# Simple Kalman Filter - A "Smoking Gun" of Shortages of Models?

Andrzej Mazur

*Institute of Meteorology and Water Management, Centre of Numerical Weather Forecasts, 61 Podleśna str., PL-01673 Warsaw, Poland*

## 1 Summary

The COSMO-LM model is currently running operationally at the Centre for Development of Numerical Weather Forecasts at IMWM, producing 72-hour forecasts of meteorological fields such as wind, precipitation intensity, cloud cover etc. Additionally it provides data for point locations (e.g., meteorological stations) in the form of meteograms. SHAWrt is a Simultaneous Heat And Water model (road temperature) dedicated for road temperature calculations for road maintenance during winter. Input data are model forecasts (temperature at 2m agl., wind at 10m agl, relative humidity, cloud cover, precipitation, i.e. rain and/or snow), vertical profile (contents of basic materials), site description (height, terrain configuration etc.) and time and date. Basic analysis of "raw" model results showed that they differ from point measurements. So, an application of additional procedure seemed to be necessary. As the beginning, simple Kalman filtering (Adaptive Regression method) was suggested. It seems to work quite good as far as "continuous" meteorological parameters, like temperature, wind speed or air pressure, are concerned.

## 2 Problem

Every forecast (even numerical forecast) comes with an error. Especially it can be seen when we are talking about point forecast (for instance, at meteorological stations). In this point location a quality of forecast may be easily verified. As an example, simple comparison between observed and predicted maximum and minimum temperatures for Warsaw station is shown in Figs. 1 and 2.

How can we handle this error? Kalman filtering seems to be an appropriate method (among others, of course). It can be used both for direct model results and for processed ones relatively easily. A basic scheme of filter (so called Adaptive Regression Method) is shown below.

$$
\begin{aligned}
y_k^f &= h_k^T b_{k-1}^a \\
P_k^f &= P_{k-1}^a + Q_{k-1} \\
e_k &= y_k^o y_k^f \\
w_k &= h_k^T P_k^f h_k + r_k \\
k_k &= P_k^f h_k w_k^{-1} \\
b_k^a &= b_{k-1}^T + k_k e_k \\
P_k^a &= -k_k w_k k_k^T + P_k^f
\end{aligned}
$$

where:
$y$ - measurement vector
$b$ - multiple regression coefficients (time dependent)
$h$ - predictors – model forecast values
$Q$ - error covariance
$r$ - observational error
$P$ - forecast covariance
$e$ - forecast error
$w$ - temporary scalar
$k$ - Kalman gain

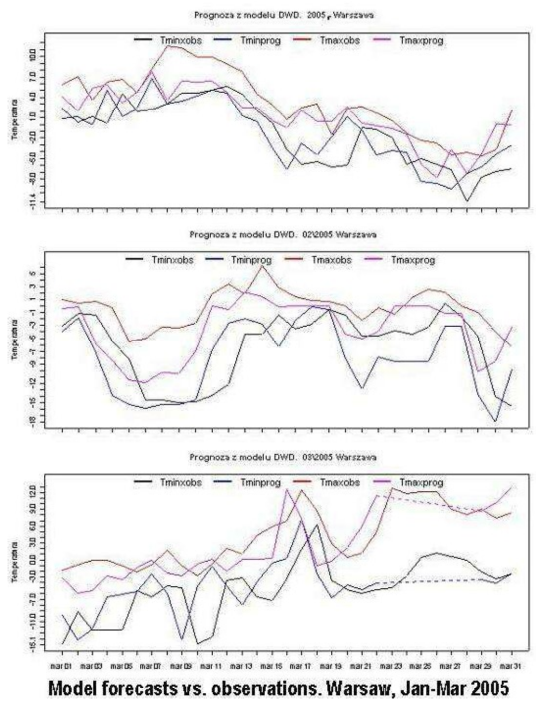



Figure 1: Model forecasts vs. observations (maximum and minimum temperature, Warsaw, Jan-Mar 2005).

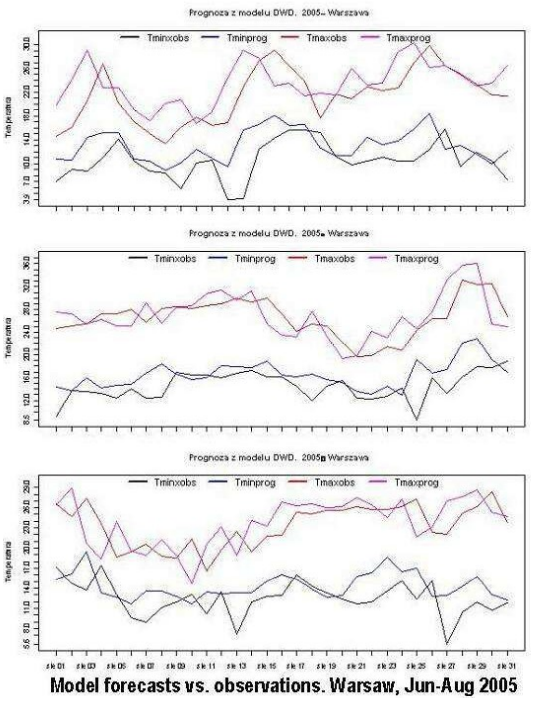



Figure 2: Model forecasts vs. observations (maximum and minimum temperature, Warsaw, Jun-Aug 2005).

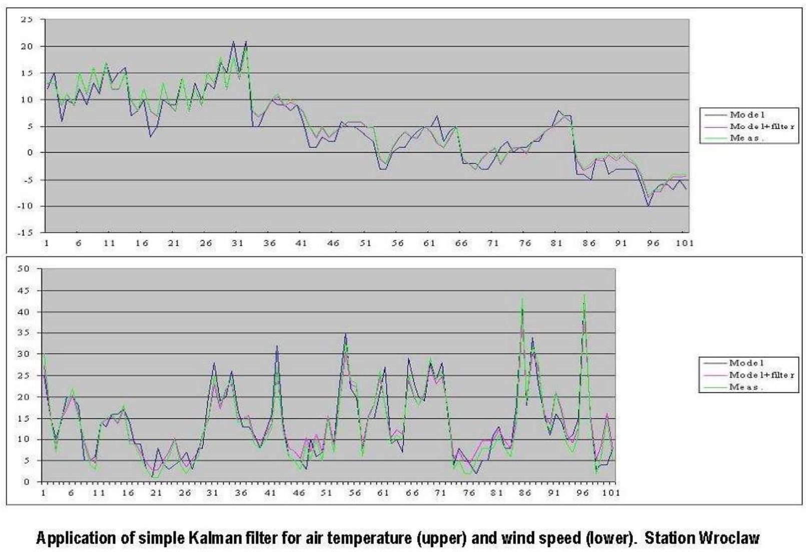
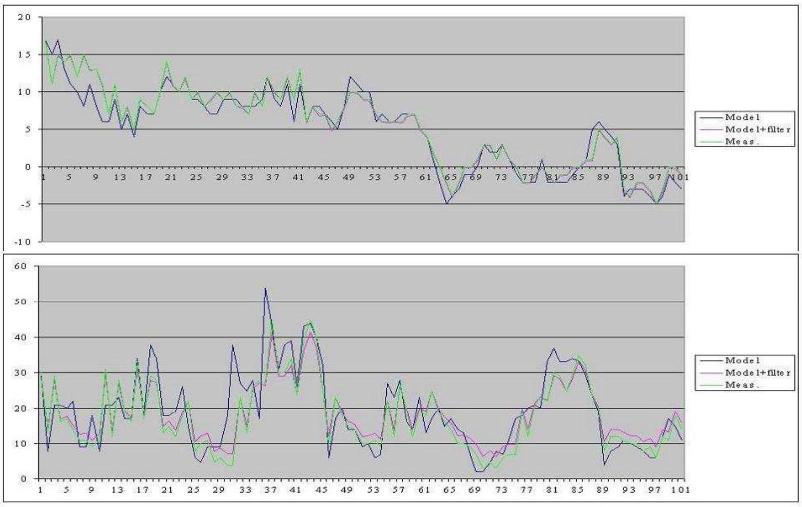



Figure 3: An adaptation of simple Kalman filter for air temperature and wind speed. Wroclaw, 2005.

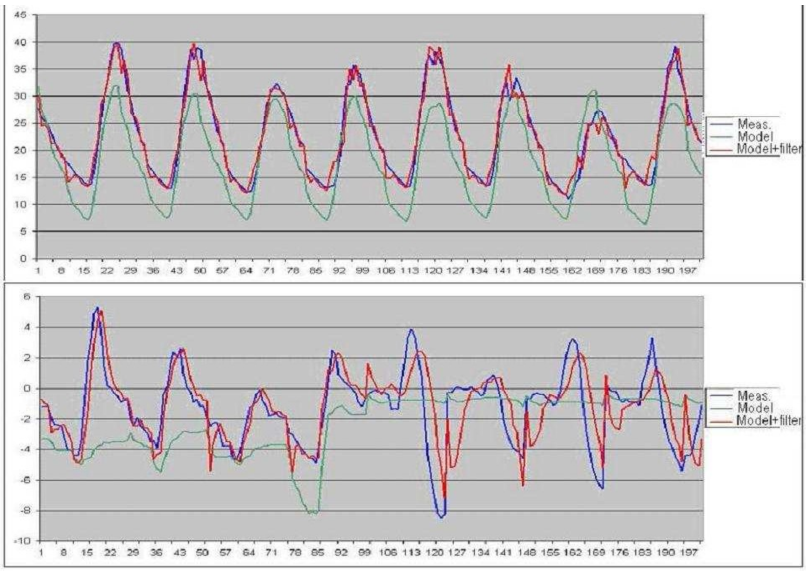
## 3 Results

In Figs. 3 and 4 results of this kind of filtering approach is presented. Figure 5 in turn shows the utilisation of Kalman filter for road temperature calculations (model SHAWrt) as an example of filtering approach to model results processed by other application. Interesting situation appear during winter season, while un-filtered model results did not take into account an appearance of snow cover (removed shortly afterwards by maintenance services).




Application of simple Kalman filter for air temperature (upper) and wind speed (lower). Station Warsaw.

Figure 4: An adaptation of simple Kalman filter for air temperature and wind speed. Warsaw, 2005.




Application of Kalman filter for road temperature assessment during summer (upper) and winter (lower).

Figure 5: Application of simple Kalman filter for road temperature assessment during summer and winter period.

This snow packet "worked" as a blanket keeping temperature more or less constant (green line in the figure). In reality, after removal of snow, the temperature of the road changed in a wide range (blue line). Filtered results were significantly closer to real observed ones.

## 4 Discussion and conclusions

Application of filter for "raw" (direct) model results have some characteristic features. First of all, it seems to work quite good as far as "continuous" meteorological parameters, like temperature, wind speed or air pressure, are concerned. Moreover, results seem to depend on differences between observations and "raw" results (i.e., BEFORE filter is applied). In other words, the greater difference - the better result. Other parameters, like precipitation, should be studied in a similar way. They might require different approach due to their different "nature". In both cases, careful selection of predictors is strongly advised. The method - even in this simple approach - can "detect" not only any factor "aside" of the model, but also systematic errors in results.

## References

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