Post-processing Techniques for Renewable Energy Forecasting.

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November 6, 2018

1 Introduction

This technical document is a review of methods used for statistical post-processing of renewable energy forecasts. Here the focus is on day-ahead forecasting of electricity generated by wind turbines or photovoltaic panels. Power generation from wind and solar is strongly linked to weather conditions therefore day-ahead renewable energy forecasting is strongly linked to meteorological forecasting by numerical weather prediction. The seven main methods are discussed here.

2 Machine Learning

This is a method in which systems can learn from the data, identify patterns and make decisions with minimal human intervention. The main methods include Artificial Neural Networks (ANN) [Das et al., 2018, Davò et al., 2016, Ding et al., 2011, Yesilbudak et al., 2018, Raza et al., 2018, Methaprayoon et al., 2007, Li and Shi, 2010, Cadenas and Rivera, 2010, Friedrich and Afshari, 2015, Chow et al., 2012, Omar et al., 2016] and Support Vector Machines (SVM) [Das et al., 2018, Mohandes et al., 2004, Yesilbudak et al., 2018, Li et al., 2016a, Long et al., 2014, Zhang et al., 2014, Santamaría-Bonfil et al., 2016].

ANNs are a collection of connected units or nodes called artificial neurons. The network consists of input and output layers as well as a hidden layer that consists of units which transform the inputs into something the output can use (figure 1). The neural network is a framework for different machine learning algorithms to process complex input data. They automatically generate identifying characteristics from the learning material that they process. As the network learns from experience the more data used then the more accurate it will become. One downside of ANNs is that they are "black boxes" in which the user feeds in data and receives answers but they don't have access to the exact decision making process.

SVMs are supervised machine learning algorithms which are mostly used for classification problems. It uses a set of training data, each marked as belonging to one of two categories and then builds a model to assign new data points to either of the two categories (figure 2).

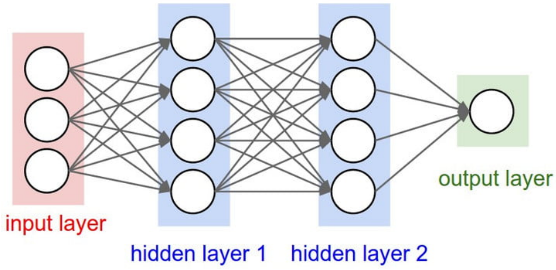

Figure 1: Artificial Neural Network - data are passed through a number of hidden layers before being output.

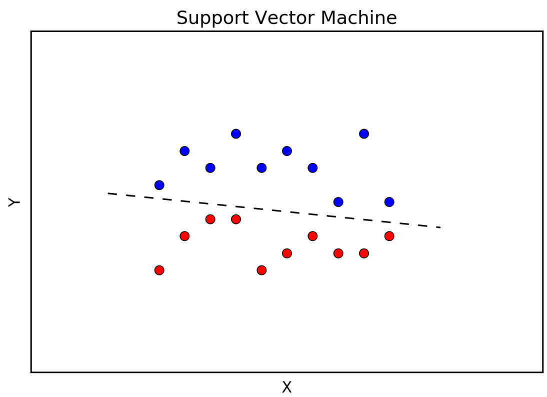

Figure 2: Support Vector Machine - data are clustered into two categories and separated by a hyper-plane.

3 Model Output Statistics (MOS)

MOS relates observed weather elements to appropriate variables (predictors) via a statistical approach. These predictors may be NWP model forecast, prior observations, or geoclimatic data [Glahn and Lowry, 1972]. By using archived model forecast output along with verifying surface observations, the resulting equations implicitly take into account physical effects and processes which the underlying NWP model cannot explicitly resolve, resulting in improved forecasts of weather quantities. This method generally requires a large historical dataset to train the model. This method often reduces systematic errors but can also be used to produce probabilities of weather events from a single model run. The majority of member states currently (2014) use MOS to post-process the ECMWF IFS [Gneiting, 2014]. This method is used for solar [Verbois et al., 2018, Diagne et al., 2014, Rincón et al., 2018] and wind [Baran and Möller, 2017, Rosgaard et al., 2016, Schuhen et al., 2012].

4 Kalman Filter

The Kalman filter [Kalman, 1960] is often used to implement or refine other post-processing techniques [Schuhen et al., 2012, Diagne et al., 2014, Gneiting, 2014, Pelland et al., 2013, Rincón et al., 2018, Sweeney et al., 2013, Sweeney and Lynch, 2011]. It is designed to efficiently extract a signal from noisy data and is therefore expected to show a more robust performance if only limited training data are available, which is the case if the training is performed on the basis of individual stations. An advantage is that it estimates the uncertainty of the variables, which can then be related to physical reasons. The Kalman filter is computationally efficient to run.

5 Regression Models

These measure the correlations between dependent and independent parameters [Long et al., 2014, Wang et al., 2016]. These include time series models which reproduce the patterns of prior movements of a variable over time and uses this information to predict its future movements.

5.1 Auto-regressive Integrated Moving Average (ARIMA)

ARIMA is used to better understand the data or to predict future points in a series. The AR part indicates that the variable of interest is regressed on its own lagged (i.e., prior) values. The MA part indicates that the regression error is actually a linear combination of error terms. The I part indicates the differencing required (replacing the data values with the difference between their values and the previous values) to make the data stationary. A stationary time series' properties do not depend on the time at which the series is observed. Each part is aimed at making the model fit the data well.

$$y_t = \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} - \theta_1 z_{t-1} - \cdots - \theta_q z_{t-q} + z_t \tag{1}$$

where $y_1, \ldots, y_n$ denotes the time series and z_t is a white noise process.

ARIMA is normally denoted as ARIMA(p,d,q) where p is the order (number of time lags) of the AR part, d is the degree of differencing (number of times the data have had past values subtracted) and q is the order of the MA model. An ARIMA model can be viewed as a "filter" that tries to separate the signal from the noise, and the signal is then extrapolated into the future to obtain forecasts [Kavasseri and Seetharaman, 2009, Erdem and Shi, 2011, Sfetsos, 2000, Shukur and Lee, 2015, Soman et al., 2010, Friedrich and Afshari, 2015, Hill et al., 2012].

Soman et al. [2010] suggest ARMA to evaluate 0-6h ahead wind speed whereas most of the models for 6h-24h ahead are based on ANN approaches among others.

5.2 Vector AR (VAR)

VAR is a multivariate version of the AR model [Erdem and Shi, 2011, Browell et al., 2017, Kazor and Hering, 2015a]. It is a model used to capture the linear interdependencies among multiple time series. VAR behaves in the same way as AR, in that the structure is that each variable is a linear function of past lags of itself and past lags of the other variables. For a VAR(p) model, the first p lags of each variable in the system would be used as regression predictors for each variable. VAR models are a specific case of more general VARMA models.

5.3 Autoregressive moving average model with exogenous inputs model (ARMAX)

The ARMAX is a linear polynomial structure to model time series data. ARMAX are typically applied to auto correlated time series data. ARMAX is a generalised model for discrete, time-varying systems. An ARMAX model simply adds in the covariate to an ARMA model (Eq. 1).

$$y_t = \beta x_t + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} - \theta_1 z_{t-1} - \cdots - \theta_q z_{t-q} + z_t \tag{2}$$

where x_t is a covariate at time t and β is its coefficient. ARMAX(p,q,b) refers to the model with p AR terms, q MA terms and b exogenous input terms [Lydia et al., 2016, Li et al., 2014].

5.4 Non-linear Autoregressive Network (NARX)

The NARX model is a type of dynamically-driven recurrent ANN. An advantage is the reasonable computational cost to run the model. NARX involves using exogenous inputs. Figure 3 shows the simplest form of the NARX model, in this case with only one input (the value of the exogenous variables) which in turn provides feed-forward to a q number of delayed memory neurons. It has only one output at one step ahead. In turn, the output provides feedback to the network through a number of q delayed memory neurons.

The model relates the current value of a time series to 1) past values of the same series and 2) current and past values of the driving (exogenous) series [Tao et al., 2010,

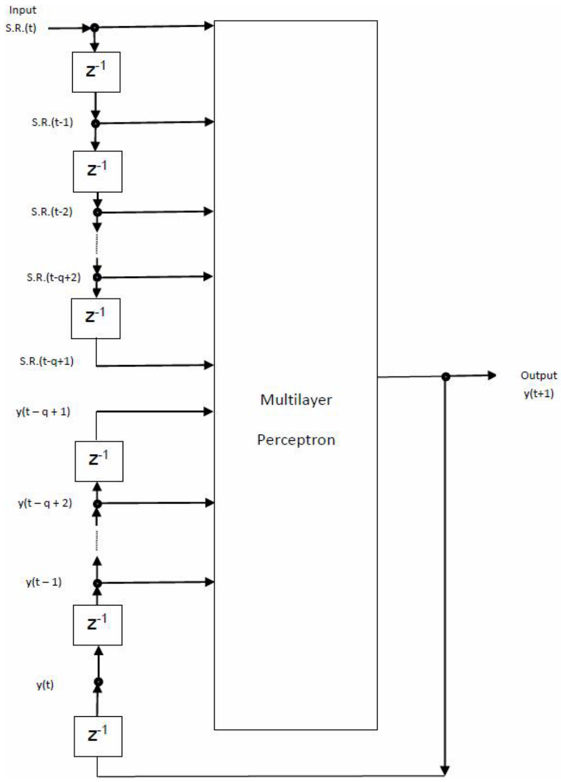

Figure 3: Architecture of the Non-linear Autoregressive Network (NARX) model [Cadenas et al., 2016].

Di Piazza et al., 2014]. Cadenas et al. [2016] use the variables: barometric pressure, air temperature, wind direction and solar radiation or relative humidity, as well as delayed wind speed to forecast wind speed.

5.5 Other

Wang et al. [2016] developed a partial functional linear regression model for forecasting the daily power output of PV systems.

Multivariate Adaptive Regression Splines (MARS) is a data driven approach without assuming the relationship between the output and predictors [Li et al., 2016b, Massidda and Marrocu, 2017].

Another form of multivariate ARIMA modelling is by switching the regime based on the current weather regime [Ailliot and Monbet, 2012, Pinson et al., 2008, Pinson and Madsen, 2012, Browell and Gilbert, 2017, Hering et al., 2015, Browell et al., 2017].

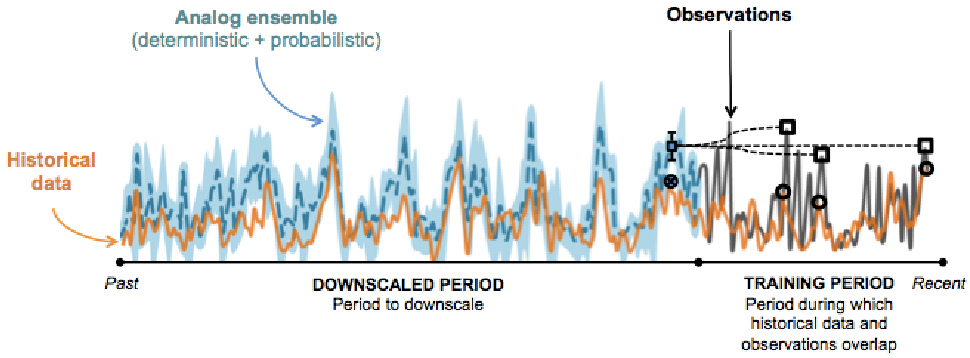

Figure 4: Analog ensemble method [NCAR, 2018]. Black dot - current value at time t. Black squares - observed values of the predictand for x best analogs.

6 Historical Analog

These are methods which use historical data to select similar days. One such method involves searching for a historical day that is similar to the day being forecasted [Hong et al., 2014], or based on satellite data [Boilley et al., 2016].

Analog Ensembles (ANEN) are one of the most common methods [Davò et al., 2016, Alessandrini et al., 2015b,a, Junk et al., 2015]. ANEN use historical data of multiple physical quantities over a training period with observations. First, the historical value of multiple analog predictors (e.g. wind speed itself, wind direction, pressure, etc.) is retrieved for a time window (known as an analog trend) (figure 4). The analog predictors are selected beforehand based on expected correlations to the predictand. Second, *analogs* (historical cases with similar conditions to those in the target window) are identified by looking at the same hour of the day throughout the training period and ranking those selected by closeness of match. Third, the x best analogs are selected and the corresponding observed values of the predictand are found. This makes up the ensemble members. It is expected that the errors will be similar to the errors of the analogs.

Another methods is a Schaake shuffle method involves ranking of historical scenarios on sorted quantiles of the forecast distributions and that connect forecasts quantiles associated with one particular historical scenario across all lead times [Schefzik, 2016, Wilks, 2015, Worsnop et al., 2018].

7 Weather Typing

This section describes post-processing methods which are dependent on other weather conditions present in observations or in the forecast [Kazor and Hering, 2015a,b]. This is essentially multivariate post-processing which come in many forms [Zhang et al., 2013, Baran and Möller, 2015, Pinson et al., 2008, Ailliot and Monbet, 2012].

There are many methods to find the variables to input to the forecasting models. Das et al. [2018] suggests looking at the correlation between PV power output and input variables; geographical location and the weather condition. The correlation of the meteorological parameters and PV power output will not be the same in different locations. Also, the proper pre-processing of input data reduces the errors, especially on models which are trained on historical data, by removing erroneous trends etc.

One method involves analysing the bias of the forecast depending on the cloud situation and solar zenith angle [Lorenz et al., 2009] and also including the condensed water amount [Morcette, 2000]. Others involve classifying the current/ forecasted weather type based on meteorological variables [Antonanzas et al., 2016, Chen et al., 2011, Shi et al., 2012, Ding et al., 2011, Yang et al., 2014].

Hoolohan et al. [2018] use atmospheric stability for a gaussian process regression and also a multivariate regression model with 4 predictor variables (time of observation, met office forecast, observed wind speed, hour of forecast), the met office forecast and 3h of observed data prior to the forecast. Basu [2018] also examined stability but using only 3 layers of wind speed data.

Steiner et al. [2017] found that the relative location of lows/cyclones with respect to Germany turned out to be of importance to the error. This led to the development of a cyclone detection algorithm to highlight these events and reduce the corresponding error.

Similarly for PV power prediction Köhler et al. [2017] found that if fog and low stratus are present the day-ahead forecast is worse. They also developed a detection algorithm as a post-processing to NWP forecasts as a warning tool for power providers.

Browell et al. [2017] propose regime-switching vector autoregressive method for very short-term wind speed forecasting at multiple locations with regimes based on large-scale meteorological phenomena.

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