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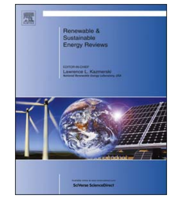

Short-term electric energy production forecasting at wind power plants in pareto-optimality context[☆]

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ABSTRACT

The paper discusses the possibilities of multi-criteria optimisation of a multi-layer perceptron (MLP) model applied to the short-term (intra- and next-day) wind power forecasting problem. The paper comprises two main parts: a theoretical background and study case using data (wind power production and historical weather forecast) obtained from two wind farms (at different power capacity levels). The problem stated in this paper is to formulate a method allowing for the estimation of a set of prediction models meeting the selected three model learning criteria: $\mathrm{n}BIAS$, $\mathrm{n}MAE$ and $\mathrm{n}RMSE$. The two-step NISE method has been used in order to estimate the non-dominated forecast evaluation set. The available data have been divided into three subsets for model learning, testing and validation. Than, a set of prediction model variants has been investigated considering different types of data subsets used for stopping the MLP learning process as well as calculating the forecast error. Additionally, different structures of MLP and learning algorithms have been analysed. Finally the paper is ended with a summary and conclusions.

1. Introduction

A sustained and rapid growth of the wind energy sector has been observed for over a dozen years. In the European Union (EU), annual installations of wind power have increased from 3.2 GW in 2000 to 11.2 GW in 2013 [1]. Wind energy as a clean and renewable resource plays a very important role in mitigating the climate change. A significant contribution of wind power in the entire energy consumption structure can be made in reducing greenhouse gas emissions. The target of a 20% share of energy from renewable sources in overall EU energy consumption by 2020 has been set [2]. Wind power generation is thus a significant part of domestic and Community (ENTSO-E) power systems.

In spite of its undoubted features such as being a clean and free energy resource, wind power is uncontrollable and highly intermittent. Major challenges are therefore faced by power system operators as well as electricity market participants. One is to efficiently handle the variability and uncertainty of wind power generation. For this purpose, professional forecasting methods and tools must be applied.

The most important duty of a transmission system operator (TSO) is to keep the balance of the electric load and power generation at any moment of time. The task of power balancing is not trivial due to the fluctuating nature of wind resources and the unsolved problem of energy storage on a large scale [3]. TSOs schedule an optimal (most cost-effective) combination of controlled generating units to meet a forecasted load, while assuming wind generation prediction, power system reserve requirements as well as generation and transmission constraints [4,5].

Wind power forecasting (WPF) is also indispensable for electricity market participants such as wind energy producers or energy trading companies [6]. For instance in Poland wind power producers conclude energy sales contracts with trading companies which are legally obligated (by the Energy Regulator Office) to buy all energy declared by the producers. The cost of imbalance between declared (a day before) and produced (measured) energy is usually covered by wind power producers. The imbalance cost can be a function of an hourly absolute forecast error or an hourly energy volume (a flat rate). In the latter case, the obligated company takes more risk of the energy imbalance. Details of an imbalance account depend on a sales contract, with a company's trade strategy being strictly related to participating in the balancing market (organised by the TSO) and implementing advanced business models of the energy trade process.

In general, prediction models implemented in the WPF systems can be distinguished into two classes [7–10]:

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(i) White-box (physical) models assuming the concepts of atmospheric dynamics and boundary-layer meteorology to carry out spatial refinement of the coarse output of numerical weather prediction (NWP) systems to specific on-site conditions as well as transformation of a predicted wind speed to the hub height of wind turbines;
(ii) Black-box models implementing simple or advanced mathematical relations between predicted power and certain input data. For this purpose different techniques are applied, such as power curves, statistical regression, grey models, artificial neural networks, fuzzy systems, and others. This approach does not consider the detailed knowledge about physical phenomena concerning wind power generation. Model parameters are to be determined a priori, statistically estimated, or tuned.

A fundamental issue in WPF tasks is numerical weather prediction NWP models which simulate atmosphere development by numerically integrating non-linear equations of motions starting from the current atmospheric state [7]. Results obtained from NWP are used in almost all WPF techniques and systems. A big challenge in the WPF process is still to obtain NWP satisfactory quality forecasts of wind speed and direction.

A typical WPF system uses input data taken as results from different sources, such as: numerical weather prediction models (NWP), local meteorological stations, supervisory control and data acquisition (SCADA) system, nearby terrain and topography model [46].

In recent years, various WPF methods have been developed in appropriate tools, just to mention a few: WPMS, WPPT, Prediktor, ARMINES, Previento, ANEMOS, Zephyr [8–10]. These models have been launched on wind farms in world-wide locations, and some of them are currently used by transmission and distribution system operators. The methodology of WPF depends on the adopted time horizon length of a forecast and its applications in business processes. The forecasting time- scale differs from several seconds-ahead (fast control of generation) up to multiple-days-ahead (energy trading, maintenance strategy of wind farms, power system balancing). The applied prediction methodology uses modelling physical phenomena of wind or statistical and learning approaches including artificial intelligence techniques. Some WPF methods provide point forecasts, and some provide the type and parameters of probability or ex-ante uncertainty measures. Below is presented a brief review of the developed and widely proven WPF methodologies.

(a) **Physical models**

The physical approach to short term forecasting consists in applying mathematical descriptions of different physical phenomena in the atmosphere and wind turbine. For this reason, such an approach can be called deterministic. It is one of the oldest and most original approaches. Physical methods, in general, are based on lower atmosphere or NWP forecasts which are recalculated to local atmosphere parameters taking into account local specific data like temperature, pressure, surface roughness and obstacles [7,11,12]. Local atmosphere parameters (mainly wind speed) are then converted to power produced by a turbine. Conversion to produced power is usually effected through the use of a simple turbine power curve [13]. It can also be attained with the application of more sophisticated turbine mathematical models, or even models describing turbines each other influences [7,14,15].

(b) **Statistical models**

Statistical models consider the relationship between wind power measurements and certain explanatory variables called predictors (both NWP and historical power measurements) applying the probability theory. Wind power generation is a continuous type variable and can be forecasted by probabilistic models which take the form of predictive density functions representing a random variable for a set of lead times. Such representation of future wind power can be directly used in stochastic optimisation tasks like: energy trading and balancing, economic dispatch and generation unit commitment, etc. [16]. The class of statistical models includes, among others, time series models, point or quantile regression, stochastic differential equations and scenario approach [17]. Various time series models have been employed to wind speed and power forecasting, also to wind volatility modelling. For wind speed prediction Modified AR models improved by second order blind identification [18] or using Bayesian approach [19] have been proposed. In Ref. [20], one can find an ARIMA model for daily average wind speed data and model seasonal variation of the volatility with a truncated Fourier series. Abilities of wind power forecasting volatility have been examined for selected types of the ARCH (autoregressive conditional heteroscedasticity) [21] and GARCH (general ARCH) [22] models. Markov regime switching model has been presented and found suitable to represent the dynamic behavior of wind power [23] and wind speed [24]. Apart from the time series models, quantile regression techniques have also been employed to the WPF process. In particular, [25] considered local regression, which uses kernels to smooth the data, while in Ref. [26] the authors analysed spline techniques for this purpose. Multivariate predictive densities in a form of scenarios are presented in Ref. [27]. The authors have assumed an interdependence structure of wind power output, which is represented by the covariance matrix of a multivariate Gaussian distribution. It is worth mentioning the technique of stochastic differential equations proposed for upgrading NWP using wind speed data and providing plausible time-path trajectories of the wind speed [28].

(c) **Artificial intelligence models**

A significant part of wind power prediction tools uses artificial intelligence (AI) models. The first commonly used were artificial neural networks [29]. They are still being used as a multilayer perceptron [30,31], recurrent [32], or as a radial base neural network [33]. The second AI method used was fuzzy systems [34,35]. Support Vector Machines (SVMs), after having become popular in other applications, are getting more and more popular in wind power forecasting [36,37].

(d) **Hybrid models**

Currently, most forecasting systems use models and methods based on the hybrid approach. Application of two or more prediction methods yields a significant synergy effect. This is obviously related to utilisation of specific features of each method. One of the most popular is the connection of artificial neural networks and fuzzy systems [38,39]. The connection may be complemented by other optimisation methods, e.g. PSO [40]. Artificial neural networks themselves can be aided by means of PSO [41], and in order to support ANN both evolutionary [42] and genetic algorithms can be used [43]. SVMs are also a part of hybrid solutions [44]. An interesting direction for the development of forecasting is the use of different methods/models to create parallel forecasts which are then integrated by the so called ensemble methods [45].

It should be emphasised that estimation or learning processes applied for the aforementioned point forecasting models use only one selected optimisation criterion. When analysing various classes of prediction models, the selection rule of estimation/learning criterion may be unknown or unproven. Hence, the following questions arise:

1. Is it possible to consider more than one criterion simultaneously in the model estimation/learning process?
2. Is it possible to obtain a good forecast by optimising the model with respect to a single criterion without simultaneously worsening other