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Wind Speed Forecasting: A Review

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ABSTRACT
Climate change causes serious impacts on the atmospheric such as violent storms, floods, fires, cyclones, acid rain and prolonged droughts. Nations of the whole world have been striving to achieve a sustainable development through the power generation from renewable resources: sun, wind, water, and biomass. Wind power grew sharply due to its advantages for power generation in large scale. Consistent wind speed forecasts are relevant and must be prepared to avoid economic losses, facilitate regulation of wind systems, and increase the operational efficiency of industries through a more reliable decision making. Many factors are able to influence the winds. For this reason, wind speed forecasting is one of the most relevant and challenging world research problems nowadays. In literature, many approaches have been proposed. This paper provides an overview of wind speed prediction and introduces strengths and weaknesses of each approach and method, as well as aimed at further direction for additional research,
Keywords: power generation, renewable resources, wind power, wind speed prediction.

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I. INTRODUCTION

The demand for energy is rapidly growing due to population growth, urbanization, and industrial evolution. In the meantime, the electricity market is increasingly competitive and energy industries are striving for producing more energy, preventing electrical issues, and preserving the population from potential social, economic and environmental impacts.

Renewable sources are the most promising alternatives for power generation, whereas the burning of fossil fuels causes severe environmental impacts, such as the increase in the atmospheric concentration of greenhouse gases, which causes acid rain, urban pollution, oil spills and deterioration of biodiversity.

The majority of the countries created a global perspective for expanding the national energy matrix by means of the renewable sources. The diversified energy production can provide cheaper tariffs and clean energy of better quality for the population, and also avoids the dependence on a single energy source.

Wind power had an overwhelming growth in the last decade. Global Wind Energy Council (GWEC), the international trade association for the wind power industry, published a projection of accumulative generation capacity, as shown in Fig1. In 2001, the world produced only 23,900 megawatts (MW), but in 2016 were 486,749 MW. In other words, more than twenty times of total in 2001. China ranks 1th in annual wind speed generation capacity, reaching 168,690 MW with an increase of 23,328 MW in relation to the previous year. United States occupies the second place, reaching 82,184 MW with an increase of 8,203 MW [1].

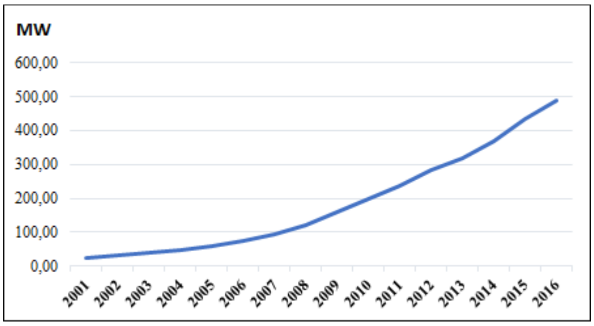

Figure 1: wind power generation from 2001 to 2016

Wind energy will continue to grow in the coming years due to its advantages over other renewable sources: (1) wind is an inexhaustible resource; (2) unlike solar systems, wind farms produce energy say and night; (3) For people, wind farms mean an increase in the supply of jobs in economically unfavorable regions; (4) wind generation does not produce polluting waste to the environment [2]; (5) wind farms have economic advantages over another system for power generation in large scale [3]; and (6), wind energy has a high social and environmental cost-benefit, as well as a cycle of short construction, low maintenance and flexibility to investment [4].

However, the biggest disadvantage of wind power systems is their intermittency and unpredictability. In fact, a robust electrical system demands relevant information to a safe supply of electricity. A stable operation can be achieved through the balance between the consistent forecasts of electricity generation and consumption.

Energy forecasting is an important requirement for operation planning on the electrical system, such as turbine control, load control, pre-load sharing, power system management, energy trading, among others [3]. The lack of consistent results is a major problem to wind farms.

There are two approaches to energy prediction: the direct prediction of the output of a wind turbine, as in [5-6], and the indirect prediction in which a wind speed forecasting is made and then it is converted into electricity.

Indirect prediction is more relevant and popular for some reasons[7]: (i) neighboring wind farms with different turbine models can share the same wind speed, in other words, instead of performing energy forecasts separately on each turbine, a single curve of the generation forecast is determined; (ii) wind speed forecasting is generally more accurate than the direct energy prediction due to the greater spatial correlation of the wind.

The transformation of wind speed into electricity can be achieved through equation 1, where *P* is the power output given in watts, *C* is a factor depending on the wind turbine design (or power coefficient), *S* is the area swept out by the rotor in square meters (m^2), *A* is the air density in kilogram per cubic meter (Kg/m^3) and *W* is the wind speed over the rotor area given in meters per second (m/s)[8][9].

$$P = ½ \cdot C \cdot S \cdot A \cdot W^3 \qquad (1)$$

In fact, the wind directly affects the wind power generation, being output power proportional to the cube of the wind speed. Wind is a natural resource, intermittent, uncertain and difficult-to-control. Its origin comes from pressure gradient between regions, caused by uneven heating of the sun on the earth's surface [10]. Moreover, complex events influence the behavior of the wind, such earth moving, physical effects of the mountain, obstacles, and roughness of the terrain [11]. Hence, estimating wind speed is a very difficult problem.

In general, the influence of obstacles and roughness decreases as a function of the height above the ground. Normally, the higher a region above ground, the greater the wind speed at any given moment. For this reason, wind turbines are installed in open spaces with low roughness and at the highest possible heights.

This paper aims to describe the wind forecasting approaches used in recent years, a survey of the most relevant method and guide future directions.

II. APPROACHES TO WIND SPEED FORECASTING

The problem related to wind speed prediction is divided into four temporal range: (1) long-term (LT), for forecasting from a week to year or much ahead; (2) medium-term (MT), from two days to a week ahead; (3) short-term (ST), from one hour to two days; and (4) very short-term (VT), from a few seconds to one hour.

Each forecasting has its purpose and importance in power plants. LT estimation is prepared to support decisions on the electricity market and to optimize cost in the planning of maintenance, while MT prediction is used for decision-making about the shutdown of wind turbines [12]. In addition, ST estimation is ideal for economic load dispatch planning, which means a decision about increment or decrement in power. On the other hand, VT prediction is relevant for configuring wind turbines, as well as clarifying additional information on the market [13].

In recent year, many approaches have been implemented for wind speed estimation. We can consider three main categories: (1) physical methods, (2) statistical approaches and (3) hybrid structures.

Physical models are mathematical models that combine a large amount of historical physical data obtained from numerical weather prediction (NWP), such as obstacles, terrain, pressure, and temperature. These models, in general, demand a lot of computational resources, including supercomputers, therefore they are only recommended for long-term prediction [14]. Normally, meteorologists and physicists recommend NWP models for the forecasts in large-scale, since they do not have good results in short-term prediction.

Statistical approaches describe the relationship between input and output data for detecting patterns in databases, through analysis of a massive training dataset. Physical data is used in statistical models, but unlike physical approach, there is no a pre-defined mathematical model in statistical approaches.

We can consider three categories of statistical methods: time-series models, spatial correlation and intelligence artificial (IA) methods. The first one examines the relation between weather data and wind speed from time series, including persistence model, autoregressive model, moving average model, autoregressive moving average, and autoregressive integrated moving. These models are simple, easy to implement and reveal good precision in short-term prediction.

The spatial correlation models estimate wind speed to exploit the spatial relationships of neighboring sites. Occasionally, spatial correlation is implemented with statistical approaches and provides good results in VT and ST prediction. However, due to strong electric market competition, it is very difficult to find available data at neighboring sites.

Recently, several papers have focused on Artificial Intelligence methods (AI) and hybrid structures. Both approaches are most suitable for the prediction and have provided best results in most situations.

IA method describes nonlinear (or linear) and highly complex statistical relationships between input and output data, such as neural networks, fuzzy logic methods, K-nearest Neighbors algorithm (KNN) and Support Vector Machine (SVM).

Hybrid structures combine, in parallel or sequentially, two or more approaches in order to describe the future state of the wind speed. In this approach, the complexity in development becomes greater as the combination of methods increase.

In fact, AI methods are good alternatives for predicting wind speed and understand the wind behavior for a particular region. However, when the knowledge of a site increases, changes in AI approaches or new considerations are implemented to improve results of the models, giving rise to a new hybrid method.

III. LITERATURE SURVEY

Lazíc, Pejanovic, and Zivkovic applied an physical model called Eta Model for wind speed forecasts and achieved reasonably good results in 2010[15].

Erdem and Shi implemented four approaches based on autoregressive moving average (ARMA) method for a short-term wind prediction in 2011. Such proposals achieved good results, but each has its advantages and disadvantages that must be evaluated for each situation [16].

Damousis, Alexiadis, Theocharis, and Dokopoulos suggested a fuzzy model for forecasting wind speed in 2004, which is trained using a genetic algorithm-based learning scheme [17]. The model demonstrated an adequate understanding of the problem when compared to a persistent method.

Mohandes, Rehman and Rahman in 2011 [18] propose an adaptive neuro-fuzzy inference system (ANFIS) to wind speed prediction at a higher height (100 m) based on wind speed knowledge at lower heights (10m, 20m and 30m). The model proved to be adequate for this type of approach.

Yesilbudak, Sagiroglu and Colak propose different models based on KNN to short-term wind speed prediction in 2013 [19]. KNN outperforms the persistence model and was able to reveal fake neighbors.

Neural networks are efficient to describe non-linear systems, therefore are relevant for predicting the wind speed. In 2007, Barbounis and Theocharis build a recurrent neural network for wind speed in a wind park, from the spatial information of neighboring sites. The proposed approach was efficiency and superior performance compared to other network types suggested in the literature [20].

Velo, López and Maseda propose a multilayer perceptron neural network to wind speed estimation in 2014 [21]. The results were very satisfactory, whereas only one month of data was used.

In 2016, Malik and Savita [22] used an artificial neural network for long-term wind speed prediction. Air temperature, earth temperature, relative humidity, daily solar radiation, atmospheric pressure, heating degree days, elevation, cooling degree days, latitude, frost days and longitude were input variables. Overall results were satisfactory for 39 sites in Maharashtra.

Kaur, Kuman and Segal implemented in 2016 five different neural networks models to short-term forecasting on the basis of historical time series meteorological data [23].The best model for short-term wind speed forecasting was composed of 19 hidden layers, 4 inputs, and 1 output.

In some cases, SVM model can be a more flexible and suitable than a neural network for predicting wind speed from a huge dataset. In 2011, Salcedo-Sanz, Ortiz-García, Pérez-Bellido, Portilla-Figueras and Prieto proposed a model for short-term wind speed prediction using meteorological variables, such as pressure, temperature, wind speed and direction in Albacete, Spain [24]. SVM algorithm had a very good performance outperforming a multi-layer perceptron.

Lahouar and Slama developed SVM models to predict short-term wind speed in 2014. The manuscript describes that the main advantage of SVM is its simplicity and rapidity, and of course its ability to predict, without using complex numerical weather prediction models [25].

Pinto, Ramos, Sousa and Vale developed SVM models and ANN models for short-term wind in 2014. SVM model using the eRBF kernel had the highest performance and precision, and outperform all NN models [26].

Liu, Kong, and Lee propose a convex optimization SVM model to wind speed prediction [27]. 2,000 sets of data to test and 500 sets to validation were used in 2014, China. Temperature, pressure, wind speed and direction were input attributes. Experimental results demonstrate that the proposed SVM is a high-efficiency convex optimization modeling technique for wind speed forecasting.

Typically, hybrid structures have good performance and relevant results over AI methods for a specific region (or wind turbine).

In 2010, Cadenas e Rivera proposed a hybrid structure composed of an Autoregressive Integrated Moving Average model and a neural network [28]. The hybrid model had a higher accuracy than the ARIMA and ANN model separately in the three examined sites.

In 2014, Wang, Zhang, Wang, Han and Kong [29] implemented a new hybrid model based on the seasonal adjustment method (SAM), exponential smoothing method (ESM), and radial basis function neural network (RBFN). Consequently, the model became known as SAM–ESM–RBFN. Overall, the proposed approach was effective in improving the prediction accuracy.

Liu, Niu, Wang and Fan proposed in 2014 a hybrid model composed of an SVM model, input selected by deep quantitative analysis, wavelet transform and genetic algorithm [30]. For a case study in China, the new proposed outperformed a persistence method and other hybrid structure.

In 2015, Wang, Qin, Zhou and Jiang [31] developed a support vector machine combined with a seasonal index adjustment and an Elman recurrent neural network to construct the hybrid models named PMERNN and PAERNN. Both hybrid structures achieved a higher degree of accuracy over other models.

Fazelpour, Tarashkar, and Rosen [32] implemented four methods to short-term forecasting based on IA method intelligence and hybrid structures in 2016: (1) neural networks with radial basis function, (2) adaptive neuro-fuzzy inference system, (3) artificial neural network-genetic algorithm hybrid, and (4) artificial neural network particle swarm optimization. Although the other models estimate wind speed with reasonable accuracy, the hybrid model with particle swarm optimization had better results.

In 2016, to medium-term and long-term prediction in three sites in China, Hu, Zhang, Yu, and Xie [33] implemented a new hybrid method called HGN-support vector regression and compared to six methods, such as gaussian noise-support vector regression, gaussian noise-KRR, feedforward neural network, recurrent neural network, persistence model, and linear regression. The new hybrid approach was better than other six techniques.

Shao, Deng and Cui propose a new hybrid model, in 2016 [34], in which an AdaBoost neural network was designed using a wavelet decomposition to solve the defects of the lower accuracy. From experiments was detected that the proposed strategy can significantly enhance the model robustness and the prediction accuracy.

Chang, Lu, Chang and Li present a network neural model with an improvement in the radial basis function and in the error feedback scheme (IRBFNN-EF) for forecasting short-term wind speed in 2017. The proposed hybrid model improved the accuracy and maintained the computational efficiency when was compared to four other neural networks [35].

IV. CONCLUSION AND FUTURE DIRECTIONS

From the papers referred, clearly, researchers have sought a single method to provide the better result if applied in any situation. In fact, developing a global and better method to wind speed forecasting is very difficult due to the fact that wind patterns are usually different and influenced by many factors.

IA methods and hybrid structures have taken advantages in relation to the other approaches. to indicate a general and initial prediction method for an industry, the neural network has proven to be a good method for most situations, involving variable data sets sizes and forecast models. However, a hybrid approach adapted to the situation can be implemented in order to increase the performance and accuracy precision of a model based on IA methods.

As future directions, we believe that an adaptive approach or method should be an interesting alternative to leverage wind speed prediction results for many situations. In the last years, most of the mentioned manuscripts only make a study to measure the accuracy of forecasting methods for a specific region. In fact, many implementations are proposed and only tested in a specific region.

In addition, there is no free system and robust for predicting wind speed. Perhaps, if a system were built, it would facilitate the work of energy operators. The research community itself could implement current and relevant method into the software to wind speed prediction, as well as adapting it for every need.

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