Estimation and prediction of road traffic flow using particle filter for real-time traffic control

Herman Y. Sutarto
SYSTeMS Research Group,
Universiteit Gent,
B-9052 Zwijnaarde, BELGIUM
herman.sutarto@ugent.be
and
Department of Electrical Engineering
Institut Teknologi Harapan Bangsa
Bandung 40132, INDONESIA

Endra Joelianto
Instrumentation and Control Research Group
Bandung Institute of Technology
Bandung 40132, INDONESIA
ejoel@tf.itb.ac.id

Taufik S. Sumardi
Research and Development Center of Roads and Bridges
Ministry of Public Works of Indonesia
Bandung 40294, INDONESIA
taufik.sugian@pusjatan.pu.go.id

***Abstract*—Real-data testing results of a real-time state estimator and predictor are presented with particular focus on the feature of enabling of detector fault alarms and also its relation to queue-length based traffic control. A parameter and state estimator/predictor is developed by using particle filter. The simulation testing results are quite satisfactory and promising for further work on developing a hybrid model of traffic flow that captures the transition between low and high intensity. By using this hybrid model, it may be more feasible to achieve the significant feature of automatic adaptation to changing system condition.**

Keywords—particle filter; traffic flow; intelligent transportation system; estimation; fault detection

I. INTRODUCTION

Excessive energy consumption and greenhouse gas (GHG) emissions are making changes to our living environment that will be damaging in the long term. Road traffic has been a major contributor to such changes. A realistic solution would be to improve fuel efficiency. High speeds, heavy acceleration and lack of anticipation in traffic have been identified as main causes of excessive emission production [1]. One of the problems of lack of anticipation is less coordination between intersections. An important aspect of traffic management for increasing coordination is signal control strategies. Generally, in Asia, signal control is the main strategy to enforce priority at junctions whereas in some European cities priorities rules and roundabouts are used more. The Asian cities have a much higher density than European cities. Clearly that geographical and cultural background will influence the success of any traffic management policies [2]. In this perspective, this paper studies the capability to estimate and to predict the variability of traffic flow which is one of the important issues for defining the performance of transportation management. The capability to accurately estimate and to predict of traffic flow has become more important for coordinating among intersections, especially to reduce congestion and to avoid the grid-lock phenomena over the urban network. By using coordination between local controllers of each intersection, the feasible planning to have efficient and effective dynamic traffic management system can be proposed.

Many papers have proposed techniques to estimate and to predict the traffic flow based upon time series analysis using time invariant linear state-space models [3],[4]. This method usually has a limited capability to characterize the inhomogeneous character of traffic flow. Therefore, it is necessary to develop traffic flow estimator/predictor technique which is working based upon a richer model such as time-varying linear state-space in order to improve an accurate prediction of traffic flow variability. In this paper, we develop a real-time traffic joint parameter and state estimation/prediction in order to give valuable information for feedback control system of each local intersection. In this perspective, traffic flow estimator/prediction is an important parameter for feedback control and it can improve significantly the performance of control system of each local intersection.

In realistic traffic model, states of the system cannot be assumed to be fully observed. In fact, vehicle sensor/detection is affected by errors. Moreover, only flows are detectable, while queues-length are undetectable. For real-time implementation, it is required that the estimator can be rapidly computed based on the measurement data. Moreover, the estimator should be based upon a dynamic and stochastic model to be able to include traffic-flow time-series and random fluctuations characteristic.

Particle filter (PF) is flexible simulation based techniques that has become popular in optimal filtering for general model.

However, standard PF methods assume knowledge of the model parameters but in real application, the parameters are unknown and should be estimated. Optimal filtering with unknown parameters, especially in model with reasonably large number of parameters, remains a challenging problem. Many approaches have been proposed to solve this problem. Important development in this problem appears in [5] and [6]. A kernel approximation of posterior for parameter based on mixture of multivariate normal has been suggested in [5]. The approach is very attractive as it can be applied to any state-space models but it may suffer from an accumulation error over time. In [6], it was proposed that the posterior distribution of parameter depends on low dimensional set of sufficient statistics that can be recursively updated. Another approach was developed by [7] to estimate the parameters obtained by gradient-free maximum likelihood and sampling within particle filtering framework. This method uses the cost function and optimization framework and this leads to highly computationally load.

In this paper, it is introduced a state and parameter estimation technique for stochastic feedback control problems. Moreover, it is studied an estimator with the on-line model parameter estimation which gives significant features besides the opportunity to combine with feedback control. The paper presents a simple stochastic traffic flow model and a particle filter technique to estimate and to predict traffic flow.

II. Problem Formulation

First, this section describes the fundamental of real-time traffic control system by showing in a simple case. Performance of the system is represented by the expected queue length and performed by using traffic flow measurement and phase data of the intersection. By using fluid-flow approach, traffic flow is considered as an important variable. Therefore, the accuracy of traffic flow in term of estimated traffic flow is crucial for defining the system performance.

Let assume that there is an intersection B as a general example case as shown in figure 1. At that intersection, let assume there are two phases, which consist of movement L_2 and L_4 in phase-1 and movement L_1 and L_3 in phase-2. Figure 2 shows phasing information in more detail. In each approach direction of the major link, there are two groups of sensors to detect the vehicles/axles. In Link AB (link between intersection A and B), the first sensor is located few meters from intersection A in order to detect the arrival flow and the second is placed near the stop line of intersection B to count the departure flow. Link CB has the same configuration. Let $\lambda_i(t), \mu_i(t)$ be, respectively, arrival flow rate $[veh/s]$ and departure flow rate $[veh/s]$ in movement L_i. Queue length movement i at time t is defined as the number of vehicles between the first sensor and the second sensor and it is denoted by $Q_i(t)$ [veh].

In this model, the cycle-time is in basic time-unit and let k be index of the cycle. As mentioned above, the basic model is based on fluid-flow approach. The evolution of the queue-length is given by the following equation

$$Q_i(t) = Q_i(t_o) + \int_{t_o}^{t} \alpha_i(t)\, dt \tag{1}$$

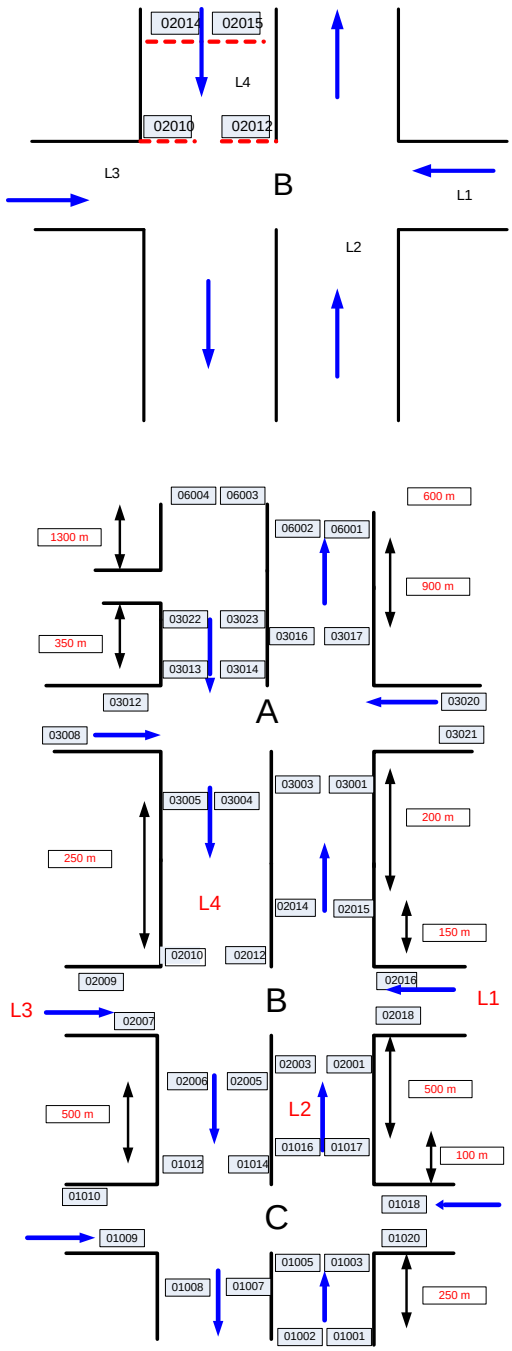

Figure 1. Intersection with sensors location

This queue-length evolution can be estimated by using the measurement of flow α_i. In the case of intersection B in movement L_4, $\alpha_4 = \lambda_4 - \mu_4$. where λ_4 / μ_4 is an arrival/departure flow rate which is a result of summation of the flows detected at sensors 02014/02010 and 02015/02012. In general, it should be noted that queue-length is not a measurable variable; therefore we need a dynamic estimator in order to know the queue-length evolution. In addition, in every measurement, we face the uncertainty/error in the data. The important phenomena that we have to consider in estimating queue-length is the existence of stop and go phenomena that can be considered as a discrete event system in terms of green/red switching times.

As shown in the figure 2, there are two decision variables $T_g[s]$ and $T_r[s]$ in each cycle, where T_g (green period) represents the duration time between switching times t_{2k} and t_{2k+1} and T_r (red period) is between t_{2k+1} and t_{2k+2}. For each cycle, we want to determine these two decision variables to minimize the cost, such as the expected queue-length.

The variability of flow rate α_i during the cycle-time is an important factor in estimating and predicting the queue-length. This variability comes from the presence of platoons released by upstream traffic-light. In this paper, we use the fluid-flow approach, aggregate and average the number of vehicles during a certain period. It is also developed a stochastic model depends on some parameters which determine the characterization of the variability of traffic flow rate. By knowing these parameters through the on-line model parameter estimation, it is possible to achieve significant features such as automatic adaptation to changing system condition and enabling of detector fault alarms etc. Standard estimator methods assume knowledge of the model parameters which are unknown in real application but the parameters should be estimated. Dealing with unknown parameter to perform optimal filtering, especially in model with reasonably large number of parameters remains, is a challenging problem. In this paper, we combine particle filter based approach, kernel smoothing and gradually reduce technique.

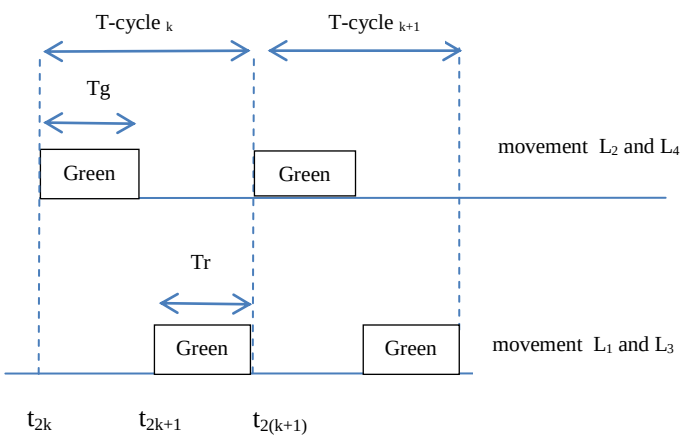

Figure 2. Signal Traffic Sequence

III. PARTICLE FILTER (PF)

State estimation can be seen as an optimal filtering within Bayesian framework. The well known method in this approach is standard particle filter (PF) that solves estimation by reconstructing the probability distribution of the state vector conditional on all available measurements. The approximation of particle filter is much different from that of conventional filters. By approximating a continuous distribution of any form by a finite large number (N) of weighted random samples/particles in the state space then PF has no functional form for the posterior probability distribution. To determine how closely the particles match the measurements, generally, the particles are propagated through dynamic model and then weighted according to the likelihood function. Those that best match the measurements are multiplied and those that do not are discarded. The particles are randomly sampled from an importance function and the importance weight associated with each particle is determined based on the ratio between the posterior pdf and importance function.

A. *PF for state estimation*

Suppose the system is given by the following state and measurement equation:

$$x_{t_k} = f\left(x_{t_{k-1}}\right) + \upsilon_{t_{k-1}}$$
$$y_{t_k} = h\left(x_{t_k}\right) + \eta_{t_k} \qquad (2)$$

where $x_{t_k} \in \Re^{n_x}$ and $y_{t_k} \in \Re^{n_z}$ are state and measurement at time instant k, respectively,

$f : \Re^{n_x} \rightarrow \Re^{n_x}$ and $h : \Re^{n_z} \rightarrow \Re^{n_z}$ are known mappings, $\upsilon_{t_{k-1}}$ and η_{t_k} are state and measurement white noises, described by known probability density function's (pdf) $p\left(\upsilon_{t_{k-1}}\right)$ and $p\left(\eta_{t_k}\right)$, respectively. The noises are mutually independent and independent of initial condition of the state x_0 given by a known $p\left(x_0\right)$.

The filtering problem means looking for an estimate of the state x_{t_k} based on the measurements up to the time instant k, which will be noted as $y^k = y_{1:t_k} = \left[y_0, y_1, ..., y_k\right]$. Due to the stochastic nature of the system, the state is a random variable described by the conditional pdf $p\left(x_{t_k} \middle| y^k\right)$. We will not discuss PF algorithm in detail here. Tutorial paper by [11] provides very good introduction to study PF.

B. *PF for parameter and state estimation*

In this section, we develop and discuss the extension of PF for parameter estimation which is a non-trivial problem.The conventional strategy is to add a random walk to the parameters and then to augment the state-space with the parameters for joint estimation. In this strategy, however, the use of a random walk implies an increase in the covariance of

the parameters. This implication will make the posteriors more diffuse than the actual ones. A natural approach in reducing the covariance is to use kernel smoothing with smoothing factor. Kernel smoothing is a flexible approach to handle both fixed and time-varying parameters [5].

If both states and parameters are to be estimated, joint posterior distribution can be defined by using Bayes's rule:

$$p\left(x_{t_k},\theta_{t_k}\middle|y_{1:t_k}\right)\propto p\left(y_{t_k}\middle|x_{t_k},\theta_{t_k}\right)p\left(x_{t_k}\middle|x_{t_{k-1}},\theta_{t_k}\right)p\left(\theta_{t_k}\middle|y_{1:t_{k-1}}\right)$$

It is clear by now that we need to deal with the problem of not knowing the form of the joint density $p\left(\theta_{t_k}\middle|y_{1:t_{k-1}}\right)$ in order to obtain posterior joint information about states, x_{t_k} and parameters, θ_{t_k}. Joint state and parameter estimation is achieved through the augmentation of the state-space with the parameter vector:

$$\begin{bmatrix} x_{t_k} \\ \theta_{t_k} \end{bmatrix} = \begin{bmatrix} f\left(x_{t_{k-1}},\theta_{t_{k-1}}\right) \\ \theta_{t_{k-1}} \end{bmatrix} + \begin{bmatrix} \upsilon_{t_{k-1}} \\ \varsigma_{t_{k-1}} \end{bmatrix}$$
$$y_{t_k} = h\left(x_{t_k},\theta_{t_k}\right) + \eta\left(t_k\right) \tag{3}$$

In this perspective, the on-line filtering is formulated as a problem of sequentially estimating states and parameters of the new system when the new observation are obtained. The ultimate aim of the estimation is to infer their posterior probability density function. Specifying unknown parameters by Gaussian random walk model enable their adaptation to the new data:

$$\theta_{t_k} = \theta_{t_{k-1}} + \varsigma_{t_k} \tag{4}$$

Where $\varsigma_{t_k} \sim G\left(0,W_k\right)$ is Gaussian zero-mean distribution and predifined covariance. In [8], it has been identified that the random walk implies an increase in the covariance that causes the posterior more diffuse than the actual ones.

We can approaximate $p\left(\theta_{t_k}\middle|y_{1:k-1}\right)$ by mixture of particles:

$$p\left(\theta_{t_k}\middle|y_{1:k-1}\right) \approx \sum_{i=1}^{N} w_{k-1}^{i}\, G\left(\theta;\theta_{k-1}^{i},W_{k-1}\right) \tag{5}$$

The distribution in equation above has a mean of $\overline{\theta}_{t_k}$ and covariance $V_{k-1} + W_k$. It means that the covariance increase over time as a consequence of the random walk. In [5], it was proposed kernel smoothing with smoothing factor $\left(1 > h > 0\right)$ to reduce the covariance:

$$p\left(\theta_{t_k}\middle|y_{1:k-1}\right) \approx \sum_{i=1}^{N} w_{k-1}^{i} G\left(\theta;m_{k-1}^{i},h^2\, V_{k-1}\right) \tag{6}$$

The kernel location m_{k-1}^{i} is used to force the particles to be closer to their means:

$$m_{k-1}^{i} = \left(\sqrt{1-h^2}\right)\theta_{k-1}^{i} + \left(1-\sqrt{1-h^2}\right)\overline{\theta}_{k-1} \tag{7}$$

This method may suffer from an accumulation error over time and it has been proved in traffic flow prediction that the parameter and state do not achieve the convergence. To handle this problem, we use Gradually Reduce (GR) factor instead of Kernel factor proposed in [9] and $p\left(\theta_{t_k}\middle|y_{1:k-1}\right)$ is then changed to:

$$p\left(\theta_{t_k}\middle|y_{1:k-1}\right) \approx \sum_{i=1}^{N} w_{k-1}^{i} G\left(\theta;\theta_{k-1}^{i},k^{-\gamma}W_k\right) \tag{8}$$

where 0< γ < 1 is GR factor.This factor can take less restraint on noise covariance at the initial stage so as to value of parameter estimation can access to true value sufficiently and take great restraint on noise covariance at the transition stage so as to stabilize the value of estimated parameter. In addition, this method needs not to compute Monte Carlo covariance which means less computational load [9].

The basic state estimation algorithm is described as follow:

- *Initialisation: the random samples (particles)* $\left\{x_{t_0}(i): i=1,.....N\right\}$ are drawn from the pdf $p\left(x_{t_0}\right)$.
- Repeat the following steps for each time instant $k\left(k=1,2.....\right)$.

Step 1: Draw N samples $\left\{\upsilon_{t_{k-1}}(i): i=1,.....N\right\}$ from the pdf of system noise.

Step 2: Generate N samples (particles) $\left\{x_{t_k|t_{k-1}}(i): i=1,.....N\right\}$ which approximate the predictive distribution $p\left(x_{t_k}\middle|y^{k-1}\right)$ via state equation (2).

Step 3: On receipt of measurement y_{t_k}, compute the importance weights associated with each predictive samples or particles by:

$$\tilde{\alpha}_{t_k}(i) = p\left(y_{t_k}\middle|x_{t_k|t_{k-1}}(i)\right)$$

and

$$\alpha_{t_k} = \frac{\tilde{\alpha}_{t_k}(i)}{\sum_{j=1}^{N}\tilde{\alpha}_{t_k}(j)} \quad \left(i=1,2,...,N\right)$$

This results in the posterior pdf $p\left(x_{t_k}\middle|y^{k}\right)$ being represented in terms of weighted samples or particles

$$\left\{x_{t_k|t_{k-1}}(i),\alpha_{t_k}(i): i=1,2,...,N\right\}$$

Step 4: Obtain N particles $\{x_{t_k}(j): j=1,.....N\}$ by the re-sampling of $\{x_{t_k|t_{k-1}}(i): i=1,.....N\}$ with sampling probabilities satisfying:

$$\Pr\{x_{t_k}(j)=x_{t_k|t_{k-1}}(i)\}=\alpha_{t_k}(i) \text{ for } j=1,2,....N$$

This results in the posterior pdf $p(x_{t_k}|y^k)$ being represented in terms of weighted particles $\{x_{t_k}(j), N^{-1}: j=1,.....N\}$.

The re-sampling in step 4 is introduced in order to select the fittest samples so as to avoid the problem of sample degeneracy and is carried out using systematic re-sampling algorithm developed in [10]. It is important to keep in mind that for the combined state and parameter estimation, the state variables change to become the augmented state variables as noted in equation (3). By using this consideration, the algorithm is able to perform states and parameters estimation simultaneously.

C. PF for prediction

Based on the filtering distribution $p(x_{t_k}, \theta_{t_k}|y_{1:t_k})$, we could predict the p step-ahead pdf:

$$p(x_{t_{k+p}}, \theta_{t_{k+p}}|y_{1:t_{k+p}})=\int p(x_{t_k}, \theta_{t_k}|y_{1:t_k})\prod_{j=k+1}^{k+p} p(x_j|x_{j-1})dx_{k:k+p-1}$$

The detailed can be seen in paper [11].

IV. THE DATA ANALYZED AND SIMULATION RESULTS

The traffic data for analysis are the discrete time-series of traffic flow recorded at every 15 minutes during Monday, 11st of June 2012 until Friday, 15th of June 2012. The data are taken from 00-24 pm in city of Bandung, Indonesia. The measurement data are used to validate the traffic flow estimator/predictor. The data were taken by using a video sensor.

In figure.3, the pattern of traffic flow during the workdays shows that there is a similarity pattern. On Friday between 12 am-14 pm, the flow pattern is decreasing. This fact comes from that in the duration, Indonesian people go to Mosque for Friday prayer. But the rest, the pattern of flow is a similar. On Tuesday between 14-15 pm, there is also jump down with unknown reason.

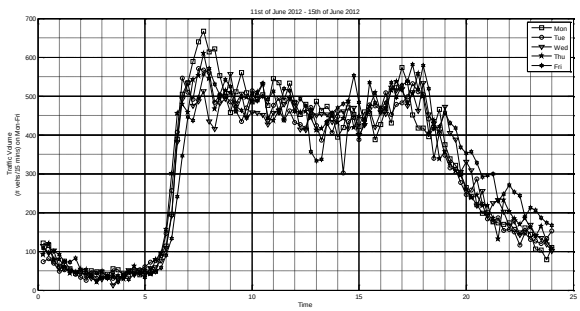

Figure 3 Observed Traffic Volume during weekdays

In this simulation study, we use measurement data only on Tuesday to know the performance of state and parameter estimator/prediction PF against jumping phenomena. For better explanation, we rewrite equation (1) with slight modification by considering only for the traffic flow. It should be noted that t is sampling time update every 15 minute.

State Equation and measurement equation:

$$\lambda(t+1)=a(t)\lambda(t)+b(t)\eta_x(t)+c(t) \quad (9)$$

$$y(t)=\lambda(t)+\eta_y(t)$$

Where $\eta_x(t)\sim N(0,1000)$, $\eta_y(t)\sim N(0,1600)$, $\lambda_0=0$, with particle number N=100, 500 and 5000. GR factor γ for parameters $\gamma_a=0.3$, $\gamma_b=0.5$, $\gamma_c=0.5$

Figure 4 shows that the estimator is able to precisely make real time estimation except during 0-6 am. The reason for this fact is that the PF estimator works with assumption that variance sensor is constant for 24-h period. It is quite unrealistic assumption due to that for variance of the video-type sensor usually depends on the intensity of flow.

Results of the prediction are shown in Figure 5 which are good enough in the real-time perspective, although that during 6-7 am there is big difference between prediction and observation/measurement. However, this is a good indication that we may need another model which has 2-3 modes/regime such as hybrid system. Because there is a big jump in the intensity of flow between (0-6am) and (6-18pm). Using this issue, the PF algorithm should include transition probability among the modes in the PF algorithm

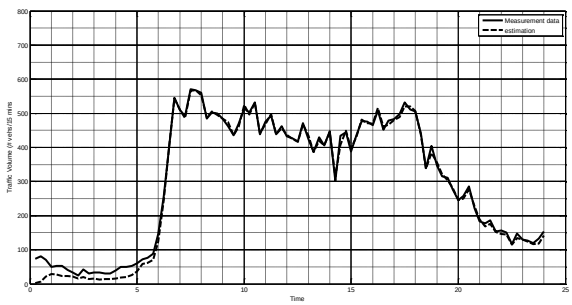

Figure 4 Estimated flow versus observed flow

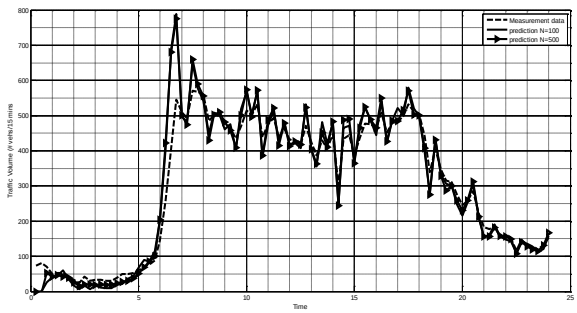

Figure 5 Predicted flow versus observed flow

To examine the performance of estimator/predictor against the fault alarms, the same measurement data on Tuesday during 15-16 pm are set to zero in order to simulate fault alarms in case of strong detector/sensor malfunction. From Figure 6, it looks that the estimator can handle these fault alarms although the transition took one hour to become convergence and the predictor took longer time than estimator. Both predictor and estimator can maintain the convergence. This predicted flow results is quite promising to be combined with stochastic model predictive control along with phase data in case of signalized intersection to reduce the expected queue-length. Figure 7 shows in case of strong detector malfunction, the estimator has a capability to adjust its model parameters radically (see parameters in equation (9)). Hence, the on-line model parameter estimates may also be used as an indicator for serious detector malfunction.

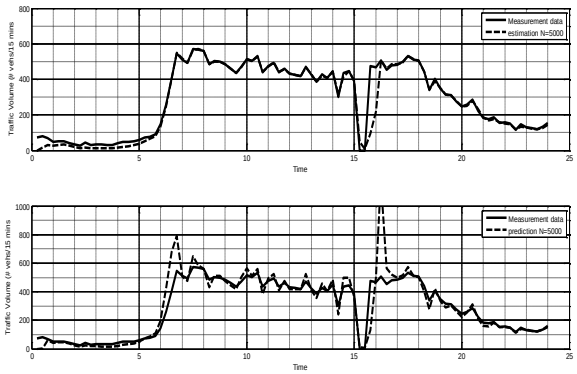

Figure 6 Estimated and Predicted flow against fault alarm

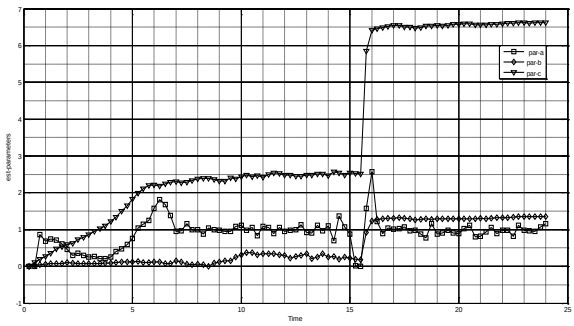

Figure 7 Changing of Estimated Parameter due to sensor malfunction

V. CONCLUSIONS

The real data were reported in this paper to evaluate the performance of parameter and state estimation/predictor. The results demonstrated that the traffic flow estimator and predictor have interesting two features of enabling of: (a) detector fault alarm and (b) automatic adaptation to changing system condition. The further work is needed to improve the quality of adaptation to changing system condition especially to use hybrid model instead of time varying linear state-space model. The predicted flow results are also promising for the development of efficient controller to reduce queue-length in signalized intersection.

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