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Wind Energy: Intelligent Manufacturing Perspective

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Abstract

The growing demand for wind power has resulted in a market that naturally favors development of new wind farms over improvement of their performance. A chain of opportunities for performance improvement of any wind energy project parallels the supply chain activities. Raising energy and transportation costs are a complicating factor of the performance improvement projects.

One of the weakest points in wind power generation is the low predictive accuracy of the energy output. Similar to industrial corporations managed by enterprise-wide systems, a software solution for prediction of wind farm performance (including the amount of energy produced) is needed. The envisioned wind farm performance prediction software should be able to predict the amount of energy to be produced on different time scales, ranging from seconds to days. Such software would transform a wind farm into to a wind power plant.

A novel approach to modeling the performance of individual wind turbines as well as their collection (a wind farm) is discussed. Besides the utility scale applications, the proposed solution can be scaled down to optimize residential wind turbines (KW range) dispersed over large areas. The lower sensory capability of household turbines will be mitigated by the wide availably of wireless communication and internet connectivity.

1. Introduction

The generation of wind energy on an industrial scale is relatively new, and the performance issue has not been thoroughly studied. This paper offers a novel approach to modeling the performance of individual wind turbines as well as their collection, which is referred to as a wind farm or a wind park. Besides the electric utility scale applications, the proposed solution can be scaled down for collective optimization of residential wind turbines (KW range) dispersed over large areas. The less sophisticated sensory capability of household turbines will be mitigated by data access from external sources (e.g., public) through wireless and internet connectivity.

From the modeling perspective, the wind industry of today can be compared with the computer industry and developments in industrial automation of decades ago. The early computer systems were developed in the absence of constraints imposed by their applications. At that time, it was assumed that the application, e.g., inventory management, needed to adapt to the software and hardware platform offered. Early manufacturing systems operated as islands of automation before more production planning and control systems were put in place. A wind turbine enters a power grid with its strengths and weaknesses without much consideration of the grid requirements. For the wind power to become an equal partner with the energy generated from traditional and other sources, it must consider the requirements of the electric grid. Wind power does not need to replicate the behavior of existing energy generating modes; however, it does need to meet a predefined set of specifications. One of the weakest points of wind power generation is the poor predictability of wind farm performance. Though numerous metrics can be used to measure performance, the most important one is the accuracy of the output prediction. The wind farm should be able to predict the amount of energy produced on different time scales, e.g., minutes *to* days in the quest of becoming a wind power plant.

Traditionally the location of a wind farm and the layout of its wind turbines are determined (see Fig. 1) using the available software and simulation tools.

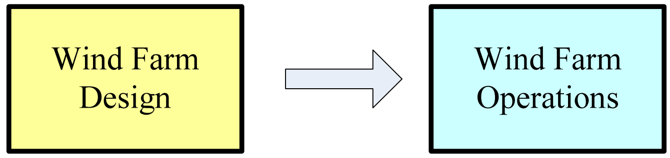

Figure 1. Traditional steps to wind farm design and operations.

The location of a wind farm is usually based on studying weather maps. The time scale considered in the location analysis is long, e.g., measured in years. Once the wind park has been designed and constructed, it is ready to operate (see Fig. 2). The operation of a wind farm, however, becomes an independent issue.

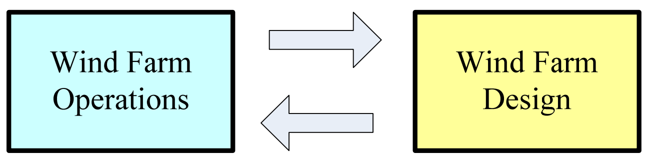

Figure 2. Proposed logic to wind farm design and operations.

This paper offers a new paradigm to increase wind farm performance by improvements in its design and operations (see Fig. 2). The data (e.g., SCADA collected) generated by an operating wind farm is used to improve the operation of the farm as well as the design of future wind farms. The bidirectional relationship between the wind farm operations and its design will should be fully explored (see Fig. 2).

2. Literature Review

The power generated by wind turbines changes due the continuous fluctuation of wind speed and direction. This causes problems for power system schedulers and dispatchers, as thus far tools for accurate prediction of wind energy production have not been developed. It is highly desirable to develop systems increasing the prediction accuracy of wind power generation. Highly accurate, localized, and timely prediction of wind parameters at the turbine and wind farm level is a key component in optimizing wind farm performance. The improved performance on the scales expected by the energy industry can be accomplished with predictive models using local (wind turbine specific) and global (area specific) data. The analysis of such a wide range of wind farm data has not been reported in the literature. The specific data parameters and their predictive power can be determined by a comprehensive analysis with data-mining algorithms.

Wind power performance has been partially addressed in the literature. Neural networks (generally one type – the back propagation network) and stochastic approaches appear to dominate the past research. Kariniotakis *et al.* (1996) developed a recurrent high-order neural network model for prediction of the power output profile of a wind park. This model outperformed classical methods reported in the literature. Alexiadis *et al.* (1999) developed a neural network model that has improved the forecasting accuracy of wind power compared to the traditional persistence forecasting model. A four-input neural network to predict power produced at a turbine level was investigated by Li *et al.* (2001). The neural network performance was shown to be superior to the single parameter model. The same authors have also noted that the neural network output could be used for turbine diagnostic purposes.

Besides the early attempts to use neural networks, other approaches have been applied for performance optimization. For example, Matevosyan and Soder (2006) applied stochastic programming to optimize wind power production bids for a short-term power market. A wind power forecast error was represented as a stochastic process. The imbalance in costs resulting from this strategy was compared to the imbalance in costs when wind power production bids on a short-term power market were based directly on a wind speed forecast.

The utilization of water storage ability to improve wind park operational economic gains and to attenuate the active power output variations due to the intermittence of the wind-energy resource was proposed by Castronuovo and Lopes (2004). A discrete optimization approach was developed to identify the optimum daily operational strategy to be followed by the wind turbines and the hydro-generation pumping equipment, provided that wind-power forecasting was available. The stochastic characteristics of the wind power were exploited in order to identify recommended operational conditions. Three operational conditions were analyzed and the results obtained were discussed.

A method for establishing the wind speed correlation between neighboring stations was presented in Bechrakis and Sparis (2004). The aim of this research was to develop a model in which given the wind speed at a particular site, the wind speed at another site nearby could be simulated. The proposed approach considered the evolution of the sample cross-correlation function of wind speed in time and used a neural network to perform the wind-speed simulation. Four separate pairs of wind-data measuring stations at two different regions were examined. Tests showed that the higher the sample cross-correlation function value between two sites, the better simulation result was achieved. Also, in a pair of stations under investigation, the reference station had to be the one that contained more information on its wind speed signal for the optimum simulation performance.

Gjengedal (2003) focused on the transient stability and application of different wind turbine technologies. Results from simulations of three different technologies showed that the responses after faults were technology dependent. The induction generator led to problems regaining a stable operating point after a fault occurred, while the two others allowed the full operation of the wind farm to continue after clearing the fault. Applying intelligent-damping algorithms at the individual wind turbines improved damping of swings in the system.

The US Doppler radar network installed software that contained over 40 algorithms that sampled the near-radar environment and generated diagnostic and predictive information. A subset of these algorithms aims at alerting forecasters of potentially severe weather. Of these algorithms, two particularly are powerful, the tornado detection and the mesocyclone detection algorithms. These algorithms are based on empirically determined thresholds. The goal of the study reported by Trafalis and White (2003) was to use Doppler radar network algorithms to uncover physically meaningful predictive patterns in weather radar data that warn of severe conditions before they occur.

The weather forecasting models are dramatically different in scope, scale, and objectives from the predictive models proposed in this research. The models to be developed in this research are highly specific, rather than area and population based, as is the case of the wind mapping and weather forecasting models. Soukissian *et al.* (2002) performed statistical analysis of wind and wave buoy measurements and wind and wave model forecasts for a two-year period (1999-2001). Comparisons between the measurements and the forecast results were performed at different locations. The overall pattern of the wind/wave climate for the entire Aegean Sea was presented in the form of a spatial distribution (a population-based representation) of the mean annual wind and sea-state intensity.

John (2004) presented a method to compare competing forecasting methods and single parameters. The method is simple to understand and apply and has proven to be useful in improving forecasting.

A thorough review of the wind power prediction software used largely in Europe was conducted by Ernst (2005). Software packages such as Prediktor, WTTP, ELTRA, Zephyr, Previento, eWind, SIPPREOLICO, and AWPT have been evaluated. The theories used to develop the existing prediction software appear to be dated and do not fully utilize the knowledge contained in the available data streams. The need for the next generation performance prediction software is apparent.

3. Shortcomings of the Existing Approaches for Wind Farm Performance Optimization

The presented in the literature approaches to optimization of wind power performance share the following deficiencies:

- The range of approaches is limited to essentially traditional single parameter models and neural networks with a limited number of inputs (e.g., 4).
- All models are based on "as-is" data, which does not allow to fully explore the value hidden in the frequency, time-scale, and location components of the data streams.
- The existing models are non-explicit and do not offer the user any insights into the knowledge governing the power performance.
- The training aspect and stability of the neural network models is not discussed. The training time is likely to be a stumbling block in using such models.
- No formal methods of selection and evaluation of input parameters have been offered.
- No method of evaluating the impact of missing parameters (e.g., due to sensor failures) on the quality of the model outcome has been presented.

4. Selected Data Mining Algorithms

The data-mining approach proposed in this paper avoids the pitfalls of the approaches discussed in the literature. The basic classes of data-mining algorithms used in the research advocated in this paper are as follows:

- Decision tree algorithms (e.g., Quinlan 1993, Tan *et al.* 2006)
- Decision rule algorithms (e.g., Michalski *et al.* 1998, Grzymala-Busse 1997)
- Association rule algorithms (e.g., Agrawal *et al.* 1993)

An extensive literature search indicates that none of the above three data-mining algorithms has been used in wind farm applications. The proposed approach is the first demonstration of data-mining algorithms that extracts explicit knowledge in the performance optimization of wind farms.

The proposed data-mining algorithms offer numerous advantages:

- Generation of explicit knowledge that is understandable to a user.
- A good notion of the prediction accuracy of the data-mining-based performance metrics.
- Evolution of knowledge. The results developed by the investigators in the combustion project sponsored by the Iowa Energy Center will be the foundation for handling highly temporal data (Kusiak and Burns 2005).

Modern neural networks, e.g., radial basis function networks (Konar 2005), as well as other data-mining algorithms are explored in the research reported in this paper.

5. Proposed Solution Approach

The data-mining approach proposed in this paper fuses data from different sources, e.g., wind data measured at individual turbines, towers, public buildings, and weather towers at diverse modalities such as altitude and temperature. The seamlessly integrated multi-source and multi-modal data may increase predictive power. Besides making high confidence performance predictions, data-mining algorithms determine the importance of parameters to be used by the proposed wind power performance predictor.

In addition to the intended benefits, the experience with data mining may result in other benefits, e.g.:

- Improvement of industrial standards and practices, e.g., power curves. The standards and practices used throughout the wind industry do not accurately reflect the process status.
- The data-mining process can be used to generate metrics and parameters outside the scope of optimization. These parameters can in turn be used to make accurate predictions, e.g., predicting potential faults before they occur.

The wind power industry has seen an unprecedented growth in the US in the last few years. The surge in orders for wind turbines has resulted in a producer's market. This market imbalance, the relative immaturity of the wind industry, and rapid developments in data processing technology have created an opportunity to improve the performance of wind farms and change misconceptions surrounding their operations.

This paper offers a new paradigm for the wind power industry, data-driven modeling. Each wind turbine generates extensive data for many parameters, registered as frequently as every six seconds. This data remains essentially unused due to, for example:

- The lack of incentives due to the producer market.
- The lack of knowledge about the recent developments in data mining and computational intelligence.
- Inadequate sharing and making use of the data that remains largely unexplored.

As the predictive performance approach is novel to the wind industry, it is essential to establish a viable research road map.

Depending on the form of its implementation and use, the proposed approach can be considered as competing against or complementing the control systems used in the power industry, e.g., analog, neural network, and other controllers. The proposed data-mining solution offers the following advantages over the existing solutions:

- The model (knowledge) is explicit and can be interpreted by a human expert.

- The model (knowledge) remains current due to a short update (learning) time and an easy way of self-determining its degradation. In fact, the model can be as current as needed.
- The accuracy of the predictions produced by the proposed solution is known in advance. This allows for an a priori distinction between high-quality solutions and low-quality solutions.
- Humans (e.g., operators, engineers, managers) gain insight into the controlled process and can learn new concepts.

6. Novelty of the Proposed Solution Approach

The proposed approach is built around a new concept of horizontal and vertical mining (bidirectional mining) of transformed data. The analysis of various temporal data sets has shown that mining "as-is" data may not produce meaningful results; however, mining transformed data may produce excellent results. This has to do with the diversity of parameter dynamics, time scales, and data noise. Different ways of forming parameter functions are explored in this paper. Horizontal parameter functions (e.g., parameter sets) have produced excellent results in the semiconductor applications, water chemistry (Kusiak and Shah 2006), aluminum processing (Kusiak 2002), and combustion (Kusiak and Song 2006). Numerous ways of creating derived parameters, including data transformation are investigated.

The concept of bidirectional mining appears to be a viable method for generating derived parameters. Besides the parameters, time functions, and parameter-decision value plots, other functions and methods can be used to derive new parameters, e.g., multi-scale matching, wavelet functions, frames, constructs of self-similar processes, Fourier transforms, and rough clusters.

One of the unique aspects of the proposed solution is that an innovation-based framework is used in conceptualizing and designing project deliverables. All aspects of the project are researched according to the basic innovation science principles outlined in Kusiak (2006a) and Kusiak and Tang (2006). The proposed research approach is data-based, and it matches the data-driven innovation approach (see Kusiak 2006a). Fostering innovative solutions maximizes the benefits of the solution and demonstrates a new paradigm to the wind power community.

7. Conclusion

Wind is an invisible fuel powering a turbine, and it needs to be studied just as coal and biomass have been studied. Unlike the construction of wind maps and weather prediction, the modeling of the wind to be advocated in this paper takes place at a local level.

A wind farm is a large-scale, energy-generating facility with its internal interactions (e.g., cross-turbine wind), specialized equipment (turbines), control systems, and large data bases (SCADA). As such, it requires its own facility-wide (enterprise-wide) control system. Wind power generation on a large-scale is new and has not seen the benefits of data-driven approaches advocated in this paper. Integrating the wind-farm generated data with wind data from other sources and possibly other farms will attract new industries. The wireless and hardware communications technology is a strong enabler.

The data-mining approach proposed in this paper is likely to establish a new paradigm of predictive control in the wind industry.

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