A State Space Model for Wind Forecast Correction

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Abstract. The accuracy of numerical weather forecasts is crucial in many engineering applications, especially for the management of renewable energy. In this paper, we give a short overview of methods used to improve local weather forecast. Then we propose a new state space model in order to correct bias and phase errors in numerical wind forecasts. We present some results for real life data.
Keywords. Wind forecast, State Space Models.

1 Introduction

The accuracy of numerical weather forecasts is crucial in many engineering applications, especially for the management of renewable energy. It is well known that the Numerical Weather Prediction (NWP) is globally good but local predictions may present some weakness, in particular bias and phase errors are frequently observed. For example, if we look at the passage of a storm, the level bias is the error on the predicted intensity of the storm and the phase error comes from an incorrect prediction of the onset of the storm. These errors are due to the presence of incorrect physical parametrizations, numerical dispersion or wrong boundary conditions.

Due to the important development of wind farms all over the world, there is an extensive litterature concerning local improvement of numerical weather forecast. In Section 2, we give a short overview of the different approaches.

Several authors (Dee and da Silva (1998), Galanis et al. (2002)) have suggested using a linear state space model, in which the hidden process describes the 'error' of the numerical model. Then, the prediction obtained by the numerical model is corrected in real time from the observations, that are enables, using the Kalman filter. A key benefit of this model is to enable adaptive learning of the forecast error.

In this paper, we extend this model. We assume that the error can be broken down into two parts: a level bias and a phase error. Because these two terms are not directly observable, they are included in the hidden state of the model, which becomes non-linear. We assume that the dynamic of the hidden state is described by an Ornstein-Uhlenbeck process, which can deal with irregular observation dates.

In Section 3, a time continuous version of the model of Dee and da Silva (1998) is described. Then, in Section 4, the phase error is added to the first model. Finally, in Section 5, the performance of the models is illustrated by some tests on real data.

2 State of the Art

There is an important litterature concerning the local improvement of Numerical Weather Prediction (NWP). The proposed models can be classified in three groups. The first consists in purely deterministic models, the second in purely stochastic models and the last in the combination of deterministic and stochastic models.

2.1 Numerical weather models

Many authors propose to improve large scale NWP by adding a local atmospheric model to the global one, in order to better take into account the local specificities of the geography. Such local models generally allow a significant improvement of the local forecasts but their development is very expensive. The classical operational approach is to assimilate observed data by variational methods (Evensen, 2007).

2.2 Purely stochastic models

The main idea, in the purely stochastic models, is that the information needed to predict the future is include in the historical data. The method of Box and Jenkins (1976) is undoubtedly the most usual model for wind time series. It consists in modelling the process by the sum of a deterministic seasonal component and a stationary autoregressive moving average (ARMA) process. No physical information is included in the model.

2.3 Combining numerical and stochastic models

The second approach consists in a combination of numerical weather models and stochastic models. In practice, the short-term numerical forecast provides a first guess of the state of the atmosphere. The observations bring then additional informations which allow to improve the prediction. The use of short-range forecasts as a first guess has been universally adopted in operational systems.

Regression models In most papers, the stochastic model is a regression model which is used to predict the local wind given atmospheric variables computed by the numerical weather model. The parameters of the statistical model are estimated from historical data. The regression model may be a simple linear model but, in many applications, artificial neural networks are used. The main advantage of linear models is their interpretability, but artificial neural networks models can lead to better predictions if the local meteorology is complex.

Some authors propose more sophisticated statistical models. For instance, Lange *et al.* (2006) use different regression models for different weather types. von Bremen *et al.* (2007) perform an Empirical Orthogonal Functions analysis in order to reduce the dimension of the space of the explanatory variables.

These regression models generally lead to a good improvement of the forecast for small scale problems. However, one of their limitations is that they do not take into account the observations sequentially.

Sequential data assimilation An alternative to regression models, discussed above, is to used state space models in order to assimilate the observations sequentially (Evensen, 2007).

When data assimilation proceeds sequentially in time, the numerical weather model organizes and propagates the information from previous observations forward in time. The information from new observations is used to modify the model state, to be as consistent as possible with them and the previous information. Extensions of Kalman filter are usually used. In these approaches, the computation of the numerical weather model is generally expensive.

Dee and da Silva (1998) and later Galanis *et al.* (2002) also consider a state space model, but where the numerical forecast plays the role of a control. In fact, the forecast error is supposed to be additive. It is then represented by the hidden process, since it is not directly observable. The model is given by

$$\begin{cases} X_t = \alpha X_{t-1} + \beta + \sigma \epsilon_t \\ Y_t^{\text{obs}} = Y_t^{\text{for}} + X_t + \sigma^{\text{obs}} \epsilon_t^{\text{obs}} \end{cases} \tag{1}$$

where X_t denotes the forecast error, Y_t^{obs} and Y_t^{for} denote respectively the observed process and the corresponding forecast process. ϵ_t and ϵ_t^{obs} are two independent Gaussian white noise processes. The parameters α, β, σ and σ^{obs} are unknown and they are to be estimated.

One of the main advantages of state space models is that they allow to compute a smooth adaptative correction of the wind predicted by the numerical model. In the sequel of this paper, we will expand model (1).

3 An adaptative biais correction

Firstly, we write a continuous time version of the model (1), in order to be able to take into account varying observation time steps. The forecast error is still additive and non observable. The model is written as follows.

- *Hidden state process*: X is an Ornstein-Uhlenbeck process in $\mathbb{R}$

$$dX_t = \alpha(X_t - \mu)dt + \sigma dW_t \tag{2}$$

  where W_t a standard Brownian motion. X_t is then a continuous time Markovian process with the transition density fonction $p(X_{t+Dt}|X_t)$ being Gaussian with mean $a_{Dt}X_t + b_{Dt}$ and standard deviation s_{Dt} and, $a_{Dt} = exp(-\alpha * Dt)$, $b_{Dt} = \mu(1 - a_{Dt})$, $s^2_{Dt} = \frac{\sigma^2(1-a^2_{Dt})}{2\alpha}$. Dt denotes a time increment.
- *Observation process*: The observation process is observed at discrete times $t_k (k = 1 \cdots, n)$ and

$$Y^{\text{obs}}_{t_k} = Y^{\text{for}}_{t_k} + X_{t_k} + \sigma^{\text{obs}}\epsilon_{t_k} \tag{3}$$

  where ϵ_{t_k} is a continuous time Gaussian white noise process with mean 0 and variance 1. The variable $Y^{\text{for}}_{t_k}$ can be seen as a deterministic control.

In order to compute a prediction at time $t + Dt$ given the available observations $y^{\text{obs}}_{t_1}, ..., y^{\text{obs}}_{t_n}$, with $t_n \leq t$, until time t, one estimates $E[X_{t+Dt}|y^{\text{obs}}_{t_1}, ..., y^{\text{obs}}_{t_n}]$ using the Kalman filter and the prediction is given by

$$y^{\text{for}}_{t+Dt} + E[X_{t+Dt}|y^{\text{obs}}_{t_1}, ..., y^{\text{obs}}_{t_n}].$$

In practice, some forecasts $y^{\text{for}}_{t_1}, y^{\text{for}}_{t_2}, ..., y^{\text{for}}_{t_n}$ and y^{for}_{t+Dt} may be unavailable. In this case, they are computed by a linear interpolation.

4 An extension: bias and phase correction

Weather forecasts may not only present bias errors but also some phase errors. In the following model, we add the phase error as a second component of the hidden state. The bias and phase errors are supposed to be independent.

- *Hidden state process*: $X = (B, \Delta)$ is defined on $\mathbb{R}^2$ with B and Δ two independent Ornstein-Uhlenbeck processes,

$$\begin{cases} dB_t = \alpha_B(B_t - \mu_B)dt + \sigma_B dW_t \\ d\Delta_t = \alpha_\Delta(\Delta_t - \mu_\Delta)dt + \sigma_\Delta dV_t \end{cases} \tag{4}$$

  where W_t and V_t are standard Brownian motions.

- *Observation process*: The observation process is given by

$$Y_{t_k}^{\text{obs}} = Y_{t_k+\Delta_t}^{\text{for}} + B_{t_k} + \sigma^{obs}\epsilon_{t_k} \tag{5}$$

with ϵ_t a continuous time Gaussian white noise process with mean 0 and variance 1.

We can notice here that the observation equation is nonlinear due to the introduction of the phase Δ_t.

To compute the prediction Y at time $t+Dt$ from observations $y_{t_1}^{\text{obs}}, ..., y_{t_n}^{\text{obs}}$ available until time t (with $t_n \leq t$), one estimates $p(X_{t+Dt}|y_{t_1}^{\text{obs}}, ..., y_{t_n}^{\text{obs}})$ by particle filtering (Doucet et al., 2001) and the prediction is given by

$$E[Y_{t+Dt}|y_{t_1}^{\text{obs}}, ..., y_{t_n}^{\text{obs}}]$$

where $Y_t^{true} = Y_{t+\Delta_t}^{\text{for}} + B_t$. Again, a linear interpolation is used to compute y_t^{for} when it is not available.

5 Numerical results

In this section, we present and discuss some numerical results obtained with the models introduced in the previous sections on 3 months (2007/11 to 2008/02) of wind data at Brest's Airport (Point coordinates : 48.3N, 4.2W).

More precisely, we consider forecast data obtained from the National Operational Model Archive & Distribution System of the National Oceanic and Atmospheric Administration (NOAA). We use the forecasts of the Global Forecast System which runs a global model. Every day, we consider the numerical forecast computed at 00:00 and we use the in situ observations available until 18:00 the same day to predict the wind speed at 19:00, 20:00,..., until 23:00 the day after. This is illustrated on Figure 1 : the observations before the vertical line are used to predict the wind for the period after the line. In situ observations are available at irregular time step (typically 30 minutes between successive observations with missing data). The 'pure' numerical forecasts obtained from the NOAA have been compared with the corrected forecasts obtained with the two models introduced in Sections 3 and 4. For comparison purpose, we have also computed forecasts obtained with a 'pure' stochastic model : Y_t^{obs} is supposed to be an Ornstein-Uhlenbeck process with parameters estimated by the maximum likelihood method.

The maximum likelihood estimates of the parameter $(a_{Dt}, b_{Dt}, s_{Dt}, \sigma^{\text{obs}})$ of the bias correction model (2)-(3) are computed by a gradient based method. But the various attempts which we have made to compute the maximum likelihood estimates for the model described in section 4 have been unsuccessful. This problem is known be to difficult ; see (Coquelin *et al.*, 2007) for a recent review of methods to compute MLE in non-linear state-space models). We hope to address this in a future paper. Finally, the parameters values have been fixed arbitrarily, based on heuristic arguments. The problems will have to be studied in a forthcoming paper. So, in practice, the estimates obtained for the linear model (2)-(3) are considered as a first guess for $(a_{Dt}, b_{Dt}, s_{Dt}, \sigma^{\mathrm{obs}})$ and then the other parameters are fitted by empirical reasoning based on the data.

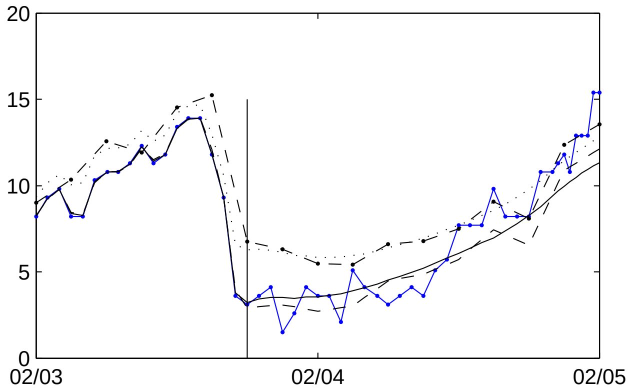

Fig. 1. Prediction obtained with the different methods for a given day. Point-solid line: observation time series, point-dashed line: prediction of pure numerical model, dashed line: linear model (bias correction), dotted line: prediction of pure numerical model shifted by the phase correction, solid line: prediction of nonlinear model (bias+phase correction).

Figure 1 shows that both state-space models allow to correct the bias present in the numerical weather prediction for this specific date.

The dotted line corresponds to the numerical forecast shifted by the estimated phase ; by looking at the peaks, on can see that some phase errors are identified. But the memory of the phase process decreases very fast.

Figure 2 shows the Root Mean Square Error (RMSE) between the prediction and the observations. It shows that pure stochastic models give better forecasts of the wind speed than NWP for short forecast horizons (until about 3 hours). The hybrid methods combining a numerical model and a stochastic model allows to improve significantly over NWP. For some specific weather situations, the phase helps the improvement. However, on specific examples the introduction of the phase error does not reduce the RMSE comparing to the bias correction linear model. The model should be validated on longer time series. Moreover, other variables like the wind direction and spatial information should be included in order to help identifying the phase errors.

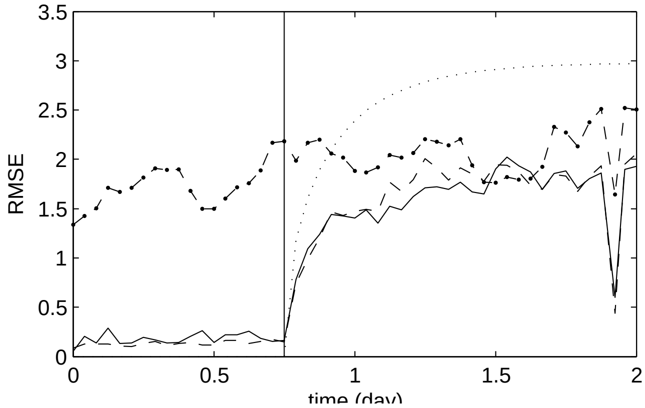

Fig. 2. Root Mean Square Errors between observations and forecasts. Point-dashed line : pure numerical model, dashed line: linear model (bias correction), solid line: nonlinear model (bias+phase correction), dotted line: pure stochastic model

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