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A HYBRID APPROACH FOR SHORT-TERM TRAFFIC STATE AND TRAVEL TIME PREDICTION ON HIGHWAYS

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ABSTRACT

Traffic management and traffic information are essential in urban areas, and require a good knowledge about both the current and the future traffic state. Both parametric and non-parametric traffic state prediction techniques have previously been developed, with different advantages and shortcomings. While non-parametric prediction has shown good results for predicting the traffic state during recurrent traffic conditions, parametric traffic state prediction can be used during non-recurring traffic conditions such as incidents and events. Hybrid approaches, combining the two prediction paradigms have previously been proposed by using non-parametric methods for predicting boundary conditions used in a parametric method. In this paper we instead combine parametric and non-parametric traffic state prediction techniques through assimilation in an Ensemble Kalman filter. As non-parametric prediction method a neural network method is adopted, and the parametric prediction is carried out using a cell transmission model with velocity as state. The results show that our hybrid approach can improve travel time prediction of journeys planned to commence 15 to 30 minutes into the future, using a prediction horizon of up to 50 minutes ahead in time to allow the journey to be completed.

INTRODUCTION

Traffic management and traffic information is essential in urban areas. This requires a good knowledge about both the current and the future traffic state. Today, the road infrastructure in urban areas is commonly equipped with different type of sensors, capturing speed, flows and travel time data. To use this data for traffic state estimation is a well-studied area and involves both data filtering techniques and traffic simulation models. Examples of filtering approaches for traffic state estimation can for instance be found in *(1), (2), (3)* and *(4).* Traffic simulation approaches are presented in *(5), (6), (7), (8)* and *(9)*. With the deployment of traffic sensors of various kinds it has become more important to combine these two approaches *(10), (11)* and *(12)*.

While traffic state prediction in general is based on the current traffic state estimate, it is usually considered to be a more complex problem than estimating the traffic state, since the future always is unknown. The literature consists of several examples of applications for traffic state prediction. First and foremost it is a critical component for real-time traffic control and management; see for example *(13), (14), (15)* and *(16)*. The ability to accurately predict the traffic state could increase the traffic manager's ability to take action before the system reaches congestion and then at least forestall that event.

Common non-parametric methods for traffic state and travel time estimation are linear time series, K-nearest neighbors, locally weighted regression, Fuzzy logic, Bayesian networks and Neural networks. For an overview of commonly used methods see e.g. *(17)*. In non-parametric models both parameters and the structure of the model need to be determined from data. Such models are created from a large amount of historical data. They can capture the traffic dynamics even though no knowledge of the traffic processes as such is needed. Non-parametric models all inherit the property that only traffic states already occurred can be predicted. Thus, they are appropriate for predicting recurring traffic conditions, but less appropriate for non-recurring traffic conditions, such as congestion due to road work, events or incidents.

There exist several examples of parametric models which can be applied for the purpose of traffic state prediction. Such examples include the microscopic simulation approach in *(5)* and *(9)*, the mesoscopic simulation approach in *(6)* and the macroscopic traffic flow models in *(7)* and *(8)*. Common for all these models is that they include parameters with a predetermined structure. Still, these parameters need to be calibrated according to empirical data. Parametric models all inherit the property of only describing traffic phenomena which follows from the predetermined relationship between model parameters. Also, they rely on boundary conditions, such as traffic demand, which need to be predicted for the entire prediction horizon.

One way of approaching the shortcomings of both non-parametric and parametric models is to combine them in a hybrid model approach *(18)*. This is for example done in *(19)* and *(20)* by using non-parametric models for predicting demand profiles, to be used in a parametric model. This will, however, require accurate measurements of inflows at on-ramps and outflows at off-ramps, which can be difficult to obtain.

For real-time traffic state estimation purpose, output from a parametric model is assimilated with live sensor data in *(11)*, using a Kalman filtering approach. In this paper we will extend the use of this approach to traffic state prediction. This results in a novel hybrid model, using the filter for assimilating parametric traffic state prediction output with non-parametric prediction of the point speed at several radar sensor locations. Thus, errors from demand profiles based on uncertain measurements can be compensated for by using point speed predictions at mainline sensor locations, which are based on more reliable speed measurements.

As parametric model we will use the cell transmission model with velocity as state (CTM-v) *(11)*, which is a macroscopic traffic flow model, from the family of cell transmission models. This family includes several models which have previously been applied successfully for traffic state estimation on highways. For non-parametric prediction we will use Neural networks, which has shown to be a powerful tool for non-parametric traffic state, travel time and demand profile prediction *(21), (22)* and *(23)*. The contribution of this paper is, however, not in the development of parametric and non-parametric models, but in the way they are combined in the hybrid framework.

In the remainder of this paper the hybrid modeling framework is presented, including the macroscopic flow model and the Kalman filter. Next, the experimental setup is introduced and the results are presented for a 7 km long section of the Stockholm ring road, followed by our final conclusions and suggestions for future work.

THE HYBRID PREDICTION FRAMEWORK

The macroscopic flow model

Both the traffic state estimation and predication will be based on the CTM-v, which is a first order traffic model, developed from the density based cell transmission model (CTM-ρ). The CTM-ρ model is in turn based on the Godunov discretization of the well-known Lighthill-Whitham-Richards model *(24)*. It is possible to directly formulate a velocity based version of the LWR model, but the resulting partial differential equation can only be solved numerically if the relationship between speed and density is assumed to be affine. Therefore the transformation from density to velocity in the CTM-v is done within the discretization scheme.

In the CTM-v, the traffic state is discretized into cells, and for each cell the velocity is used as traffic state. At each time step the LWR partial differential equation is solved numerically using the CTM-v. For each cell the relationship between speed and density is given by a fundamental diagram. Using the velocity as state makes it easy to combine the model output with actual speed measurements from traffic detectors. This is the main reason for adopting the CTM-v rather than the CTM-ρ. The CTM-v, however, requires the velocity function to be strictly decreasing and invertible. Thus, the commonly applied Daganzo-Newell fundamental diagram cannot be used and instead a hyperbolic-linear velocity function is adopted with a linear expression in free-flow and a hyperbolic expression in congestion

$$v = V_{HL}(\rho) = \begin{cases} v_f\left(1 - \dfrac{\rho}{\rho_{max}}\right) & if\ \ \rho \leq \rho_{cr} \\ -w_f\left(1 - \dfrac{\rho_{max}}{\rho}\right) & otherwise, \end{cases}$$

where ρ_{max} is the jam density, v_f the free flow speed, w_f the backward propagating shock wave speed and ρ_{cr} the critical density.

The demand is specified in terms of inflow rates and split ratios at diverging nodes. Inflow rates are considered as boundary conditions to the CTM-v, and the split ratios are specified as parameters in the model. For a comprehensive description of the CTM-v we refer to *(11)*.

Traffic state estimation using ensemble Kalman filtering

As basis for the traffic state and travel time prediction, the current traffic state needs to be estimated. The data fusion model, developed within the Mobile Millennium project and described in *(11)* and *(25)*, is appealing for many reasons. First of all it is developed to run in real-time and for a large network. Furthermore, it can fuse different types of point speed measurements, but the Kalman filter also enables the possibility to include travel time measurements *(26)*. The state-space model of the system is formulated as

$$\begin{aligned} v^n &= M(v^{n-1}) + \eta^n \\ y_k^n &= h_k(v^n) + \chi_k^n \\ \eta^n &\propto (\mu_{\text{mod}}, Q^n) \\ \chi_k^n &\propto (\mu_{obs}, R_k^n) \end{aligned}$$

where v^n is the state vector in time step n, including the speed for each part of the road network (cell) according to the spatial resolution of the system. $M(\cdot)$ is the system model, here the CTM-v model. y^n is the observation vector in time step n and $h_k()$is the observation model for observation type k. η and χ are the possibly time-varying model uncertainty (with mean μ_{mod} and covariance Q) and observation noise (with μ_{mod} and covariance R), respectively.

A number of different adaptions and extensions to the Kalman filter have been proposed over the years. The basic Kalman filter is designed for linear problems but the extension of the CTM-v to networks implies a non-linear and non-differentiable state equation. There exist different extensions to the Kalman filter that can manage non-linearity, where one commonly used example is the extended Kalman filter that has been used for traffic estimation by *(27)* and others. However, in the extended Kalman filter all functions have to be differentiable, which is not the case for CTM-v. An alternative to the extended Kalman filter is the Ensemble Kalman filter (EnKF). The EnKF, first presented by *(28)*, is an extension of the classical Kalman filter that has shown good performance also for non-linear dynamical models *(29)* and can handle non-differentiability. The EnKF belongs to a class of particle methods that use Monte Carlo representation of the probability density functions (PDFs) and their time evolution, and can be viewed as a combination of the Kalman filter and the Particle filter.

In the EnKF the state estimate distribution, the error covariance matrix, is represented as a set of ensembles which makes it suitable for problems with a large state vector, such as traffic state estimation for large networks. The ensemble of model states is propagated forward in time which makes it possible to calculate the mean and covariance of the error needed in the measurement update step. Although the EnKF uses Gaussian assumption on the PDFs, the integration of ensembles through the model will inherit important characteristics of potentially non-Gaussian PDFs as well as non-linearity in the model. For a detailed description of the EnKF the reader is referred to *(28)*.

The traffic state estimation framework is presented in Figure 1. Currently only data from fixed sensors are available in the Stockholm area. This data is pre-processed and later assimilated with the CTM-v every 60 seconds. The framework, however, support multiple data sources as is illustrated, including probe data (e.g. data collected using GPS probes *(30)*).

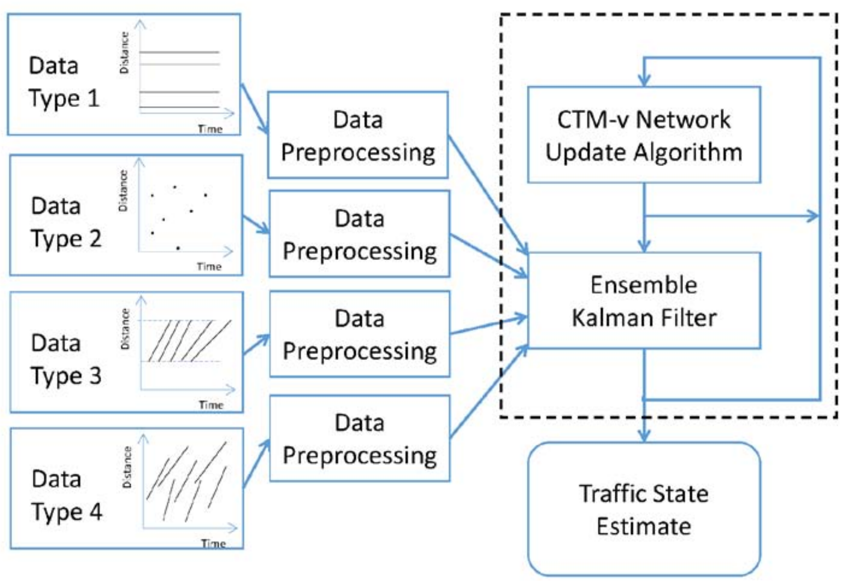

FIGURE 1 The traffic state estimation framework.

The prediction framework

The traffic state prediction framework involves similar components as the estimation framework presented in the previous section, and is illustrated in Figure 2. Starting from a known traffic state (given by the most recent estimation) and predicted inflows and split ratios, the CTM-v can be run forward in time from a known traffic state estimation. Prediction of inflows and split ratios can either be done using non-parametric methods, as is done in *(19)*, *(20)* and *(31)*, or by simple averaging of historical data. Accurate measurements of both inflow rates and split ratios can be difficult to obtain during congested periods. Curbside driving together with blocking back of either the mainline or the ramps may for example result in measurements which does not represent the actual inflow and split ratio profiles. Also, as is pointed out in *(31),* mainline flows are actually aggregations of upstream on-ramp flows, and mainline sensor measurements thus have a reduced noise. This makes non-parametric prediction of mainline flows more accurate in comparison to predictions of on-ramp flows.

It is also possible to combine the CTM-v model with non-parametric prediction of the mainline sensor data, through the EnKF. This results in an alternative hybrid traffic state prediction. Thus, it is possible to take advantage of both the parametric and the non-parametric prediction methods. Using EnKF parameters to govern the influence of each method, either the parametric or non-parametric prediction can be trusted more or less depending on the current traffic situation. As example the non-parametric method may be more trustworthy during recurring congestion situations, and the parametric estimation more reliable when we have non-recurring events such as incidents, which can be modeled as reduced capacities in the CTM-v. This, however, introduce additional filter parameters related to predicted measurement uncertainty, which need to be calibrated.

Prediction of sensor data, to be used in the hybrid prediction, can be done with a number of non-parametric methods. Here, we will use a nonlinear autoregressive neural network with exogenous input (NARX) model. Such a model is commonly used for short-term predictions based on time series analysis, and can include time delay of inputs as well as time delayed feedback loops of outputs. In *(32)* such a model is successfully applied for travel time predictions on a freeway. A similar approach is the state space neural network, applied in *(15)* for prediction of travel times using travel times and flows from fixed traffic sensors as input.

The input for predicting speeds at a specific sensor, with the NARX neural network, will be speeds measured at the specific mainline sensor location, as well as speeds from the surrounding sensors. The NARX model will include time delays of inputs as well as time delayed feedback of outputs. Thus, the predictions will be based not only on the most recent measurements, but on the trend from several recent measurements. Also, time of day and day of week (clustered in Mondays to Thursdays as one cluster, and Fridays and weekend days as their own clusters). Outputs are the speeds for coming time periods at sensor locations.

The setups of both the parametric and non-parametric estimation methods are further described in the next section.

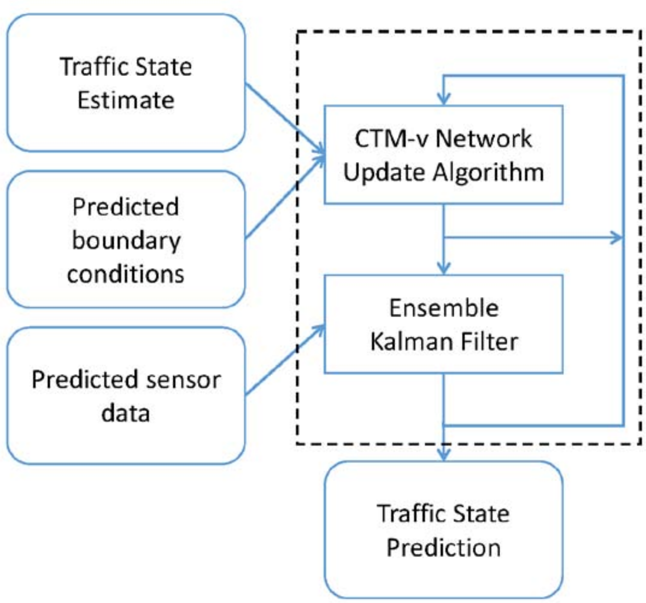

FIGURE 2 The prediction framework.

EXPERIMENTAL SETUP

The Stockholm test site

To analyze the prediction framework we will study a section of the highway just north of central Stockholm. The section is 7 km long and part of the southbound Stockholm ring road. Data from January to March 2013 is used, and for this period radar detector data is available. During March Bluetooth sensor data is also available. The radar detectors collect speed and flow for each lane, aggregated at one-minute intervals, and are illustrated in Figure 3. Bluetooth sensors are placed every 500-1000 meters and collect travel times from all active Bluetooth units which pass two consecutive sensors. The sections with Bluetooth measurements are marked in Figure 3 with BT1 up to BT7, together with the length of each section. There are three on-ramps and three off-ramps within the studied section, and the number of lanes varies between two and four. Bluetooth data is only available for a limited number of days and has only been used for calibration of EnKF parameters and for validation of the results presented in this paper.

In Figure 3, radar sensors with available data are marked with "+". For sensors which are used for the non-parametric prediction, the sensor-ids are included for future references.

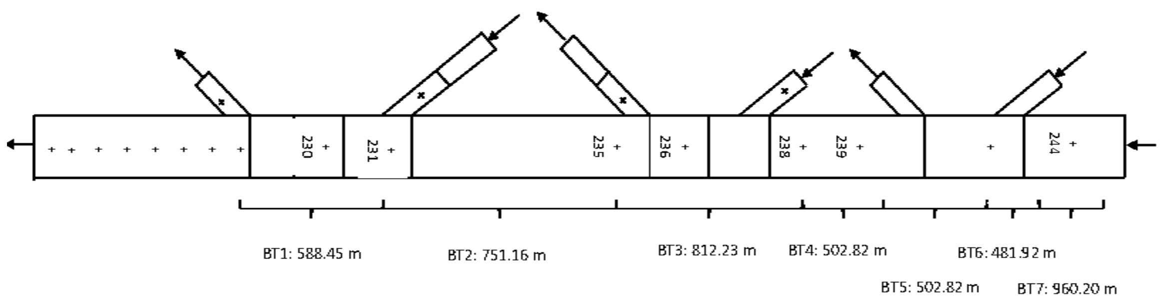

FIGURE 3 The Stockholm test site (not drawn according to scale).

Set-up and calibration of the CTM-v model

Speeds and flow measurements from 23 days (only Mondays to Fridays are selected) have been used for calibrating the fundamental diagrams as well as the inflow at on-ramps and split ratios at diverging nodes.

For cells within each of the marked sections in Figure 3, the same fundamental diagram is used. All fundamental diagrams are specified using the same jam density, which is measured from aerial photos over the Stockholm highway system *(33)*. Free flow speed has been measured using data from Bluetooth sensors. The most downstream section is a bottleneck, which usually is activated both during the morning and afternoon peak period. Capacity measurements has been used for calibrating the shockwave speed (given jam densities and free flow travel times) for the bottleneck. For the remaining sections standard capacities been applied from *(34)*, and for merging sections manually adjusted for the model output to better fit measured data.

Profiles with daily variations of inflows and split ratios are constructed by taking mean values for 15 minute periods from the 23 days used for calibrations. For the most upstream on and off-ramp this is done by comparing the flow before and after the on/off-ramp respectively. For the remaining on-ramps the inflows are measured on the ramp itself, and for the split ratios, flow measurements from the mainline and off-ramp sensors are compared. In the presence of queues, this computation of inflow and split ratios introduces potential errors. The measured split ratios may be an effect of the mainline lane functioning as an extended ramp and the inflows may be restricted by blocking back of queues from the mainline. With no other available information, this is however the best available information to use. Although one should be aware of these shortcomings in the evaluation process.

Sink capacities can be used for restricting the outflow, marked by outflow arrows. If the outflow exceeds the sink capacity, the flow will block back. This can be used to model capacities in the surrounding network, or to model blocking back from the surrounding network. For the studied highway section sink capacities are only set for the outflow at the most downstream subsection, since blocking back from the remaining network is mainly an issue in this subsection. The sink capacity is only lower than the bottleneck capacity at the most downstream section during the afternoon. A sink capacity, as well as, start and end time of the reduced capacity period, has been calibrated based on the 23 calibration days. Length of the afternoon congestion period and the maximum queue length have been the main comparisons used for this calibration. Overall, the afternoon is more difficult to model, due to the blocking back from the remaining traffic network. Validation of the model has been done with data from the 21st of March, and the resulting mean average percentage error (MAPE), as well as mean and maximum errors, are presented in Table 2.

Prediction of sensor data

The non-parametric prediction of speeds at radar sensor locations, using the NARX neural network, is done for sensor 230, 231, 235, 236, 238, 239 and 244. We will refer to these predictions as "predictions of measurements". The time resolution of the predicted measurements is important in order to capture changes in the traffic state. We use a prediction horizon of one hour, and for the first 10 minutes we predict measurements for 2 minute periods, based on mean speed measurements of all sensors for 2 minute periods. For predictions 10 to 30 minutes ahead in time we use a time resolution of 5 minute periods and for 30 to 60 minutes ahead in the future we use 10 minute periods. Using a time delay of five periods in the NARX neural network we look 10 minutes back in time for prediction 10 minutes ahead, 25 minutes back when predicting 10 to 20 minutes ahead in time and 50 minutes back when predicting 30 to 60 minutes ahead in time. The NARX neural network is set-up with an output feedback loop of the two most recent time periods and one layer with ten neurons. Each time period result in a neural network to train and in total we train 12 neural networks for each sensor location, using hour of day and day of week (grouped into working days and weekends), and speed measurements from all sensors. The training is done using 53 days during January, February and March 2013.

MAPE values for predicted measurements on the 21st of March 2013 are presented in Table 1. The MAPE values are based on the difference between predicted and a measured mean value for 2, 5 and 10 minute periods, depending on how far ahead in the future the prediction is. While the MAPE values are not necessarily increased when we predict one time period further ahead in time, the overall trend is that it is an increased uncertainty when predicting measurements further ahead in time. Sensor 244 stands out with the lowest MAPE value, and this is because there are very few time periods of a day when the congestion has reached this sensor, and predicting speeds during non-congested traffic states has shown to be much easier than to predict speeds during congested periods.

TABLE 1 MAPE for predicted measurements

	Prediction horizon measured in minutes ahead in time											
Sensor	1-2	3-4	5-6	7-8	9-10	11-15	16-20	21-25	26-30	31-40	41-50	51-60
230	4.41	4.51	4.77	4.60	4.76	5.61	5.12	5.44	5.42	7.10	7.35	7.48
231	6.05	6.17	6.37	6.55	6.50	7.41	7.62	7.65	7.98	8.46	9.23	10.23
235	6.15	5.65	6.21	6.15	6.09	6.71	7.11	7.00	6.36	11.51	13.01	11.42
236	4.91	4.99	6.38	5.03	6.08	6.82	5.93	6.20	5.97	11.88	13.59	11.89
238	4.70	4.27	5.11	4.88	5.23	7.52	7.01	7.28	7.08	14.69	16.56	15.26
239	4.46	4.35	4.80	4.54	4.67	5.69	6.17	5.97	6.89	9.97	10.07	9.16
244	2.73	2.84	2.92	2.78	2.79	3.29	3.28	3.18	3.06	4.56	4.86	4.98

Estimation and calibration of Ensamble Kalman filter parameters

The measurement noise is assumed to have zero mean and the standard deviation has been estimated to 1 m/s from measurements. The model noise is assumed to have zero mean and standard deviation 0.8 m/s. The model noise standard deviation has been calibrated by evaluating MAPE values between estimated and Bluetooth travel times for a number of different parameter settings. The resulting MAPE values are presented in Table 2.

Predicted measurement uncertainty is assumed to have zero mean and our initial guess of standard deviation was to use the same as for the measurement noise. There is, however, an increased uncertainty in the predicted measurements and the best result has been obtained with a standard deviation twice the one of the measurement noise (2 m/s).

Evaluation of the prediction framework

For evaluation of the hybrid prediction framework we will present results using data from the 21st of March 2013. This data has not been used for either calibration or training purposes.

Speed maps will be used for comparing predictions of the traffic state, with and without measurements, with estimation results. Here the estimation will be used as reference, since it is the best available information, based on all available sensor data and CTM-v output.

Travel times will be predicted for a car entering the highway at time t, by driving a car through the speed map corresponding to the prediction done at time t. Thus this travel time prediction will make use of predicted traffic states ranging from 0 to 20 minutes ahead in the future, depending on how long time it will take to drive through the evaluated highway section (i.e. depending on the level of congestion). Similarly a travel time prediction for a car starting 30 minutes from now will make use of information from a prediction horizon ranging from 30 to 50 minutes into the future. As comparison, a naïve prediction, assuming the current traffic conditions will prevail during the next 60 minutes, is computed (resulting in an instantaneous travel time). Note that the naïve prediction only makes use of the most recent traffic state estimation. A MAPE value based on five minute averaged travel times will be used for comparing the predicted travel times with the reference travel time obtained from driving a car through the estimation speed map. This comparison will be biased from the fact that the estimation may not correspond to the ground truth. Also, since the prediction is done for a car driving the whole section, predicted traffic states further ahead into the future will be used for predicting the later part of the journey in comparison to the early part of the journey. The size of this difference depends on how long time it will take for a driver to drive through the complete highway section and is thus depending on the level of the congestion.

To avoid the shortcomings of comparing predicted and estimated travel times, MAPE values of predicted travel times versus measured travel times (also for five minute averages), using Bluetooth sensors, are computed for seven subsections for which there exists Bluetooth data. The seven subsections cover all but the last section of the highway in Figure 3, and we will compute two different MAPE values based on the measurements. The first one is the mean error across all sections, for the other one we sum up the subsection travel times into a total travel time across all subsections. Thus, the latter one will give approximate travel times for the seven subsections. For the total travel times we also provide mean and maximum absolute errors. Note that all errors computed between predicted and Bluetooth travel times will be based on cars starting at different locations (the beginning of each Bluetooth segment) of the highway at the same time. Each subsection is, however, short and thus predictions at most 35 minutes ahead into the future will be used.

The error values related to the estimation in Table 2 and 3 are based on a car driving through the speed map corresponding to an estimation done after the arrival of the car. Thus, the estimation makes use of measurements which were not available at the time the car entered the section. In comparison, the naïve prediction makes use of the most recent estimation, and assumes prevailing traffic conditions during the time it takes to drive through the section.

RESULTS

Table 2 show MAPE as well as mean and maximum absolute error value for comparison of predicted travel times with measured travel times. For comparison we also provide these error values for the estimation and for the prediction done by running only the CTM-v with boundary conditions but not using the EnKF framework for assimilating the output with speed measurements. This can be done off-line and therefore is a simple approach for predicting the travel times. It should be noted that the entry marked "Estimation" is not a prediction but based on the realized travel times as given by the estimation framework. Similarly "CTM-v" refers to the case when using the CTM-v with historical boundary conditions only. In the other three methods we always start our prediction from the current estimation (denoted "Naïve prediction", "CTM-v prediction" and "Hybrid prediction"). Table 3 shows the same error values for comparison of predicted travel times with estimated travel times.

TABLE 2 Comparison of Predicted and Estimated Travel Times with Measured Travel Times

Prediction/estimation method	Horizon 0	5	15	30
MAPE based on subsection travel times				
Estimation	11.5%	-		
CTM-v	19.3%			
Naïve prediction	13.8%	14.7%	18.5%	27.0%
CTM-v prediction	13.0%	17.6%	16.9%	16.9%
Hybrid prediction	13.0%	15.7%	15.3%	16.6%
MAPE based on total subsection travel times				
Estimation	4.8%	-		
CTM-v	12.8%			
Naïve prediction	5.3%	6.6%	19.5%	19.7%
CTM-v prediction	5.1%	9.2%	10.1%	10.9%
Hybrid prediction	5.5%	6.8%	7.7%	7.9%
Mean absolute error in seconds based on total subsection travel times				
Estimation	22	-		
CTM-v	56			
Naïve prediction	28	32	50	87
CTM-v prediction	25	45	48	49
Hybrid prediction	28	32	39	41
Maximum absolute error in seconds based on total subsection travel times				
Estimation	205	-		
CTM-v	378			
Naïve prediction	245	342	397	571
CTM-v prediction	304	423	445	378
Hybrid prediction	213	237	367	374

The three prediction methods which are based on the most recent estimation plus a prediction show similar results for a car starting its journey at the time of the prediction time, when compared with the Bluetooth reference travel times. For a journey taking place 15 and 30 minutes ahead in time, the hybrid prediction is the best preforming one considering subsection MAPE values, although the differences are rather small when comparing with CTM-v prediction. For the case of a prediction 30 minutes ahead in time, the naïve prediction is performing worse than the CTM-v. Considering the total travel time in Table 1, the hybrid prediction results in lowest maximum absolute error values for all prediction horizons, but for predictions far ahead into the future it tends to the same value as the CTM-v prediction. This could be related to the quality of predicted measurements being less reliable for predictions further ahead in time.

For shorter prediction horizons the use of predicted measurements clearly reduces the maximum error, in comparison to the other approaches.

When comparing against estimated reference travel times, the hybrid prediction is the best performing one from a mean value perspective, for all time horizons. For a worst case scenario the hybrid prediction perform best for a journey taking place 15 and 30 minutes ahead in time, and the CTM-v prediction perform best for journeys taking place 0 and 5 minutes ahead. For prediction of journeys taking place up to 15 minutes ahead, the differences between all three approaches are quite similar. The major difference appears for journey taking place 30 minutes ahead, for which the naïve prediction performs poorly, but for which the CTM-v and hybrid predictions have similar results as for a journey taking place 15 minutes ahead in time.

In Figure 4 the estimated and predicted travel times are shown for a journey taking place at the time of the prediction, and journeys taking place 5, 15 and 30 minutes ahead into the future. For a journey taking place at the time of the prediction (Figure 5a), the naïve prediction is very similar to the estimated travel time. For journeys taking place 5, 15 and 30 minutes into the future, the naïve prediction will simply be offset by 5, 15 and 30 minutes respectively. Thus, since we are comparing with estimated travel times, the height of each peak will be correctly predicted by the naïve prediction but it will be offset in time. During the morning peak period, both the CTM-v and hybrid predictions manage to follow the estimation well, but for the afternoon peak period the hybrid prediction performs better, both in terms of capturing the start and end of the congested period, as well as the length of the travel time.

Figure 5 show speed maps for the estimation, CTM-v, CTM-v prediction and hybrid prediction starting in a known estimation for a 30 minute prediction horizon. The upper part of the speed map corresponds to the end of the highway section illustrated in Figure 3, and vice versa for the lower part. First of all one can notice that the morning peak period is predicted rather well by the CTM-v, the CTM-v prediction and the hybrid prediction. The afternoon peak period is, however, more difficult. For the afternoon it is only the hybrid prediction which capture the last part of the congestion period. Overall the afternoon is more challenging to model since there is a blocking back from outside the modeled network. Clearly the predicted measurements in the hybrid prediction approach capture this better.

TABLE 3 Comparison Between Estimated and Predicted Travel Times

Prediction method	Horizon			
	0	**5**	**15**	**30**
MAPE				
Naïve prediction	4.5%	6.1%	10.7%	17,4%
CTM-v prediction	3.9%	5.7%	7.1%	8,4%
Hybrid prediction	3.9%	4.8%	5.7%	6,1%
Mean absolute error in seconds				
Naïve prediction	27	40	67	107
CTM-v prediction	28	35	44	52
Hybrid prediction	26	32	38	41
Maximum absolute error in seconds				
Naïve prediction	443	518	525	562
CTM-v prediction	225	285	389	341
Hybrid prediction	285	333	248	287

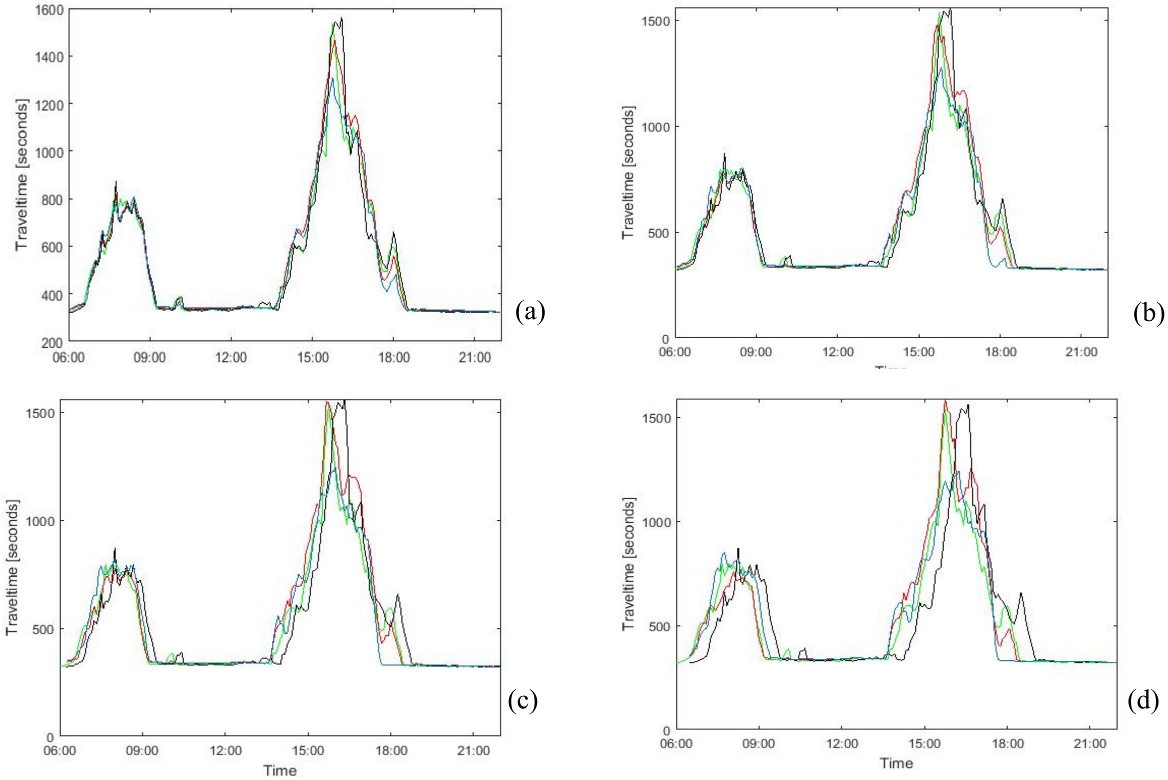

FIGURE 4 Travel time for a journey beginning in 0 (a), 5 (b), 15 (c) and 30 (d) minutes. Showing estimation (green), naïve prediction (black), only CTM-v prediction (blue) and hybrid prediction (red).

CONCLUSIONS AND FUTURE WORK

This paper evaluates a hybrid prediction approach for assimilating parametric and non-parametric traffic state predictions, and applies the approach on a highway section in Stockholm. In our study we have limited the non-parametric prediction to seven sensor locations. Both the CTM-v and hybrid predictions outperform the naïve prediction for longer prediction horizons, but between the two approaches there are smaller differences. Our findings also suggest that the hybrid prediction is an improvement in comparison to the CTM-v prediction for all prediction horizons. Especially for the afternoon peak, for which there are large uncertainties in the input flows, split ratios, and capacities, used within the CTM-v model. In terms of worst case performance, the hybrid prediction is performing better than the CTM-v prediction when comparing with Bluetooth measurements.

Overall the results are encouraging for continuing the work with the hybrid prediction approach. For further improvement the work should focus on:

1. The combination of more advanced techniques for predicting inflows and split ratio, together with predicted measurements.
2. Calibration of EnKF parameters related to predicted measurement uncertainty.
3. Evaluation of alternative techniques for predicting measurements.
4. Evaluation with an increased number of sensor locations used for prediction of measurements.

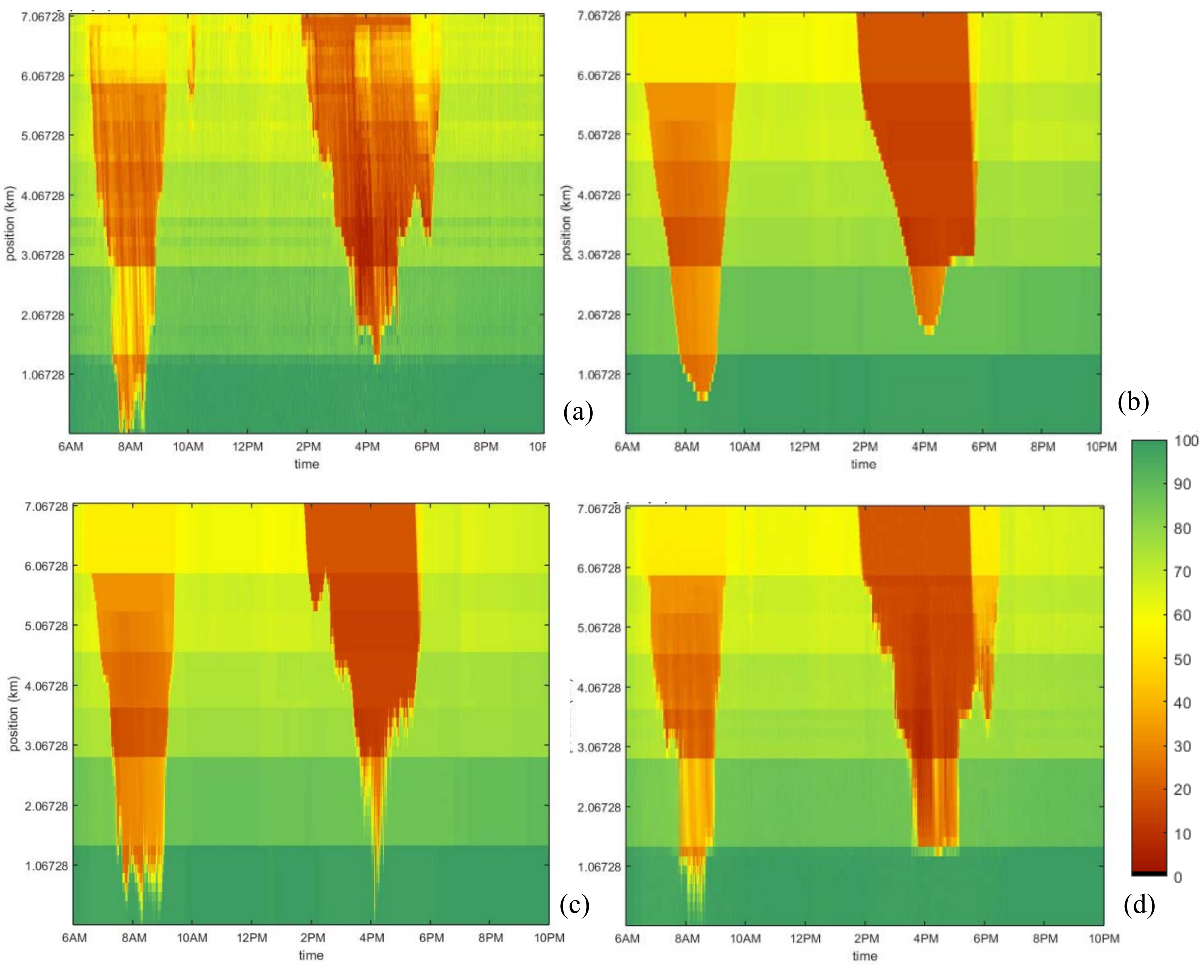

FIGURE 7 Speed maps for estimation (a) and CTM-v (b), 30 minute predictions are presented for CTM-v prediction (c), and hybrid prediction (d). The legend shows velocity in km/h.

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