of roadway were analyzed in the laboratory to manually extract the required data. The flow data at the entry location were extracted for every one-minute interval by counting the number of vehicles traveling in all the three lanes. The classified counts were obtained and converted to PCU per hour flow values using PCU values recommended by the Indian Road Congress [22]. Three vehicle classes were considered in this study namely, Two wheelers (TWs), Three wheelers (ThWs) and Four wheelers (FWs). The average traffic composition of different vehicles present in the study stretch were observed to be around 51%, 7%, 34%, 6% and 2% of TWs, ThWs (auto rickshaw), passenger cars, LCVs and HCVs (Buses and Trucks) respectively. In this study, a weighted average value of PCU was calculated for FWs, considering the proportion of different categories of vehicles coming under the category of FWs as the weights. The variable that is needed for corroboration of the scheme was traffic density and was obtained using input-output analysis [21]. In the input-output technique, an initial count of the number of vehicles existing in the roadway between the entry and exit points is made, to which the number of vehicles entering the section is continuously added and the number of vehicles leaving the section is continuously subtracted to get the density inside the section. The initial numbers of vehicles present inside the section required for the input output analysis were measured from the aerial picture of the section taken at the start of the data collection.

V. CORROBORATION OF MODEL BASED ESTIMATION SCHEME

The developed model based estimation was implemented using the flow data collected from field and by assuming the initial values of the state variables. The results obtained were corroborated by comparing the estimated values of density with that of the actual density values measured from field using input output analysis. The performance was quantified by calculating the Mean Absolute Percentage Error (MAPE) given by

$$MAPE = \left[\frac{1}{N} \sum_{k=1}^{N} \frac{\left| \rho_{est}(k) - \rho_{obs}(k) \right|}{\rho_{obs}(k)} \right] .100, \qquad (16)$$

where $\rho_{est}(k)$ and $\rho_{obs}(k)$ are the estimated and observed or measured values of density in the section during the k^{th} interval of time respectively and N is the total number of observations. The MAPE values for traffic density estimated for all days are given in Table 2. The plots of the estimated values of densities against the measured/observed values for two representative days, one during peak and one during off peak traffic are shown in Figures 3 and 4.

Table 2 MAPE for Density Estimation

Section	No.	Day	Peak/Off Peak	MAPE for Density (%)
AB (L=1 km)	1	28 July2009	Peak	24.4
	2	30 June2010	Off Peak	8.5
	3	03 December 2010	Off Peak	11.3
BC (L=0.738 km)	4	29 December 2008	Peak	17.5
	5	02 January 2009	Peak	17.1
	6	12 September 2009	Peak	28.1
	7	03 December 2010	Off Peak	20.0
AC (L=1.738 km)	8	23 September 2010	Off Peak	14.0
	9	03 December 2010	Off Peak	9.7

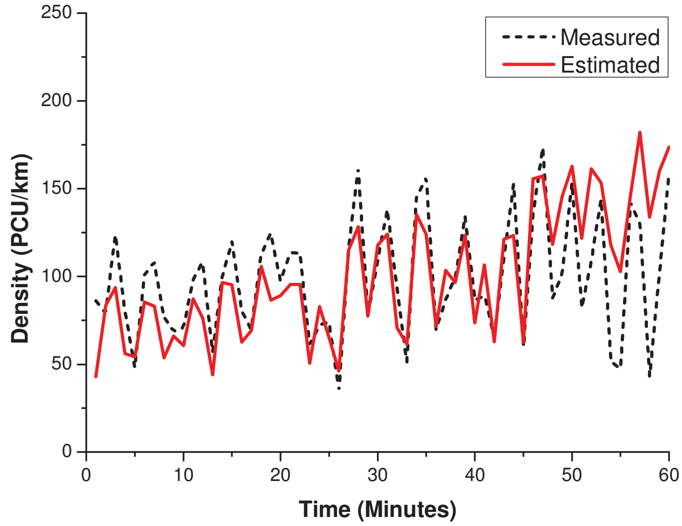

Figure 3 Comparison of actual and estimated density during peak period on Day 1.

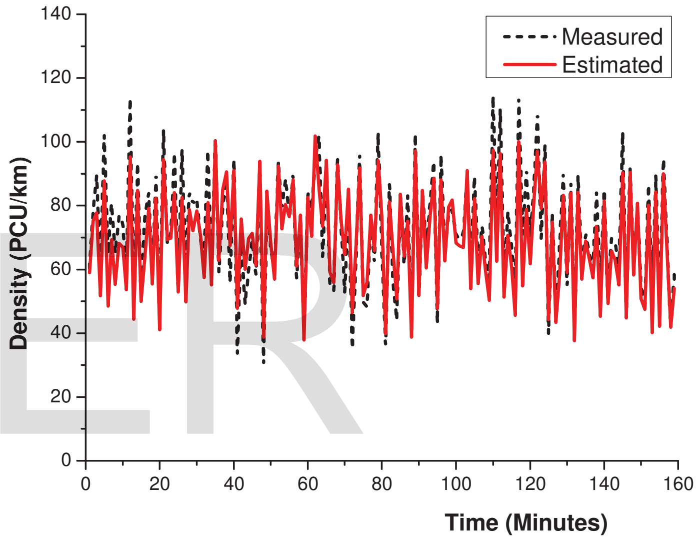

Figure 4 Comparison of actual and estimated density during off peak period on Day 2.

From the results shown in Table 2, it can be seen that the MAPE values for density estimation is varying from 8.5% to 28.1%. According to Lewis' scale of interpretation of estimation accuracy [27], any forecast with a MAPE value of less than 10 % can be considered highly accurate, 11% - 20% is good, 21% - 50% is reasonable and 51% or more is inaccurate. According to this table the results are very good for two days, good for five days and reasonable for remaining two days. These results show that the proposed scheme is giving comparable results and will be useful in real time estimation of traffic density.

VI CONCLUSIONS

This study proposes a macroscopic model based scheme for the estimation of traffic density in real time for managing and controlling traffic congestion through ITS. The details on the formulation of the flow based model, design and corroboration of the estimation scheme using extended Kalman filter are discussed. A macroscopic dynamic traffic flow model based on the lumped parameter approach is proposed in this study. The model was developed based on the conservation of vehicles equation and empirically developed traffic stream model. Using this model and based on extended Kalman filter, the model based estimation scheme was designed. traffic density and flow passing the exit section were considered as the state variables and flow entering through the main road and through the side roads were used as inputs to the scheme. The output variable was the flow passing the exit section and was used for correcting the a priori estimates given by the model equations. Using data collected from the three sections along a study stretch, the proposed scheme was implemented and corroborated. Heterogeneity was incorporated at an aggregate level by expressing the heterogeneous traffic into a homogeneous equivalent using standard static Passenger Car Units (PCU) suggested by IRC. As the model proposed in the present study is macroscopic in nature the aggregate approach using PCU values suggested by IRC is considered to be sufficient. Other approaches namely use of dynamic PCU values and multi-class approaches can form part of future research. Considering the stochastic nature of Indian traffic, the results are promising. Successful implementation of this scheme will be useful in managing traffic congestion through real time ITS.

References

[1] G. R. Jagadeesh, G. R. Dhinesh, and T. Srikanth, "Method for accuracy assessment of aggregated freeway traffic data", IET Intell. Transp. Syst., October 2013, pp. 8.

[2] S. E. Jabari, and H. X. Liu, "A stochastic model of traffic flow: Gaussian approximation and estimation", Transportation Research *B,* 2013, Vol. 47, pp. 15-41.

[3] Y. Wang, M. Papageorgiou, "Real-time freeway traffic state estimation based on extended kalman filter: a general approach.", Transpo. Res. *B*, 2005, Vol. 39, No. 2, pp. 141 – 167.

[4] L. Mihaylova, R. Boel, and A. Hegyi, "Freeway traffic estimation within particle filtering framework", Automatica, 2007 , Vol.43, No. 2, pp. 290-300.

[5] C. M. J. Tampere, and L. H. Immers, "An extended Kalman filter application for traffic state estimation using CTM with implicit mode switching and dynamic parameters", IEEE Intell. Transp. Syst. Conf., 2007, pp. 209-216.

[6] V. Tyagi, S. Darbha, and K. R. Rajagopal, "A dynamical systems approach based on averaging to model the macroscopic flow of freeway traffic", Nonlinear Anal.: Hybrid Syst., 2008, Vol. 2, No. 2, pp. 590-612.

[7] A. Padiath, L. Vanajakshi, S. C. Subramanian, *et al*., "Prediction of traffic density for congestion analysis under Indian traffic conditions", Proc. of the 12th IEEE Intell. Transp. Syst. Conf., Missouri, USA, 2009, pp. 1-6.

[8] I. C. Morarescu ,and C. Canudas –de-Wit, "Highway traffic model-based density estimation", American Control Conference, San Francisco, 2011, pp. 2012-.2017.

[9] C. Dorny, Understanding Dynamic Systes, Prentice-Hall: New Jersey, 1993.

[10] J. Wolf, and A. Paronesso, "Lumped-parameter model and recursive evaluation of interaction forces of semi-infinite uniform fluid channel for time-domain dam-reservoir analysis", Earthquake Engineering and Structural Dynamics, 1992, Vol. 21, pp. 811-831.

[11] R. Pietrabissa, S. Mantero, S., T. Marotta and L. Menicanti, "A lumped parameter model to evaluate the fluid dynamics of different coronary bypasses", Med. Eng. Phys., 1996, Vol. 18, pp. 477-484.

[12] K. M. Nasser, "Development and analysis of the Lumped parameter model of a piezo hydraulic actuato", MS Thesis submitted to Virginia Polytechnic Institute and State University, Blacksburg, Virginia, 2000.

[13] J. V. C. Vargas, and J. A .R. Parise, "Simulation In transient regime of a heat pump with closed-loop and on-off control", International Journal of Refrigeration, 1995, Vol. 18, pp. 235-243.

[14] C. Tulapurkar, and R. Khandelwal, "Transient Lumped parameter modeling for vapour compression cycle based refrigerator", General ElectricInternational Refrigeration and Air Conditioning Conference, 2010, Purdue.

[15] H. Mellor, D. Roberts, and R. Turner, "Lumped parameter thermal model for electric machines of TEFC design", IEE Proceedings on industry application, 1991, p. 138.

[16] D. Gerling, and G. Dajaku, Novel lumped parameter thermal model for electric machines. Technical Report 11, 2004, Institute for Electrical Drives, University of Federal Defense Munich.

[17] E. A. Coddington, An introduction to ordinary differential equations, Dover Publications: New York, 1989.

[18] P. A. Ioannou, and C. C. Chien, "Autonomous intelligent cruise control", IEEE Trans. Veh. Tech., 1993, Vol. 42, No. 4, pp. 657-672.

[19] D. Swaroop, J. K. Hedrick, and C. C. Chien, et al., "A comparison of spacing and headway control strategy for automatically controlled vehicles", Veh. Syst. Dyna. J., 1994, Vol. 23, No. 8, pp. 597-625.

[20] T. Ajitha, and L. Vanajakshi, "Development of optimized traffic stream models under heterogeneous traffic conditions", Proc. of 91st Transp. Res. Board Annual Meeting, Washington, D. C., USA, 2012.

[21] A. D. May, Traffic flow fundamentals, Prentice Hall: New Jersey, 1990.

[22] IRC 106, Guidelines for capacity of urban roads in plain areas, 1990.

[23] F. L. Hall, 'Traffic Stream Characteristics', in Gartner, N. H., Messer, C. J., & Rathi, A. (Ed.): 'Traffic Flow Theory: A State-of-the-Art Report' (Washington, D.C., Transportation Research Board of the National Academies, 2001).

[24] R. E. Kalman, "New approach to linear filtering and prediction problems", Trans. of ASME, J. of Basic Eng. Series D, 1960, Vol. 82, pp. 35 – 45.

[25] P. S. Maybeck, Stochastic models, estimation and control, McGraw-Hill: Singapore, 1984.

[26] F. L. Lewis, Optimal estimation, John Wiley & Sons: New York, 1986.

[27] D. L. Kenneth, and K. K. Ronald, Advances in business and management forecasting, Emerald books: U.K., 1982.