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Kalman Filter Preprocessing within METRoSTAT Project and Application of the New Method in the Roadcast System

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ABSTRACT

In this paper we describe the application of Kalman filter preprocessing of selected input parameters for the METRo road forecast model. The Kalman filter corrections to atmospheric and dew point temperatures improve surface temperature as it is shown in selected case studies. The improvement is significant mainly in cases when the turbulent heat exchange is not negligible. We present the statistical analyses of the studied parameters as well. This new method will be implemented as independent module within the statistical METRoSTAT package. The new approach in surface temperature predictions is presented as well.

Keywords: Road Forecasting, Kalman Filter, Air Temperature, Surface Temperature, Heat Diffusion, FFT, METRo model, METRoSTAT project

1 INTRODUCTION

The necessity of specialized weather forecasting for road maintenance companies is well known. One of the main parameters important for road maintenance companies are road surface temperature (RST) and 2m air temperature (AT). The most natural approach to forecast RST is the energy-balance model, based on a one-dimensional diffusion equation [1]. Forecasting of RST is bind directly with an AT throughout turbulent heat flux (H) and water vapor flux (E) indirectly. There are also other indirect relations between AT and RST. The AT enters into road forecast model like METRo from numerical weather prediction (NWP) model like ALADIN and therefore it has systematic error compared to AT measured at road weather stations (RWS). This systematic error could be reduced with the use of Kalman filter. This is the primary goal of this article which is one part of the METRoSTAT project. The road forecast system that was developed at our institute now is using this method in our operational suite and our experience is with this method promising. Other way how to improve our road-cast system is improve the road forecast model like METRo. There was developed a simple heat conduction model based on Fast Fourier Transform (FFT) that could be used directly for prediction of RST or with combination with METRo model it could be used for prediction of all important road forecast parameters. Results are quite promising and we hope that this model will be integrated to METRo model soon.

2 KALMAN FILTER PREPROCESSING OF THE 2M AIR TEMPERATURE

The Kalman filter is state estimation technique developed originally by Kalman [2] in 1960. Its basic idea is simple: Knowing the previous state estimate of the system, try to estimate the next state of the system as accurately as possible, by using the mathematical model of the dynamical system plus measurements of a system state parameters. In theory, evolution of the idealized system can be fully described by its mathematical model (usually given in the form of differential equations). In real world however any mathematical model is always only some approximation of the real system and it is accurate only to some degree. Therefore in the evolution of the mathematical model there is always some uncertainty about the true state of the system. Idea behind the Kalman filter is to combine predictions of the mathematical model with the measurements (observations) of state parameters in order to obtain better estimate about the true system state then it would be possible from either of two alone. Note that true state of the system is inaccessible, since measurements are also not identical with a true state. In first measurements are also inaccurate although their measurement error is usually small, and in second we can measure only some parameters of the system state, not the state itself. For example we can measure pressure and temperature of the gas but we don't know the true microstate of the gas.

The single Kalman filter iteration consists of two steps: prediction followed by measurement update. In the prediction step, estimate in time step n (prediction) is obtained from estimate at time step n-1 using the model operator f. Then if measurement in time n becomes available prediction is updated using this measurement and measurement operator h to obtain the best possible estimate of state in time step n. This procedure can be repeated forward in time arbitrary number of times. In linear KF measurement update is designed as linear minimum mean-squared error estimator [3]. This is why Kalman filter is known as optimal estimator for linear systems (Both f and h operator are required to be linear). Further details about Kalman filter theory can be found in specialized works.

Central object of Kalman filter is state vector $\boldsymbol{x}$ which contains all relevant information about the system state. Observation vector $\boldsymbol{y}$ contains actual measurements related to the system state. Since there must not be one to one correspondence between measurement and state vector, thus generally some mapping is needed between two domains. This mapping is described by measurement operator h.

2.1 Method

Our goal is to produce a most accurate forecast of 2m AT to force METRo road model with most accurate inputs. First, we have AT predictions from NWP model Aladin for RWS locations. Second, we have direct 2m AT measurements (both actual and historical) exactly from the RWS which can be used to improve accuracy of AT forecast.

Homleid [4] developed a special type of Kalman filter which was used to improve surface temperature forecast from numerical weather prediction (NWP) model LAM50 used at Norwegian Meteorological Institute. Inspired by this work we have developed a variant of such KF which can be used to correct arbitrary forecast quantity in principle, although presently we have used it only to correct 2m air temperature which is important parameter for road maintenance by itself, but in addition it is one of the most important input parameter which drives the Metro road model. Homleid type of KF is elegant solution of two main difficulties:

1. Air temperature evolution is given by complex nonlinear NWP model while Kalman filter, as presented in original paper [2], requires a linear system model **F** and also a linear measurement model **H**.
2. We need to correct the 72 hour forecast for air temperature, however KF in its original setup corrects only the actual value of parameter (AT in our case) using the actual measurement. It's not makes correction to future evolution of parameter (forecast)

Solution to the first problem is that it works not directly in parameter space but rather in parameter error space. That means that instead of estimating directly the parameters like AT for example, we are working rather with a model of their errors. This allows using a very simple linear process model of errors development in time along with linear Kalman filter. This greatly reduces a complexity of a problem. However such a simplification of problem goes in hand with some limitations.
Solution to the second problem is specific form of state vector $\boldsymbol{x}$. It consists of N_x parameters each of them representing forecast error in different hour of day. In air temperature preprocessing we are using 24 parametric state vector so that first parameter x_0 is estimated AT forecast error in hour 00, parameter x_1 is error in hour 01 and so on until last parameter x_{23} which is error at hour 23. Drawback of this approach is that it is not fully consistent with Kalman filter formulation because it is using actual measurement to correct forecasted value in some later time (correction backward in time is also possible). To make this work there must be some diurnal variation in weather. If the weather changes abruptly, then filter must not do a good job. However there are techniques to turn off KF in such cases.
Our state vector $\boldsymbol{x}$ represents estimated forecast errors (=forecast value minus true value) for each hour of the day:

$$\vec{x} = (\varepsilon_0, \varepsilon_1, \ldots, \varepsilon_{23}), \text{ where } \varepsilon_i = AT_{fcast} - AT_{true}$$

Observation vector $\boldsymbol{y}$ in our case represents forecast to observation error for actual time:

$$\vec{y} = (e), \text{ where } e = AT_{fcast} - AT_{obs}$$

Thus state space has dimension N_x=24 while observation space has dimension N_y=1.

System model is given with **F**, **H**, **Q**, **R** matrices. Process model is represented by system transition matrix **F** (dimension N_x x N_x). In our case it is a unit matrix which can be explained so that estimated forecast errors $\boldsymbol{x}$ doesn't develop in some predictable way. Measurement model is represented with observation matrix **H** which maps from state domain into measurement domain thus it is N_y x N_x matrix. In our case it has 1 row and 24 columns each of which corresponds to specific hour of the day. All columns are zero except the one corresponding to hour to which current observation **y** belongs to. Process and measurement noise are represented with **Q** and **R** error covariance matrices. Dimension of **Q** is N_x x N_x while dimension of **R** is N_y x N_y. We have used diagonal matrices (no correlations) with equal diagonal elements corresponding to variances σ_Q^2 and σ_R^2. By varying this elements sensitivity of KF to measurements can be set. Note that in actual KF setup they represent in fact error covariance of systematic errors $\mathcal{E}$ and e. **F**, **Q** and **R** were considered constant in time while **H** matrix has changed with time so that unit element was moved between consecutive iterations always by one element to the right.

Starting Kalman filter requires knowledge of previous state vector $\boldsymbol{x}_{n-1}$ and previous covariance matrix $\mathbf{P}_{n-1}$. Two initialization variants are implemented in our code:

- From previous state
- From scratch

By default, if previous state is found in KF internal database then this is used to start KF. If not then initialization from scratch is used, this means initialization from default preset state. Initialization from scratch can be also forced by user from command line. This type of initialization doesn't require any access to database of KF states since it uses default initial state which is hard-set in the code. However at the other hand this state is only a pure guess and it wasn't obtained as a result of previous KF iterations therefore it is good to let KF adapt on previous historical data until the present weather situation, although this adaptation consumes some extra time. In adaptation phase forecasts are not corrected and Kalman filter states are not saved to internal database.

2.2 Results

Presented results were obtained using the 72 hour adaptation period prior to reference time 22 November 2013 00:00 UTC. Starting with this date Kalman filter was iterated for 10 days until 1 December 2013 23:00 UTC. This time range was chosen because we had feedback from Motorway Company that AT forecast produced directly from Aladin model had large errors in this period. Kalman filter was used for all (approximately 72) road weather stations located mostly along main motorways in Slovakia. Stations located on the bridge were intentionally excluded from the list.

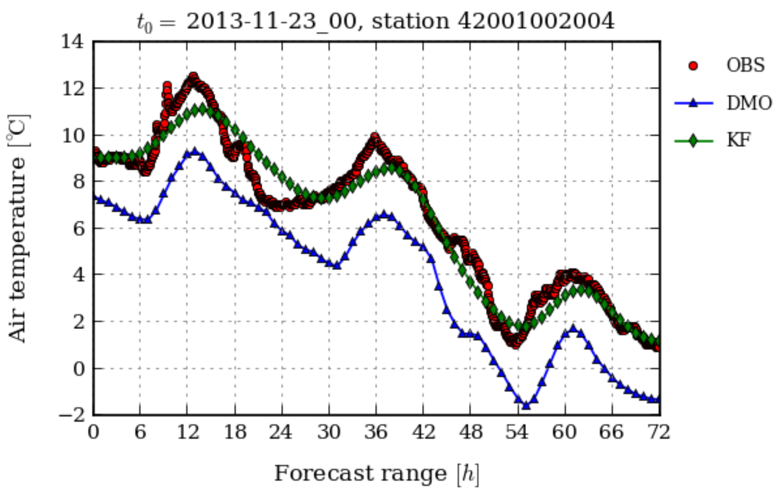

Figure 1. Air temperature 72 hour forecast for reference time 23 Nov 2013 00:00 and for station OMV Bratislava. Comparison of direct model output forecast (DMO), KF corrected forecast and measurements from RWS.

Figure 1 shows a 72 hour forecast of 2m AT for one of the RWS. Forecast corrected by KF shows substantial improvement of Aladin forecast in whole 72h validity time range. Figure 2 shows other example for later reference time and other station. Now in first 30 hours of forecast range KF have done a very goof job improving on Aladin forecast by 2 degree Celsius. In remaining forecast range however it can be seen that KF can no longer follow a large changes in AT. Especially extremes are not reproduced very well.

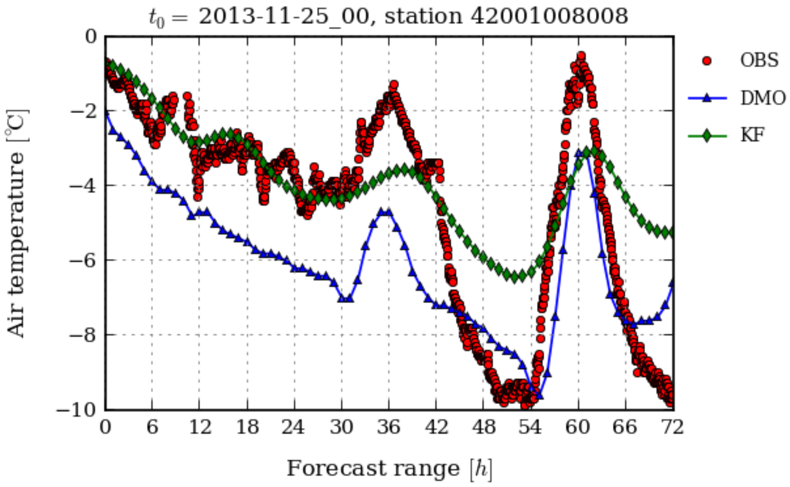

Figure 2. Air temperature 72 hour forecast for reference time 25 Nov 2013 00:00 for station Jánošíkova – Liptovský Mikuláš. Comparison of direct model output forecast (DMO), KF corrected forecast and measurements from RWS.

2.3 Statistical verification

The aim of using Kalman filter was to reduce mainly the bias of Aladin NWP model output 2m air temperature. Reducing the bias reduces also the RMS error (RMSE). Statistical validation is required to see how well Kalman filter accomplish this task.

Verification was done for all road weather stations which were processed by Kalman filter. Majority of stations show substantial improvement of air temperature bias. For some of them bias was reduced by more then 2 degrees for each hour of the day. Minority of stations show only small bias reduction. It was usually those which had small bias already before KF. For none of the stations KF resulted in deterioration of bias for each hour of the day. At worst very few stations showed a little higher bias after KF but only for specific hour of the day while for other hours bias was still better with Kalman filter correction. In figure 3 is shown a typical bias reduction after processing AT forecast by Kalman filter.

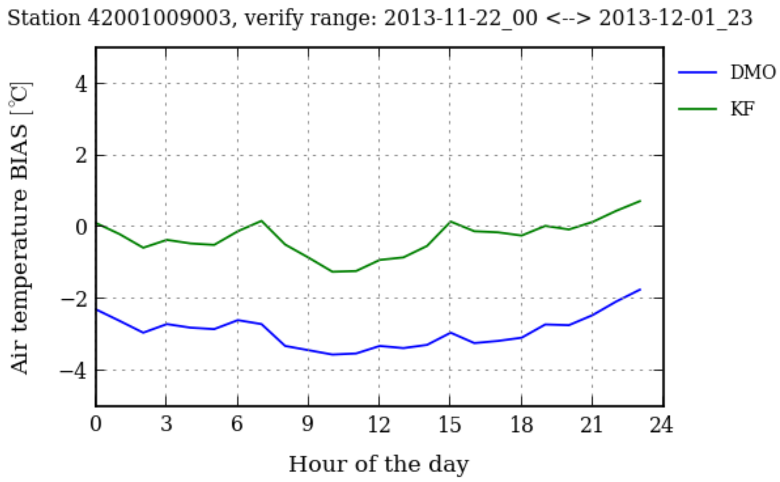

Figure 3. Air temperature bias to hour of the day for station Štrba.

Standard deviation (STDE) in most shows increase by small amount ~0.2 degree after application of Kalman filter (figure 4). However most importantly, root mean square error (RMSE) was substantially improved thanks to substantially improved bias (figure 5). Figure 6 show a development of bias with forecast range. It is seen that for first forecasted hour bias is reduced almost to zero which was expected since first forecast hours are closest to actual measurement used in KF measurement update. After first hours bias grows little bit but it is still much smaller then without KF.

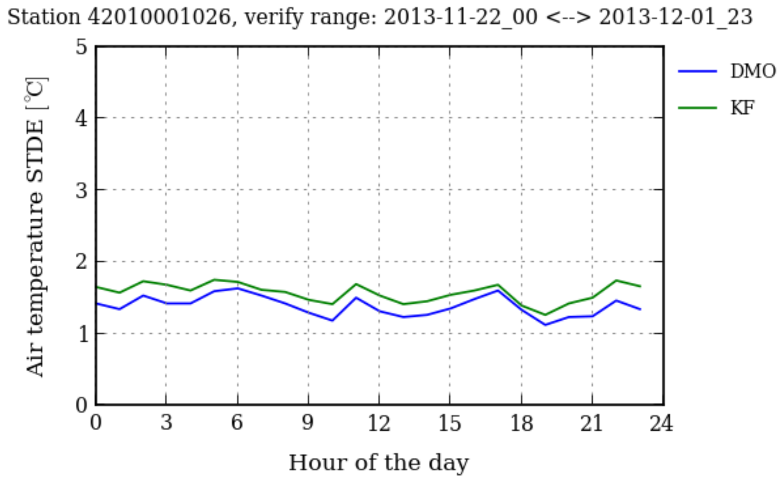

Figure 4. Air temperatur STDE to hour of the day for station Nové Mesto n. V.

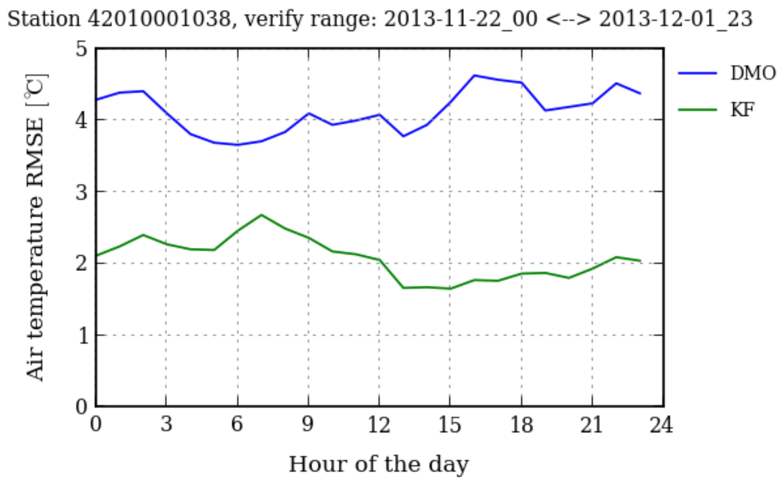

Figure 5. Air temperatur RMSE to hour of the day for station Voznica.

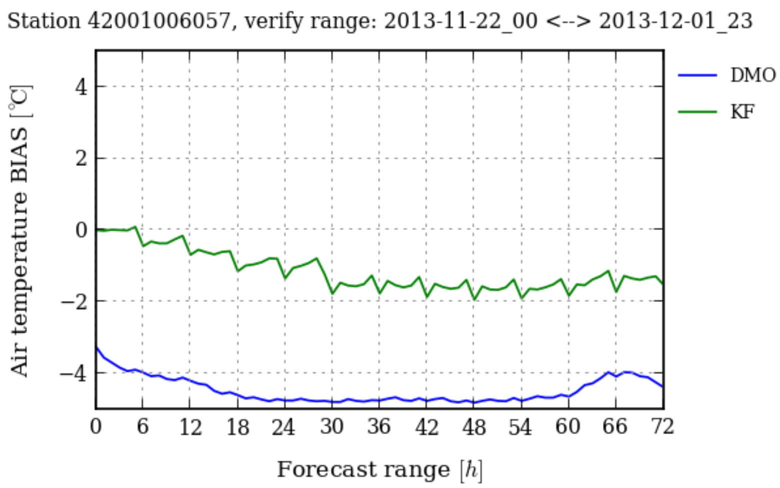

Figure 6. Air Temperature BIAS to forecast range computed from 10 day statistics (from 22 nov. 2013 to 1 dec. 2013) for station 42001006057 – Svrčinovec.

3 APPLICATION OF A NEW HEAT DIFFUSION MODEL

In near past we developed new heat diffusion model for calculation of temperature profiles from upper bound condition – observed surface temperature. This model could be used as a core-stone for creation new road forecast model as it will be shown in the second part of this section. The second possibility is to use this model within METRo model to improve initial condition – starting temperature profile of the road. This could improve forecasted RST because METRo model is using approximated heat diffusion model for all road layers.

3.1 Using heat diffusion model for calculation of temperature profiles

The basic idea of the new linear diffusion model is to use Fast Fourier Transform (FFT) for decomposition of observed RST to elementary trigonometric functions with different frequencies. This upper bound functions could be used for calculation of whole temperature profile that is function of space-position in road profile and time. Temperature profile is also a superposition of solutions for upper sine and cosine functions and also depends on the same frequencies and on depth and corresponding material parameters for different layers like volumetric capacity and heat conductivity. Example of such calculated temperature profile is on fig 3.1.
Here we see typical phase shift and decreasing of amplitudes of individual RST which are located in distance of 5cm between each depths of studied temperature profile.

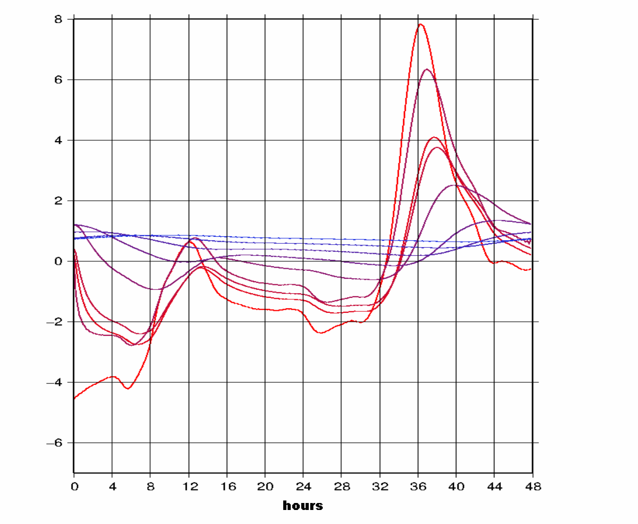

Figure 7. Temperature profile [°C] for RWS Donovaly from 16-02-2011

We tested this model on different RWS data with different depths of subsurface measured road temperature. Results are promising. Even when the starting conditions are different after some relaxation time calculated road subsurface temperature (SST) is going to follow its measured counterpart. If we set road material parameters and thicknesses of individual layers correctly, RMSE for SST in the depth from 10 to 20 cm, without taking to account relaxed time window, is around 0.1- 0.3 degrees. Comparison of such calculated and measured data are on the next pictures:

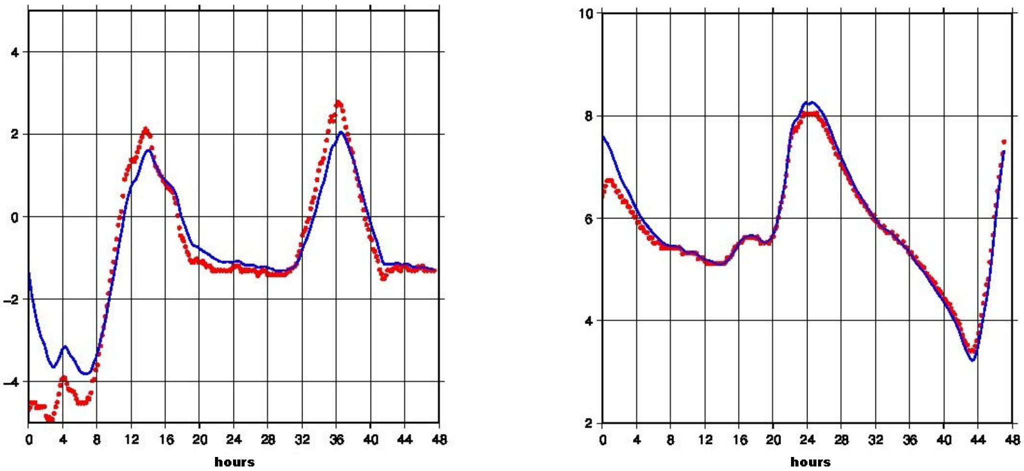

Figure 8. Subsurface temperature [°C], red – measured, blue – calculated, in the depth 10cm for each RWS. Station Korytné for initial date and time 22-12-2013 00:00 (left), station Nové Mesto nad Váhom for date and time 28-12-2013 12:00 (right).

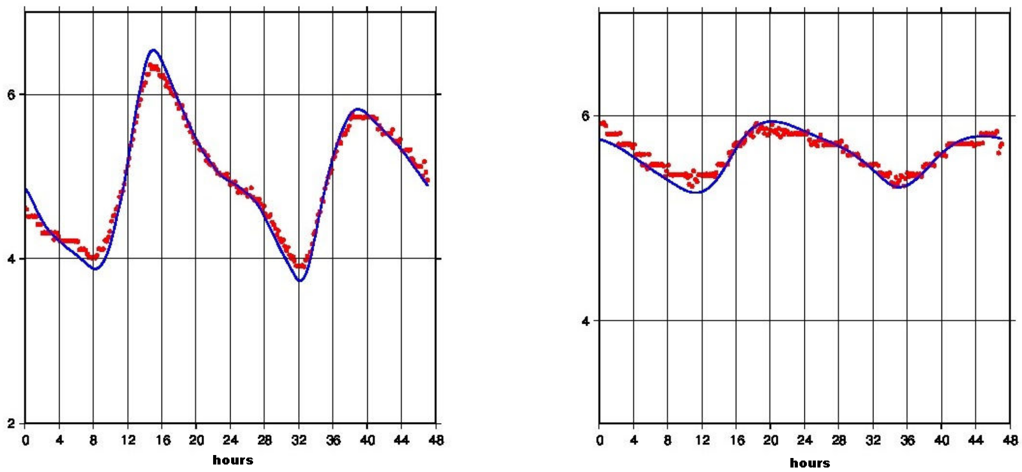

Figure 9. Subsurface temperature [°C], , red –measured , blue calculated in the depth 20cm (left) and 43cm (right) for each RWS Lozorno initial date and time 28-12-2013 00:00

3.2 Comparison of simplified energy budget model with METRo model

In this section possibility of application of above mentioned heat diffusion model for prediction of surface temperature was tested. Simplified model with inclusion of radiative fluxes and black body radiation was compared with observations and METRo roadcasts. It is clear that simplified model has limited applicability for the cases where upper mentioned elements of budged equation determined time evolution of the RST. The rest part of the budget equation could be included to our model within iterative manner. The work on this topic is in the progress. Other probably more sophisticated method of implementation of diffusion model is its application for determination of initial temperature profile. In this case it is necessary to rewrite some core routines of METRo model. We believe that this will be done in the near future.
Case study was done on several RWS with starting time of prediction from 13-01-2014 00:00. It was clear day condition almost without any cloudiness for the first 24h of forecast for both selected locations.

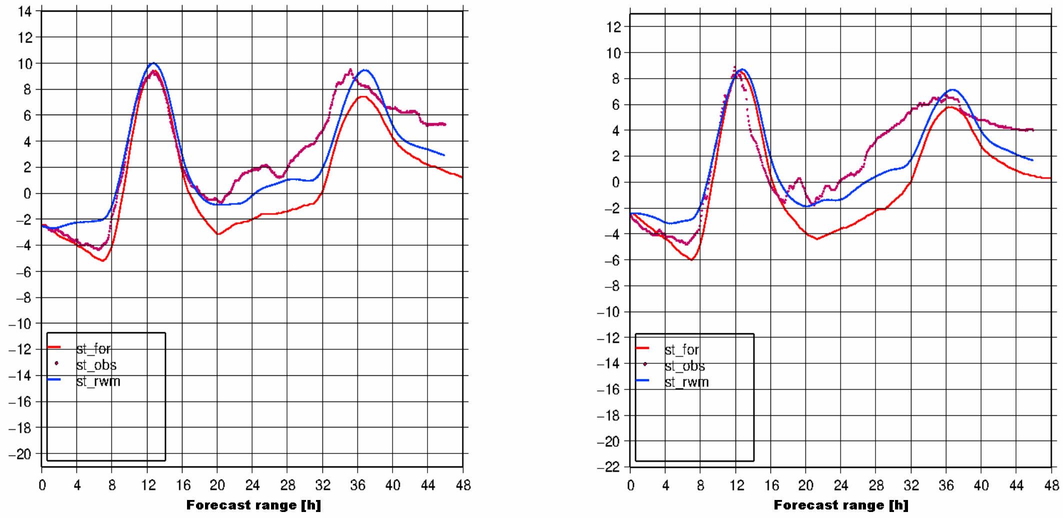

Figure 10. RST [°C] forecast for RWS Lozorno (left) and Nové Mesto nad Váhom (right): Red – METRo model, blue – new model, violet – observations.

4 CONCLUSIONS

The newly developed Kalman filter of Homleid type turns to be a very good debiasing tool for 2m air temperature forecast. Thanks to bias reduction also the RMSE statistics show considerable improvement even if standard deviation has increased a little bit. Results presented in this paper were obtained without a special tuning of the Kalman filter parameters. We believe that even better results would be then possible. Presented results were obtained for air temperature however our Kalman filter is fairly general and can be used also for other meteorological parameters. In the near future we expect improvement on our Kalman filter by using a lagged ensemble forecasts instead of single deterministic forecasts. Developed Kalman filter is intended to be used in operational service at Slovak Hydrometeorological institute in the near future (now it is running in trial operation). It will be used directly for correcting 2m air temperature forecast from Aladin NWP for RWS locations and also as pre-processor for METRo road model. Kalman filter preprocessing of METRo inputs is also developed as a part of a statistical package under the METRoSTAT project with our project partner CGS+.

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