Calibration of road surface temperature forecasts

J. Kilpinen [1]

[1] Finnish Meteorological Intitute (FMI)

Corresponding author's E-mail: juha.kilpinen@fmi.fi

ABSTRACT

At FMI there is a long tradition to forecast physical road conditions. The first attempts date back to 1970's and nowadays an operation road weather model is used to provide guidance for forecasters and customers.

The present operational road weather model is a 1-dimensional energy balance model, which calculates vertical heat transfer in the ground and at the road-atmosphere interface, taking into account the special conditions prevailing at the road surface and below it [5].

The meteorological forcing variables are ambient temperature, relative humidity, wind speed, short-wave radiation, long-wave radiation (mostly from clouds) and precipitation. The forcing data is from operational HIRLAM model or from ECMWF model.

A calibration test with Kalman filter has been made using local road surface temperature observations and corresponding forecasts for several road weather stations in Finland. The focus of the work is to find optimal ranges of measurement noise and system noise for a practical application. A simple adaptive estimation algorithm for system noise is presented. The results have been promising so far and show strong support for operative application.

Keywords: road surface temperature forecast, Kalman filter, verification

1 INTRODUCTION

One of the most important parameters road weather models provide is road surface temperature. It has been forecast for road maintenance purposes for decades in Finland. The present operational road weather model is a 1-dimensional energy balance model, which calculates vertical heat transfer in the ground and at the road-atmosphere interface, taking into account the special conditions prevailing at the road surface and below it [5]. The forcing for the road weather model comes from Numerical Weather Prediction (NWP) and observations. The meteorological forcing variables are ambient temperature, relative humidity, wind speed, short-wave radiation, long-wave radiation (mostly from clouds) and precipitation. The forcing data is from operational HIRLAM model or from ECMWF model. It is also possible to used gridded NWP output which is modified by duty forecasters.

NWP models have random errors and biases. Some of these biases are even conditional and associated to special weather situations like inversions. All these errors together with errors in road weather model itself create the complex error structure to road surface temperature forecasts. This error structure is studied and some methods to minimize the error are tested.

2 METHODS

Standard statistical forecast verification methods are applied to the data and some methods are tested in post-processing of the output of road surface temperature model.

2.1 Verification methods

For forecast verification standard verification methods are applied. Mean Error (ME) and Root Mean Squared Error (RMSE) are defined by equations

$$\mathrm{ME} = \frac{1}{n}\sum_{i=1}^{n}\left(f_i - o_i\right) \quad \text{and} \tag{1}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(f_i - o_i)^2}\ , \tag{2}$$

where f_i is a forecast and o_i is the corresponding observation and n is the number of cases in the sample.

These error statistics are computed from original and Kalman filtered road temperature forecasts and the results are in chapter 4.

2.2 Post-processing with Kalman filter

There are several statistical post-processing methods which have been used remove biases and other error from weather forecasts. Here some of those methods are tested with road surface temperature forecasts.

In this case, Kalman filtering has been chosen to be applied in post-processing due to the fact that only surface level data is available. If upper level data would be available, also traditional MOS [3] would also be an appropriate method as well. These methods have been applied successfully earlier to different continuous atmospheric variables but not so much to variables like road surface temperature.
A small test was made by MOS techniques applying linear regression. In the test only simple regression was used and results from dependent data set at Karhusaari station were shown.

A two state variable Kalman filter is applied to make the linear (slope and intercept) correction. The update of filter is made recursively once a day with latest observations and forecasts valid at the same time. Kalman filter theory is well known and the method is widely used on post-processing of NWP model output (e.g.[1], [2], [4]). The advantages compared to traditional Model Output Statistics (MOS) (e.g. [3]) are fast adaptation to model changes and less demanding requirement of historical training data. This advantage may also be a disadvantage if the phenomena which were considered do not happen very often. In these phenomena MOS could be in most cases a better method.

Kalman filter is often considered in the framework of a linear dynamic system. The principal problem is to estimate the state of a stochastic dynamic system from noisy measurements. The estimator of state should be optimal in the sense that it minimizes the mean square estimation error and it should be unbiased. The sub-sequent discussion follows mainly the notations in [4] for discrete (time) Kalman (Kalman-Bucy) filter.

The state of a physical system is allowed to change according to a stochastic state equation

$$x_k = x_{k-1} + w_{k-1}, \tag{3}$$

where

x_k is a random vector of system state variables at time t_k ,

$\mathbf{w}_{k-1}$ represents the error of state extrapolation at time t_{k-1} (system noise).

The measurement equation (measurement process) expresses how noisy measurements are given as linear combination of system state variables

$$y_k = H_k x_k + v_k \tag{4}$$

where

$\mathbf{y}_k$ is a random vector of measurements that becomes available at time t_k,

$\mathbf{H}_k$ is an exactly known (nonrandom) matrix of predictors (observation matrix) and

$\mathbf{v}_k$ is measurement noise.

The assumptions associated with measurement process are the same as those in multiple linear regression analysis. The variables in matrix $\mathbf{H}_k$ should be independent from each other and they should be known exactly.

These assumptions are seldom fulfilled in practice because the variables are very often correlated to each other and there are also errors in variables, both systematic and random error.

In the following discussion refers to an estimator, x_k to actual value and to estimation error. The principal issue in Kalman filter is to estimate system state and estimation error covariance from noisy measurements. The other problem is to find the extrapolated system state and estimation error covariance in a noisy physical system.

Equation (7) gives the updated version for of system equation

$$x_{k/k} = x_{k/k-1} + K_k\left(y_k - H_k x_{k/k-1}\right), \tag{5}$$

where $\mathbf{K}_k$ is then

$$K_k = P_{k/k-1} H_k^T \left[H_k P_{k/k-1} H_k^T + V_k\right]^{-1}. \tag{6}$$

It is the so called Kalman gain matrix. The notation $\mathbf{x}_{k/k-1}$ is the estimate of $\mathbf{x}_k$ given observations up to time (k-1). In the following similar notation is used for estimation error covariance $\mathbf{P}_{k/k-1}$ of $\mathbf{x}_{k/k-1}$. Consequently $\mathbf{x}_{k/k}$ is the estimate of $\mathbf{x}_k$ given observations up to time k and $\mathbf{P}_{k/k}$ the estimation error covariance of the effort of $\mathbf{x}_{k/k}$.

The update of estimation error covariance is given by

$$P_{k/k} = \left[I - K_k H_k\right] P_{k/k-1}. \tag{7}$$

The estimation error covariance extrapolation can be written in form

$$P_{k/k-1} = P_{k-1/k-1} + Q_{k-1} \tag{8}$$

These equations provide a priori estimates for next update step.

If we assume that the noise processes are Gaussian i.e.

$$w_k \approx N\left(0, W_k\right), \tag{9}$$

$$v_k \approx N\left(0, V_k\right), \tag{10}$$

the algorithm is exactly the Kalman-Bucy filter.

2.3 Estimation of the noise covariance $\mathbf{W}_k$ and $\mathbf{V}_k$

Both measurement noise $\mathbf{V}_k$ and system noise $\mathbf{W}_k$ have affect on Kalman gain vector $\mathbf{K}_t$ and therefore there is no single solution for the optimizing problem. The minimum of RMS error can be found with several combinations of noise estimates. The tested new system noise algorithm has two scalar gain parameters g_1 and g_2. Gain g_1 determines the rate of change and g_2 the level of increment in the update.

The recursive filter algorithm is as follows:

$$W_k = \left(g_1 - 1\right)\frac{W_{k-1}}{g_1} + \frac{g_2}{g_1}\left(x_{k-1} - x_k\right)^2, \tag{11}$$

where gain parameter g_1 determines the rate of change and g_2 the level of increment in the update of system noise $\mathbf{W}_k$. The increment is the squared difference between the consecutive state $\mathbf{x}$-vectors $\mathbf{x}_{k-1}$ and $\mathbf{x}_k$ corresponding day-to-day variations. This algorithm has some similarities with the approach of Galanis and Anadranistokis (2002) but the main feature is tuning. This algorithm was not tested in this study. In an earlier study the method seems to need some boundary values for accepted noise to keep it optimal.

The optimizing procedure is as follows. Three parameters $\mathbf{V}_k$, g_1 and g_2 have to be chosen so that the minimum available RMS error is received. The other requirement is that parameters g_1 and g_2 are chosen so that the RMSE minimum will be available to longest range on $\mathbf{V}_k$ values. Some test results are given in chapter 4. This algorithm has been applied to atmospheric variables and it has proved to be working. In this new variable it has not been tested earlier.

3 RESULTS

3.1 Testing data

The used testing data includes 3 stations covering period December 2008 – January 2012. On spring time the road weather season ends at the end March and start mostly at the end of October. The period contained very different winters. Winters 2009-2010 and 2010-2011 were much colder and there was much more snow than during the other winters in this chosen period.

The first station is Karhusaari at Helsinki area (City of Espoo) near coat line. This station should differ quite much from the others in terms of climatological conditions (Figure 1). The two other stations are located at Vierumäki (near City of Heinola) (Figure 2) and at Onkiniemi (in Sysmä) (Figure 3) along E75 highway about 120-150 km north of Helsinki. The Vierumäki station is located at a slope facing south-west and there are no major shadowing forests around. Onkiniemi station is on a flat area slightly above average altitude of the area with a small shadowing forest on the eastern side of the road.

Figure 1. Vierumäki (Heinola) (on left) and Onkiniemi (Sysmä) (on the right) road weather stations at highway E75.

3.2 Testing results

MOS testing was only made with Karhusaari station data. Simple linear regression test was made both in dependent and independent data. The test in independent data can show how good a method can be. Tests in independent sample can eventually give comparative results with other methods. The results for Karhusaari station regarding MOS are given in Table 2. To help the comparison with Kalman filtering, verification results of both methods are shown in this table. In verification of road surface temperature forecasts Mean Error (ME) and Root Mean Squared Error (RMSE) are used.

Kalman filter road temperature forecasts and original road temperature forecasts were verified using the same traditional verification measures ME and RMSE as before. The results are in Table 1. The results in Table 1 indicate that Kalman filtering is able to reduce the error even when it is not fully optimized. Normally Kalman filter is able to reduce the bias (ME) and in this case it also happens. In some cases the error characteristics are much better but in some cases the increase of quality is only marginal. Typically these are the cases when the bias is already small in original road temperature forecasts.

Road surface temperature		ORIGNAL		KALMAN FILTER	
	lead time(h)	**RMSE**	**ME**	**RMSE**	**ME**
Vierumäki	**12**	**2.18**	**0.69**	**2.01**	**-0.08**
	24	**2.44**	**1.34**	**2.10**	**0.02**
	36	**2.51**	**0.56**	**2.45**	**-0.12**
	48	**2.67**	**1.27**	**2.38**	**-0.01**
Onkiniemi	**12**	**2.11**	**0.54**	**2.00**	**-0.08**
	24	**2.62**	**1.21**	**2.37**	**0.06**
	36	**2.43**	**0.32**	**2.39**	**-0.08**
	48	**2.73**	**1.16**	**2.53**	**0.01**
Karhusaari	**12**	**2.23**	**1.11**	**1.89**	**-0.05**
	24	**2.74**	**1.95**	**1.88**	**0.04**
	36	**2.32**	**1.12**	**1.99**	**-0.06**
	48	**2.89**	**1.84**	**2.25**	**-0.01**

Table 1. Root Mean Squared Error (RMSE) and Mean Error (ME) of road surface temperature forecasts and Kalman filtered forecasts for three stations over period December 2008 – January 2012. The forecasts are valid in the afternoon (14 local time) for +12h and +36h forecasts and at midnight (02 local time) for +24h and +48h forecasts. For all stations and lead times same noise options were used (g_1=96. g_2=5. $\mathbf{V}_k$=20).

An example of observations. original read surface temperature forecasts and Kalman filtered forecasts is in Figure 2. Note that the time series is not continuous. There are breaks between March and October. The examples are from stations Karhusaari and Onkiniemi. The scatter diagrams of Karsusaari station are in Figure 5.

In Karhusaari station the bias (ME) of original forecast (FOR) is 1.95 degrees Celsius and after Kalman filtering bias is 0.04 degrees Celsius

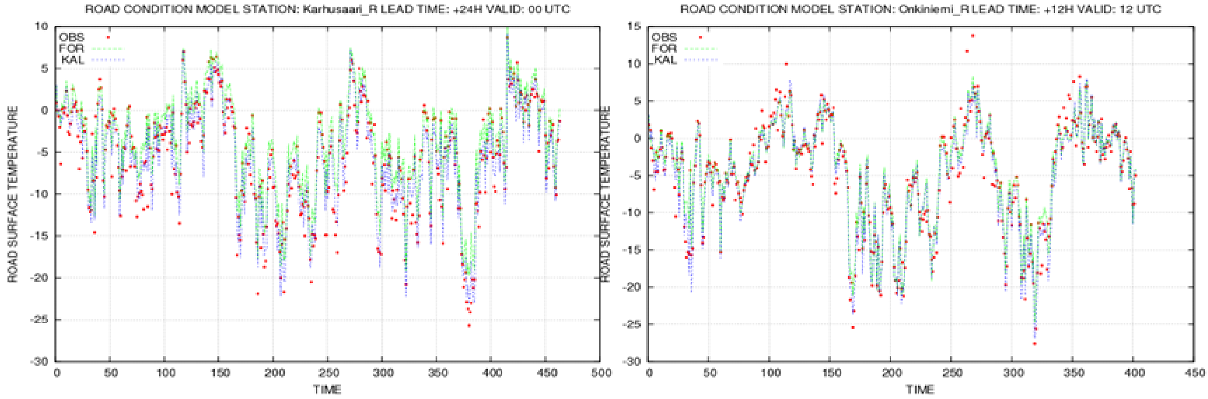

Figure 2. An example of time-series of observed (OBS). forecasted (FOR) and Kalman filtered (KAL) road surface temperature for Karhusaari and Onkiniemi stations during the test period.

It is well known. that if the Kalman filter works optimally. the innovation sequence (the output prediction error) is a white noise. The whiteness property reflects the state estimation quality. For evaluation the filter performance it is necessary to inspect the whiteness property of the innovations. Here auto-correlations functions are computed from all estimation error time series. The examples of these are shown in Figure 3. The results indicate that original errors are still correlated with the previous day's errors (lag -1 days) (correlation is 0.0-0.25). With longer lag times the correlation is quite close to zero but still slightly above it. Auto correlation of error after Kalman filtering is lower than in the original error signal. These results show that the filter is not working in a fully optimal way because there is a slight indication that the output prediction error is not white noise. This feature is typically more evident in pure atmospheric signals like NWP model 2 metre temperature.

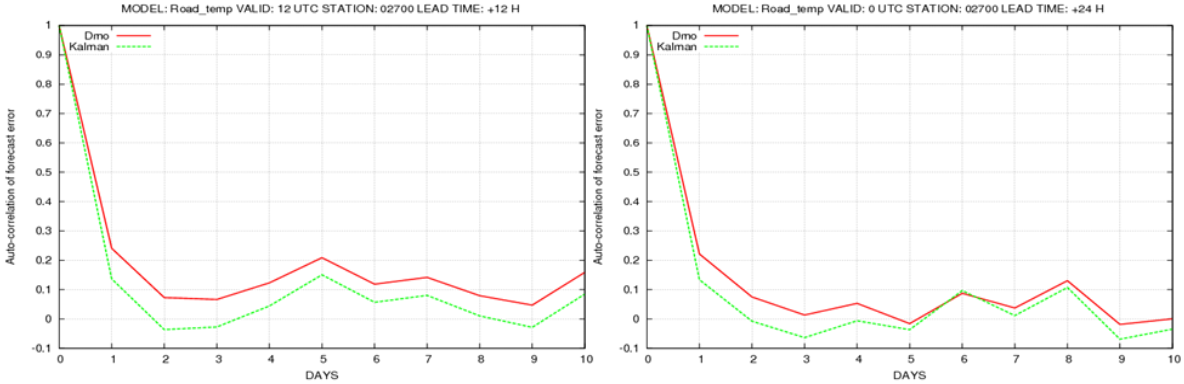

Figure 3. Auto-correlation functions for original (DMO) and Kalman filtered forecast errors of road surface temperature at Vierumäki station (+12h and +24h forecasts).

The optimizing procedure to minimize RMSE of the whole sample was made. At first all Kalman filter estimations were made with first guess values for noise (g_1=96. g_2=5. $\mathbf{V}_k$=20) in Eq. (11). This first guess was made based on tests with atmospheric 2 meter temperature forecasts in Finland. This produced gives a reasonable good results but some fine tuning may be needed. In the proceeding analysis the time evolution of state parameters $\mathbf{x}_1$ and $\mathbf{x}_2$ is shown together with accumulative RMS error. $\mathbf{x}_1$ corresponds the intercept (in linear regression analysis) and $\mathbf{x}_2$ corresponds the slope.

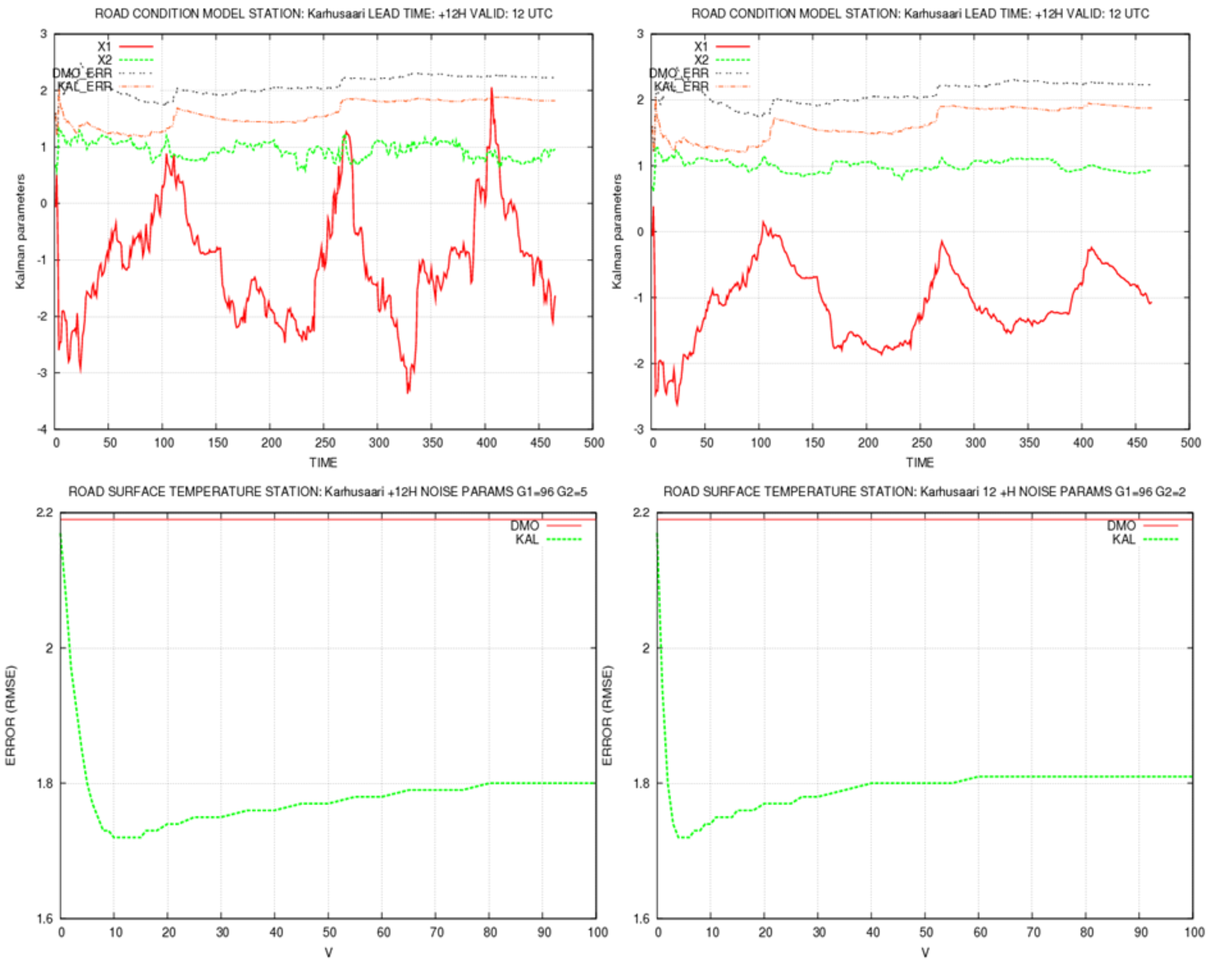

Figure 4. The time evolution of Kalman filter parameters (x_1 and x_2) and accumulative RMSE error for Karhusaari stations (+12h forecasts) (upper panel) and RMSE distribution with different g_2 values in terms of measurement noise V_k (lover panel). In the right column optimized values g_2=5 and V_k=10 are used while in right column suboptimal values g_2=2 and V_k=20 are used.

In Figure 4 (upper panel) the variations of state variables $\mathbf{x}_1$ and $\mathbf{x}_2$ are larger in optimal case (left) than in sub-optimal case (right). One can even see a damping effect in time from winter to winter. One can see the upward kink in cumulative RMSE (DMO_ERR and KAL_ERR) when there is a shift in data from spring time conditions to fall conditions. The same behaviour can also be seen in clearly in variation of state variable $\mathbf{x}_1$ (intercept). This might suggest that the use of larger system noise during the start of new season in fall time could make the filter adapt quicker to new conditions.

Larger g_2 offers more flexibility and a slightly better performance in terms of RMSE (Figure 4. lower panel). In practical applications a broader range of maximum performance is a desirable feature.

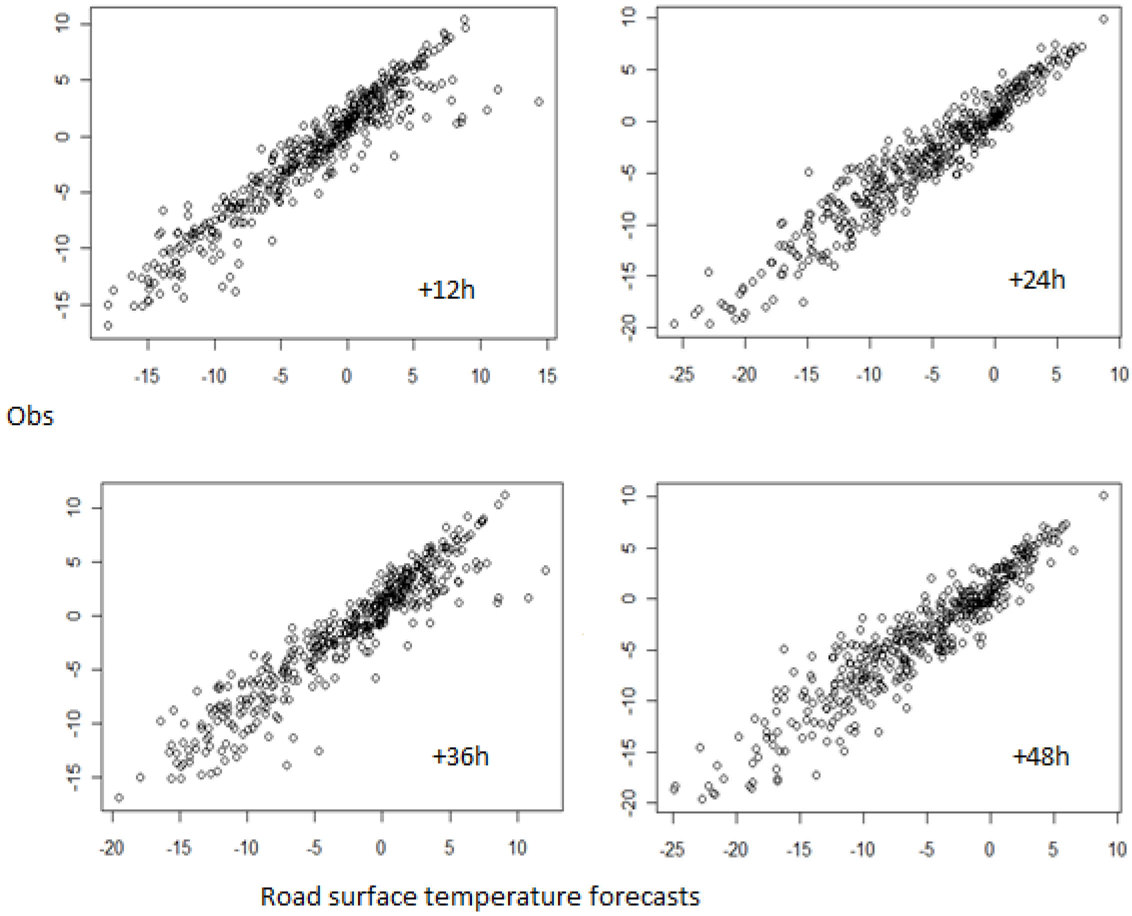

Figure 5. Scatter diagrams of observed (y-axis) and forecasted road surface temperature (x-axis) at Karhusaari station in different lead times (+12h. … . +48h). +12h and +36h forecasts represent local afternoon temperatures and +24h and +48h represent night temperatures slightly before typical minimum temperature.

Road surface temperature		ORIGINAL		MOS		KALMAN	FILTER
Karhusaari	**lead time**	**RMSE**	**ME**	**RMSE**	**ME**	**RMSE**	**ME**
	12	**2,23**	**1,11**	**1,93**	**-0,03**	**1,89**	**-0,05**
	24	**2,74**	**1,95**	**1,89**	**-0,1**	**1,88**	**0,04**
	36	**2,32**	**1,12**	**2,03**	**0,02**	**1,99**	**-0,06**
	48	**2,89**	**1,84**	**2,29**	**0,22**	**2,25**	**-0,01**

Table 2. Verification error statistics for Karhusaari station of original road surface temperature forecasts, MOS forecasts in independent data sample and Kalman filtered forecasts.

Tests with dependent simple regression give results which are slightly better in terms on RMS error than Kalman filtered results. The decrease of error was on average 0.16 degrees compared to Kalman filtering. The decrease on error using Kalman filtering was at Karhusaari station on average 0.54 degrees compared to original forecasts. In the dependent data sample (Table 2.) MOS method provided slightly worse results compared to dependent sample. These error scores also show slightly worse results than for Kalman filtering. However, the difference is only marginal has no meaning on practical applications.

4 CONCUSIONS

Post-processing is able reduce the error of operational road surface temperature forecasts. Kalman filtering offers a practical tool for this work. Other methods like MOS with linear regression would also be possible but they maybe need more effort to implement. In optimizing noise configuration same principle can be applied as in atmospheric variables.

In an operative environment there might be about 50000 separate equations to manage. Kalman filter would therefore be more easy method to implement to operational environment than a MOS system with same amount of correction equations.

5 REFERENCES

[1] Crochet. P.: Adaptive Kalman filtering of 2-metre temperature and 10-metre wind-speed forecasts in Iceland. Meteorol. Appl. 11. 173-187. 2004.

[2] Galanis. G.. and Anadranistokis M.: A one-dimensional Kalman filter for the correction of near surface temperature forecasts. Meteorol. Appl. 9. 437–441. 2002.

[3] Glahn. H. R.. and Lowry D.A.: The use of model output statistics (MOS) in objective weather forecasting. J. Appl. Meteor.. 11. 1203–1211. 1972.

[4] Homleid. M.: Diurnal corrections of short-term surface temperature forecasts using the Kalman filter. Wea. Forecasting. 10. 689–707. 1995.

[5] Kangas M. Hippi M. Ruotsalainen J. Näsman S. Ruuhela R. Venäläinen A. Heikinheimo M. 2006. *The FMI Road Weather Model*. HIRLAM Newsletter no. 51. October 2006. Available from: http://hirlam.org/index.php?option=com_docman&task=doc_details&gid=476&Itemid=70.