An Adaptive Kalman Filter based Traffic Prediction Algorithm for Urban Road Network

Zeeshan Hameed Mir[1] and Fethi Filali[2]

Abstract— **Frequent traffic congestion and gridlocks are causing global economies staggering cost in terms of fuel consumption, time wastage, and public health. To rectify this problem, many advocates combining Information and Communication Technologies (ICT) and traffic engineering concepts for better traffic management. Timely and accurate traffic prediction and management are central to the ICT-based Intelligent Transportation Systems (ITS). In this paper, we presented a traffic prediction model based on Kalman filtering theory, which optimizes the prediction of speed by minimizing the variance between the real-time speed measurement and its estimation. The prediction model predicts the speed across high-level roadway segments using historical and real-time speed measurements (spot speed) reported by the vehicles traveling on the urban road network. The performance evaluation of the proposed prediction model includes a number of case studies. Each case study is conducted with different parametric settings to explain the different characteristic of the model. The results show that provided the spot speed measurements don't fluctuate significantly over the time, the proposed model is capable of predicting traffic with 54% more accuracy.**

I. INTRODUCTION

The rate with which urban population and vehicle ownership have increased in last few decades has put immense pressure on the city resources especially the transportation infrastructure. The growing number of vehicles on the roads frequently results in severe traffic congestion with serious economic and social consequences. It has been recently noted that the monetized impact of congestion in Los Angles USA is $23.3B for the year 2013 [1]. In another report, it is revealed that cost of public health only due to traffic gridlocks is projected to reach $4000M in the year 2030 [2]. Traffic gridlocks necessitate an Intelligent Transportation System (ITS) that combines road traffic engineering and emerging Information and Communication Technologies (ICT) to provide information on the current and future highway traffic conditions. With traffic management system in place, commuters can make intelligent decisions before starting a trip or choosing a roadway path, thus effectively minimizing traffic congestion cost in terms of fuel and time wastage, driver frustration, and air pollution.

Maintaining free-flows of traffic on urban highways through traffic prediction and management is an important component of Intelligent Transportation Systems (ITS). To this end, traffic prediction has been extensively studied, and numbers of models and their algorithmic implementations have been proposed. In the literature two main approaches were used to perform traffic prediction, i.e., parametric approach and non-parametric approach [3] [4]. The parametric approach mainly rely on historical averages and smoothing methods such as parameter-based regression [5], Kalman filter [6] [7] [8], Autoregressive Integrated Moving Average (ARIMA) [9] [10] whereas non-parametric approach [11] make use of large datasets and require training process. Non-parametric approach includes techniques like machine learning [12], fuzzy logic [13] and neural networks [14].

Kalman filter had many applications and been utilized to measure noise filtering, estimation, and prediction in a different domain such as economics, signal and image processing, object tracking, etc. Kalman filtering based traffic prediction algorithms have been proposed in [7] to estimate accurate travel time. The proposed model combines data from multiple sources such as vehicle probes and road embedded inductive loop. Similarly, authors in [8], modeled traffic management using extended Kalman filter. Based on the traffic demand captured in the form of sensory traffic information the model predicts evolving traffic dynamics including volume density distribution and rates.

In this paper, a scalar adaptive Kalman filter based prediction model is implemented and evaluated. The given algorithm adjusts process variance based on current speed measurement in each iteration, which qualifies it as an adaptive. The main objective is to predict the forthcoming travel time (average speed) in step of five minutes time interval. The algorithm relies on historical and real-time speed measurement data reported by the vehicles traveling on the urban road network of Doha city in the State of Qatar. A one-month long dataset was obtained from the Masarak™[15]. Masarak™[15] captures information such as speed, location, time stamp, etc. from some vehicles equipped with GPS devices. Each vehicle (also floating probes) reports on this information to a backend server every 10 seconds. The Masarak™system stores the vehicle identification number, speed, location along with a time stamp (date and time) information that would later be used to estimate travel time, extract traffic demand for Intelligent Transportation Systems (ITS). The evaluation of Kalman filter based traffic prediction algorithm is performed with a variety of parameter settings. The evaluation includes speed prediction for each week of the month, by taking into account both process noise and measurement noise for five minutes time intervals. Finally, several instances of the prediction model are also evaluated in terms of RMSE, MAE, and MAPE prediction error.

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The rest of the paper is organized as follows. Section 2, explains the Kalman filter based traffic prediction model. Section 3, describes the data structure and the algorithmic representation of the proposed prediction model. In Section 4, evaluation of the proposed model under different parameter settings are discussed. Section 5 concludes this study.

II. KALMAN FILTER BASED PREDICTION MODEL

The Kalman filter is a discrete-time linear dynamic system [16], described using two equations given in Eq. (1),

$$\begin{aligned} x_k &= Ax_{k-1} + Bu_k + w_k \\ z_k &= Hx_k + v_k \end{aligned} \tag{1}$$

The first equation shows how the current value of the state represented by variable x_k changes at each time steps k. The equation states that the current value of the variable x at time step k is equal to the previous value of the state, i.e., at time $k-1$ multiplied by a parameter A. The other terms in the equation are control input u_k multiplied by a constant B and the noise given as w_k (also *process noise*). The second equation deals with how the measurement value of the state represented by z_k relates to the current state x_k as multiplied the parameter H and noise v_k (also *measurement noise*). For our purpose of speed prediction, we assume the values of parameters A, B, H to be numerical constants and set to 1 with no control signal u_k. Both w_k and v_k noises are considered Gaussian noise and represented by the normal probability distribution functions $N(0, Q)$ and $R(0, R)$, respectively. These noise functions with 0 mean and Q and R variances also termed as process variance and measurement variance, respectively.

The Kalman filter algorithm consists of two distinct steps, namely the *time update* step, and the *measurement update* step, each with its set of equations termed as prediction equation and correction equation, respectively. The time update step uses previous time step state to predict the current time step state while taking into account the noise. This is done by mean of prediction equations, given in Eq. (2),

$$\begin{aligned} \hat{x}_k^- &= A\hat{x}_{k-1} + Bu_k \\ p_k^- &= Ap_{k-1}A^T + Q_k \end{aligned} \tag{2}$$

Eq. (2), predicts the next estimate of state and its variance, respectively. Here, $\hat{x}_k^-$ is a prior state estimate and p_k^- is a prior state estimate variance and is used in the measurement update step. The measurement update step incorporates new measurement in a priori estimate using correction equation. The correction equation finds a posteriori state estimate $\hat{x}_k$ as the linear combination of a priori state estimate $\hat{x}_k^-$ and weighted differently between an actual measurement z_k and the measurement prediction $H\hat{x}_k^-$, as given in Eq. (3).

$$\hat{x}_k = \hat{x}_k^- + G_k(z_k - H\hat{x}_k^-) \tag{3}$$

Here the term $z(k) - H\hat{x}_k^-$, is the residual which represents the discrepancy between the predicted measurement $H\hat{x}_k^-$ and the actual measurement z_k. Whereas G_k, given in Eq. (4) is the gain (also *Kalman Gain*) that minimizes the a posteriori variance given in Eq. (5).

$$G_k = \frac{Hp_k^-}{H^T p_k^- + R_k} \tag{4}$$

$$p_k = (I - HG_k)p_k^- \tag{5}$$

Both prediction equations rely on the a posteriori state estimate and variance values from the previous time step. Therefore, at the start of the Kalman filter process initial estimates of these two parameters referred as $\hat{x}_{k-1}$ and p_{k-1} are required.

III. DATA STRUCTURE AND ALGORITHMIC REPRESENTATION

Before the algorithmic representation of the Kalman filter is described, the dataset obtained from Masarak™[15] is explained. It also includes the detail process with which the raw speed data is mapped into data structures for more convenient consumption by the Kalman filter algorithm.

A. Dataset and Data Structure

The raw dataset contains one-month long spot speed observations for the month of April 2014. It includes more than 1.5 million observations made by vehicles traveling across 33 unique high-level segments. Each observation is a semi-colon separated record with fields, given in (Segment Number, Timestamp, Spot Speed) format, for example (2575; 2014-04-05 00:00:20.039157+03; 58.39). Firstly, each field is stored as a separate column in a tabular format. Additional information such as the month of the year, the day of the week, time of the day and whether weekdays or weekend are extracted and stored in the tabular data structure for facilitating further processing. Secondly, a high-level segment with most observations is shortlisted and selected for further processing.

The spot speed data for the selected segment are not directly used by the prediction algorithm. Instead, the reported observations are aggregated based on multiple factors. Along with the segment number s on which the vehicles were traveling, the day , d_m^n and time t of the speed measurement are also used to calculate the average speed value. After filtering dataset for the given time duration of the day and day of the week, all the measurements are aggregated within the specified time interval t as the sum of all observations within the given time interval, averaged over the number of observations during specified interval t as shown in Eq. (6). Table I, shows the notation used to describe the algorithm.

$$\overline{S}(s, d_m^n, \tau) = \frac{\sum_{i=1}^{N} S_i(s, d_m^n, t)}{N} \quad t_0 \le t \le t_0 + \tau \tag{6}$$

The average speeds of the same day and time duration are further aggregated across multiple consecutive weeks for one month to perform an evaluation on a weekly basis, as shown in Eq. (7). For example, the average speed for four or

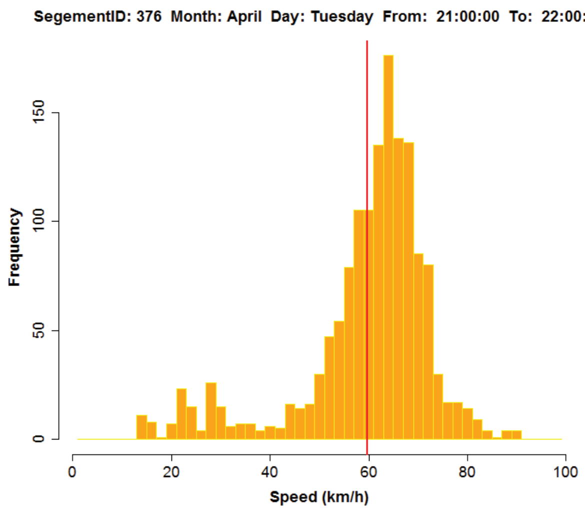


Fig. 1: Speed histogram for one hour time duration between 21:00 to 22:00 over one month period.

TABLE I: Notation used in the algorithmic representation.

Variable	Notation
average speed for given s, d, and τ	$\overline{S}(s, d, \tau)$
i^{th} spot speed reported	S_i
high-level roadway segment	s
day or date	d
time of the day	t
time interval (minutes)	τ
start of time interval	t_0
total number of observations during τ	N
day of n^{th} week in a month (4 or 5)	n
m^{th} day of the week (7)	m

five consecutive Tuesdays in the month of April 2014, over a particular segment, divided in five minutes time interval can be calculated using following equation.

$$\overline{\overline{S}}(s, d_m^n, \tau) = \frac{\sum_{n=1}^{5} \overline{S}(s, d_m^n, \tau))}{n} \tag{7}$$

Some common statistics such as mean, standard deviation, range values regarding the obtained, filtered and aggregated dataset are extracted. For example, the mean value of spot speed for a particular segment, day and time duration over one month is calculated using Eq. (8).

$$\overline{\overline{\overline{S}}}(s, d_m^n, \tau) = \frac{\sum_{m=1}^{7} \overline{\overline{S}}(s, d_m^n, \tau)}{m} \tag{8}$$

Segment number 376, and Tuesday between 21:00 and 22:00 are selected as an input to the Kalman filter algorithm. Fig. 1 shows the histogram of spot speed for the chosen one hour, averaged over one month period. Fig. 2, shows the average speed observations for all four Tuesdays along with basic statistic during the month of April, at the selected segment of the roadway, between the specified one hour time duration and averaged over five minutes time interval.

Algorithm 1 Kalman Filter based traffic prediction

Steps:

$k \leftarrow 1; A \leftarrow 1; H \leftarrow 1;$ ▷ Initialize Iteration
$\hat{x}_0 \leftarrow \overline{\overline{\overline{S}}}(s, d_m^n, \tau)$ ▷ Initial a posteriori speed estimate
$p_0 \leftarrow (\overline{\overline{S}}(s, d_m^n, \tau) - \overline{\overline{\overline{S}}}(s, d_m^n, \tau))^2$ ▷ Initial a posteriori speed variance
$R_k \leftarrow 18$ ▷ Measurement noise
$Q_0 \leftarrow (\overline{S}(s, d_m^n, \tau) - \overline{\overline{\overline{S}}}(s, d_m^n, \tau))^2$ ▷ Process noise
for each k **do** ▷ for next time interval
  $\hat{x}_k^- \leftarrow A\hat{x}_{k-1}$ ▷ a prior speed estimate
  $p_k^- \leftarrow Ap_{k-1}A^T + Q_{k-1}$ ▷ a prior speed variance
  $predict_k \leftarrow H\hat{x}_k^-$ ▷ Predict
  $z_k \leftarrow \overline{S}(s, d_m^n, \tau)$ ▷ Current speed measurement
  $residual_k \leftarrow z_k - predict_k$ ▷ Residual (error)
  $G_k \leftarrow \dfrac{p_k^-}{p_k^- + R_k}$ ▷ Kalman Gain
  $\hat{x}_k \leftarrow \hat{x}_k^- + G_k(residual_k)$ ▷ a posteriori speed estimate
  $p_k \leftarrow (I - HG_k)p_k^-$ ▷ a posteriori speed variance
end for

B. Algorithmic Representation

The algorithm operation starts with the initialization of parameter values such as system gain, process and measurement noise. For simplicity, we assumed the value of A and H to be 1. In traffic prediction model based on Kalman filtering theory R (measurement noise) is based on GPS error. For the given time step, if no speed measurements are available then the R is set to some very large value (i.e., 1000000). Based on dataset available through the Masarak™[15] system R is found to be 18 and remain constant through all the iterations. Alternatively, the value for R can be estimated based on some observations during the time interval t and how far the prediction interval is from the current time stamp. The process noise is initialized to be the speed variance between the average speed measurement during first five minutes time interval and the mean speed over one month, as given in Eq. (9). The algorithm dynamically adjusts the process noise Q based on current speed measurement.

$$\hat{x}_0 = \overline{\overline{\overline{S}}}(s, d_m^n, \tau) \tag{9}$$

Next, to start the Kalman filter process the initial estimates of a posteriori state and its variance is determined by Eq. (10) and Eq. (11), respectively.

$$p_0 = (\overline{\overline{S}}(s, d_m^n, \tau) - \overline{\overline{\overline{S}}}(s, d_m^n, \tau))^2 \tag{10}$$

$$Q_0 = (\overline{S}(s, d_m^n, \tau) - \overline{\overline{\overline{S}}}(s, d_m^n, \tau))^2 \tag{11}$$

Once the model and the initial values of the variables are determined an iterative procedure between the time update step and measurement update step is carried out. The time update step predicts the current state estimate whereas the measurement update step adjusts the prediction and the

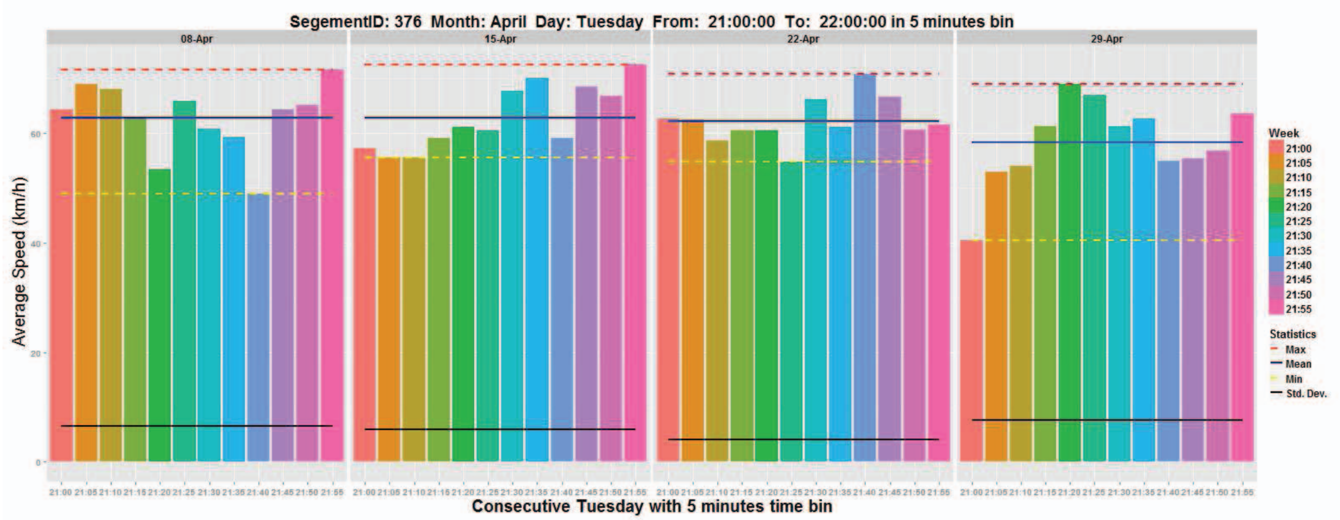


Fig. 2: Average speed for four consecutive Tuesdays, over one month period with five minutes bin between 21:00 to 22:00.

corresponding variance based on the actual state at that time. During each iteration of the Kalman filter, the time update step provides a rough evaluation of a prior state estimate $\hat{x}_k^-$ and estimate variance p_k^- using prediction equations. The measurement update step first calculates the Kalman Gain G_k to refine the prior estimate. The correction equations use prior estimate values and G_k to obtain an improved a posteriori state estimate $\hat{x}_k$ and estimate covariance P_k which are necessary to find the a priori estimate in the subsequent iteration, i.e., future estimate. The algorithmic presentation is formally given in Algorithm 1.

IV. PERFORMANCE EVALUATION

For evaluation of the proposed traffic prediction model three case studies are presented. To understand the characteristics of underlying prediction model each case study is conducted with a different set of parameter settings. Three metrics are used as the criteria to evaluate the accuracy of the prediction models for each case study. (1) Root Mean Square Error (RMSE), (2) Mean Absolute Error (MAE), and (3) Mean Absolute Percent Error (MAPE).

A. Case Study 1: Two different weeks of the month

In the first case study, the evaluation of first and third week data is performed. Fig. 3 show the evaluation for the first week of the month. The a posteriori speed estimations $\hat{x}_k$ are closer to the actual values of speed as compared with the a priori speed estimates $\hat{x}_k^-$. The a priori variance p_k^- begins with large values but quickly decrease except for the time step at *21:40*. For the most time steps, the Kalman Gain G_k drops making the correction lesser and lesser significance and depends more on the prior estimate to get the new a posteriori estimate $\hat{x}_k$. It is important to explain the impact of actual speed value at time step *21:40* where we observed an abrupt change (decrease) in average speed (see Fig. 2). The process noise Q is calculated as the variance between the actual speed value at the current time step and the mean of week-long speed value. The sudden drop in speed at *21:40* results in higher process noise Q, which in turn causes Kalman Gain to attain a very high value. Consequently, a larger correction has to be made where the actual speed value is trusted more instead of a prior estimate $\hat{x}_k^-$ to calculate the a posteriori estimate $\hat{x}_k$.

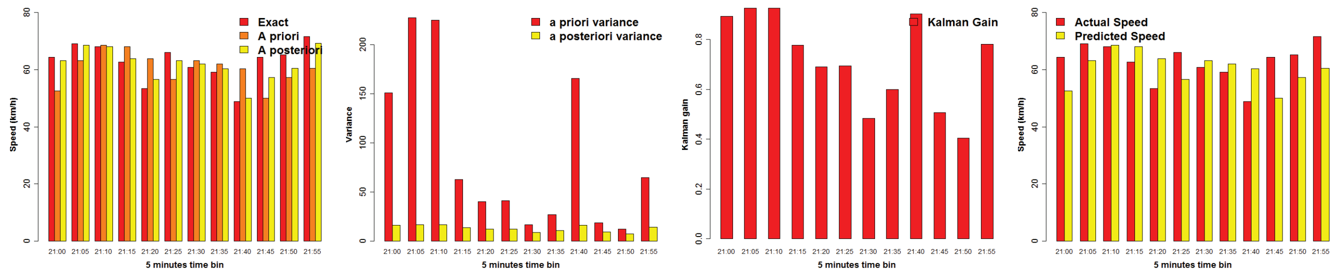
Similar observations are made for other weeks of the month. For example, Fig. 4 show the evaluation of Kalman filter for the 3rd week for the month of April. If the speed measure doesn't fluctuate significantly and the first estimate is good (i.e., smaller a prior variance) there is very little need to correct a prior estimate which means lower Kalman Gain G_k. Therefore to calculate a posteriori speed estimate, the past a prior estimate is highly relied. Fig. 7(a), shows the impact of different weeks on the prediction accuracy of the Kalman filter based speed prediction model. For example between week 1 and week 3, there is 54%, 75% and 80% increase in terms of RMSE, MAE, and MAPE, respectively.

B. Case Study 2: No process noise Q_k

For the second set of results, we assumed no process noise, i.e., Q=0 and compare this setting with the adaptive process noise calculation. As shown in Fig. 5, when process noise is negligibly low or 0, a prior variance p_k^- becomes small as well (by prediction equations). A drop in Kalman gain G_k results in a less significant correction to a prior speed estimate. The drop in G_k is significantly higher in the case where no process noise is assumed. In this scenario, the past a prior speed estimate $\hat{x}_k^-$ is used to form the new estimate, i.e., a posteriori estimate $\hat{x}_k$. On the other hand, if the process noise is high, the Kalman Gain grows high as well. In this case, a posteriori speed estimate takes on the value of the current measurement. Fig. 7(b), shows the prediction model performance for both cases. The scenarios where no process noise is added results in 12%, 17% and 17% decrease in RMSE, MAE, and MAPE errors, respectively.

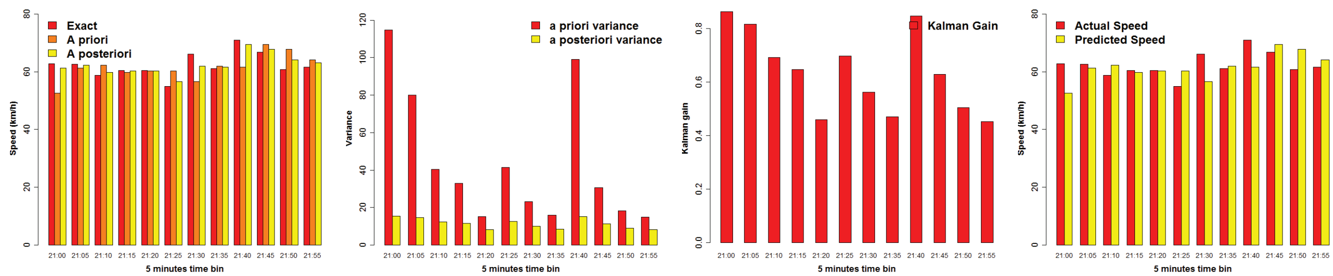
C. Case Study 3: No measurement noise R_k

Finally, the Kalman filter based speed prediction algorithm is evaluated with no measurement noise, i.e., R=0, as shown



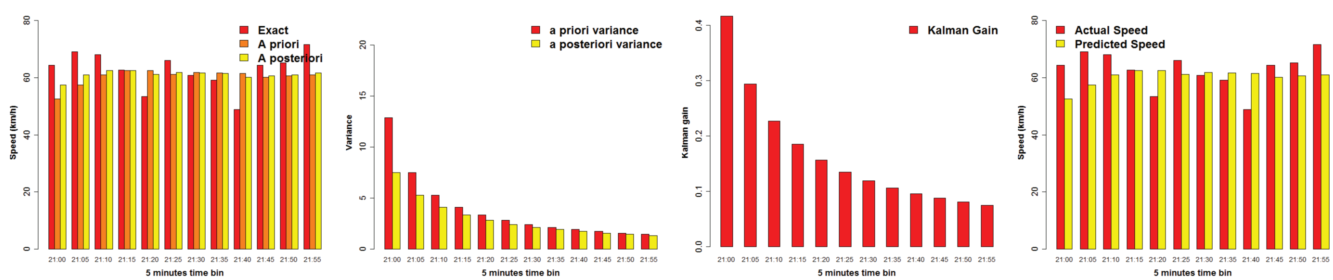
(a) (b) (c) (d)

Fig. 3: Case study 1: (Week 1) (a) x_k, $\hat{x}_k^-$, $\hat{x}_k$ (b) p_k^-, p_k (c) G_k (d) z_k vs. $predict_k$.



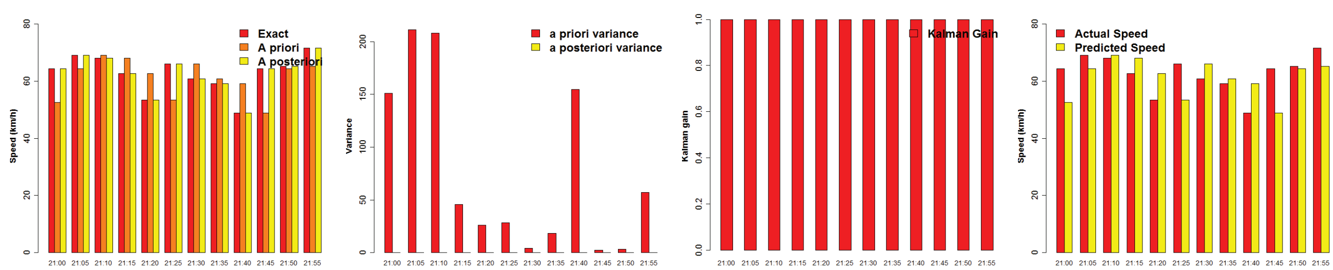
(a) (b) (c) (d)

Fig. 4: Case study 1: (Week 3) (a) x_k, $\hat{x}_k^-$, $\hat{x}_k$ (b) p_k^-, p_k (c) G_k (d) z_k vs. $predict_k$.



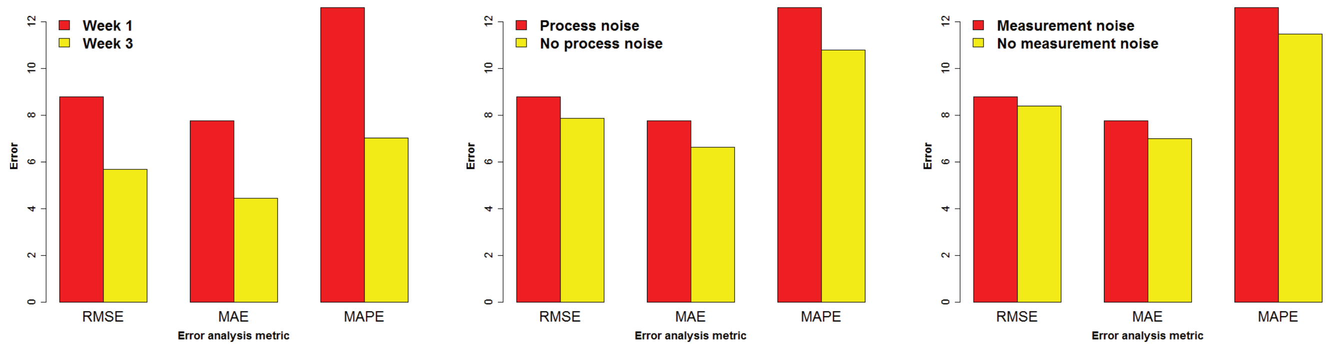
(a) (b) (c) (d)

Fig. 5: Case study 2: (Q_k=0) (a x_k, $\hat{x}_k^-$, $\hat{x}_k$ (b) p_k^-, p_k (c) G_k (d) z_k vs. $predict_k$.



(a) (b) (c) (d)

Fig. 6: Case study 3: (R_k=0) (a) x_k, $\hat{x}_k^-$, $\hat{x}_k$ (b) p_k^-, p_k (c) G_k (d) z_k vs. $predict_k$.



(a) (b) (c)

Fig. 7: Error analysis metric for: (a) Case study 1 (Week 1 vs. Week 3). (b) Case study 2. (c) Case study 3.

in Fig. 6. The value of measurement noise R is based on GPS error which can result in discrepancies in the speed measurements. No measurement noise means that the speed observations made without any discrepancies which may arise due to an error in the GPS error. The larger value of R causes Kalman gain G_k to drop, disregard current measurement and rely on or a prior estimate for the calculation of a posteriori speed estimate. On the contrary, in the case where R is set to 0, G_k remain stagnant at the value of 1, thus result in throwing away of a prior estimate and using of current measurement to calculate the a posteriori estimate. This is true because if the measurement noise is too high, i.e., the error in GPS is too high then we have lower confidence in the speed measurement and the current estimate depend on more upon the previous estimate. Fig. 7(c), shows the prediction model performance for both cases. The case where measurement noise is included results in 5%, 10%, and 11% increase in RMSE, MAE and MAPE errors, respectively.

V. CONCLUSIONS

In this paper, a scalar adaptive prediction model is proposed based on Kalman filtering theory. The proposed prediction model utilizes historical and real-time spot speed measurements obtained from the vehicles traveling on the high-level segments of the roadways. The Kalman filter based prediction dynamically adjusts the process noise Q in each iteration based on the current speed measurement while the measurement noise R remain constant for all the iterations. The objective is to optimize the prediction of speed by minimizing the variance between the actual speed measurement and its estimation. Some case studies are included in the performance evaluation section. The evaluation includes evaluating the prediction model with adaptive process noise, no process noise, with and without measurement noise. The study concludes that given that speed measurements do not fluctuate significantly, this simple scalar model was able to predict with reasonable errors.

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