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# Wind forecasting using Principal Component Analysis

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ABSTRACT

We present a new statistical wind forecasting tool based on Principal Component Analysis (PCA), which is trained on past data to predict the wind speed using an ensemble of dynamically similar past events. At the same time the method provides a prediction of the likely forecasting error. The method is applied to Meteorological Office wind speed and direction data from a site in Edinburgh. For the training period, the years 2008–2009 were used, and the wind forecasting was tested for the data from 2010 for that site. Different parameter values were also used in the PCA analysis to explore the sensitivity analysis of the results.

The forecasting results demonstrated that the technique can be used to forecast the wind up to 24 h ahead with a consistent improvement over persistence for forecasting more than 10 h ahead. The comparison of the forecasting error with the uncertainty estimated from the error growth in the ensemble forecast showed that the forecasting error could be well predicted.



## 1. Introduction

Wind energy is one of the most established renewable energy forms. It has been the world's fastest renewable energy resource in growth for the past 7 years [1]. Wind energy has also the characteristic of a strongly variable form of energy. To achieve a high level of performance, a good quality of wind speed or generation forecasting is vital. Wind speed and direction are the most important factors that determine the power output and they can vary at all time scales. Different cycles with time scales ranging from daily to seasonal and interannual can be observed in addition to turbulence and gusts. For example, for mean daily or hourly wind speed forecasts, the underlying atmospheric dynamics become of great importance [2]. In addition, the turbines have to adjust to the wind fluctuations at all time but often have a delay in their response. Hence, the methods of analysis and prediction of wind behaviour are indeed of extreme importance for a good operation of wind turbines and wind farms.

### 1.1. Forecasting methods

Because the wind variability can be characterised by slow cycles (daily and longer), fast (unpredictable) turbulence, and synoptic weather changes which tend to change only slowly, the forecasting horizon can be divided into the three following categories: 1: immediate-short-term (up to 8 h ahead), 2: short-term (8–24 h ahead), and 3: long-term (multiple-days-ahead) forecasting [3–5]. It is more common to use hourly forecasts in order to determine daily forecasts of hourly winds [6].

Several forecast models have been created which can be categorised into physical, such as the Numerical Weather Prediction systems (NWPs) [3], statistical, including linear methods such as Auto Regressive Moving Average models (ARMA) or methods coming from artificial intelligence and machine learning fields such as Artificial Neural Networks (ANNs), or even by hybrid approach methods which are a combination of statistical and physical methods with a use of weather forecasts and analysis of time series [4]. Erdem and Shi [7] used four ARMA approaches in order to obtain wind speed and direction forecasts and found that the ARMA model based on the decomposition of wind speed into lateral and longitudinal components was better in predicting direction in comparison to the traditional ARMA model. However, that was the opposite case for wind speed. De Giorgi et al. [8] used ARMA models in combination with different types of ANNs and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) for several testing period models but also time horizons. For all the attempts it was found that the forecast was progressively worse as the prediction length was increasing.

An integration of ANNs with NWPs for forecasting purposes was undertaken again by De Giorgi et al. [9]. The neural network was

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initially based on the statistic model of wind power time series and was later integrated with NWPs which indicated a significant improvement on the performance. Specifically, pressure and temperature as NWP parameters seemed to improve the forecasting model. Früh [10] explored a simple a linear predictor and based on the observed mean daily cycle model with wind speed or power output data as inputs and noted that increased sophistication in the forecasting methods surprisingly seemed to deteriorate the predictive ability.

Hybrid approaches typically employ an ARIMA model for the linear characteristics and an ANN or SVM (Support Vector Machine) model for the nonlinear characteristics. Wang et al. [5] found that depending on forecasting horizon, hybrid methods or ARIMA method perform better in forecasting than the ANN and SVM methods. They also concluded that hybrid methods add significantly in the short-term forecasting modelling for wind speed and power generation, but in general, they do not outperform the other methods [11].

### 1.2. Principal Component Analysis of time series

Underlying all statistical and empirical approaches is the need to separate the predictable component from the turbulent component in an effective and efficient manner. For example, for mean daily or hourly wind speed forecasts, i.e., short-term horizons, the underlying atmospheric dynamics become of great importance [12]. The wind related data could be treated as dynamical systems so that cycles and random unusual behaviours that often characterise them can be identified, explained and understood. Based on this understanding, we propose to use a time series analysis technique based on the dynamical systems theory which was devised to separate coherent dynamical information from noisy experimental data, known as Singular Systems Analysis [13,14], which is effectively the standard Principal Component Analysis (PCA) [15] from Statistics applied to a suitably formatted time series. It is also known as Empirical Orthogonal Function (EOF) Analysis in the Meteorological and Oceanographic community to identify the main circulation patterns in the Atmosphere and oceans, e.g., [16,17]. This technique is now widely used for time series analysis of nonlinear dynamical systems in general, e.g. Refs. [18,19] as the analysis is very powerful to separate coherent dynamics from noise.

The principle in terms of a dynamical system is that the dynamic evolution of the system takes place on a time-invariant object, called 'attractor', after initial transients have decayed. This attractor is a geometric object in the phase space defined by the dynamic variables of the dynamical system. In the example of a harmonic oscillator, the phase space is defined by the position and momentum of the oscillating object, and the motion of it takes place on a limit cycle. This cycle is the attractor, and the trace drawn by the oscillation, or its 'orbit', would draw repeating copies of that cycle over and over.

In complex systems, where the phase space is not fully accessible from measurements, one can use Takens' method of delays [20] to create a space equivalent to the phase space but this phase space reconstruction cannot separate the important dynamics from measurement noise or turbulence. Applying PCA to the set of delay time series is a method to redefine the phase space to concentrate the coherent information in a few directions (or dimensions) of the phase space, which then allows to 'delete' the weaker and uncorrelated dynamics from the description of the system. The creation of this system based on a training set of wind data defines the model for the forecasting. New measurements can then be mapped onto the cleaned-up attractor to find previous measurements which are, in dynamical terms, similar to the current measurements. Finding one or more 'similar' previous measurements, then allows us to the evolution of those measurements as equivalent to predicting the current measurements. In addition to a prediction, however, this method predicts a number of similar events and following how their distances change over the lead time of the prediction also provides a measure of how sensitive the system is to uncertainties in measurements or out-of-system perturbations. Hence, it provides a measure of the uncertainty of the prediction at the same time.

### 1.3. Aims and outline

The aim of this paper is to develop a wind speed forecasting tool which, by being based on PCA, provides a forecast based on the slow dynamics of the atmosphere alone and also provides an intrinsic measure of the quality of each forecast.

To develop the tool, we will in Section 2 first introduce the formalism of PCA applied to a time series of wind speed and direction, and then the forecasting method. Section 3, introduces the main data set, the parameter settings, and the error measures used to develop and evaluate the approach. The results of this analysis are presented in Section 4.

## 2. Principal Component Analysis for forecasting

This section contains background information regarding phase space reconstruction as well as PCA and explains in detail how they will be used for the forecasting purposes. The stages for the training of the predictor are preparation of the phase space using the training set of data (e.g., wind speed and direction), Principal Component Analysis of the phase space to optimise the phase space and truncation of the phase space to the relevant components only to define the predictor.

The application of the predictor goes through the preparation of the test data to the same specifications as the training set, mapping the test data onto the truncated phase space, finding an ensemble of nearest neighbours on the attractor as defined by the test data, tracing the evolution of that ensemble for the lead period of the prediction, and finally re-transforming the ensemble of predictions into the original variables (e.g., wind speed and direction). A summary of the forecasting algorithm is presented in Table 1, and the remainder of this section will describe each of these steps in turn.

**Table 1**
The forecasting algorithm.

| | |
|---|---|
| *Training* | |
| 1) Normalise measurements | |
| 2) Create time-delay matrix; eq. (1) | $Y^{i,j+(j_o-1)M_w} = y_{j_o}(j+(i-1)\tau),$ |
| 3) Perform PCA to optimise; eq. (2) | $Y = P\Lambda S$ |
| 4) Truncate to the relevant components to define predictor; eq. (3) | $Y_r = P_r\Lambda_r S_r$ |
| *Forecasting* | |
| 5) Normalise new measurements using Training normalisation | |
| 6) Create time-delay matrix using same parameters as for Training | |
| 7) Map time-delay matrix onto attractor coordinates; eq. (5) | $P_n = Y_n S_r^T \Lambda_r^{-1}$ |
| 8) Find number of similar events in training period and follow evolution of past events i.e. nearest neighbours; eq. (6) | $d_i = (1/n_x)\sum_j \left\| P_n^j - P_r^{i+j-1} \right\|$ |
| 9) Find distance vector due to $n$. neighbours; eq. (7) | $D_j = P_r^{k_j} - P_n^{n_x}$ |
| 10) Use ensemble prediction based on $n$. neighbours; eq. (8) | $P_f^j(T) = P_r^{k_j+T} + D_j$ |
| 11) Map back to delay matrix and return predicted wind speed; eq. (9) | $Y_f^i = P_f\Lambda_r S_r$ |
| 12) Re-scale back to proper units | |