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Optimization of wind turbine energy and power factor with an evolutionary computation algorithm

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ABSTRACT

An evolutionary computation approach for optimization of power factor and power output of wind turbines is discussed. Data-mining algorithms capture the relationships among the power output, power factor, and controllable and non-controllable variables of a 1.5 MW wind turbine. An evolutionary strategy algorithm solves the data-derived optimization model and determines optimal control settings. Computational experience has demonstrated opportunities to improve the power factor and the power output by optimizing set points of blade pitch angle and generator torque. It is shown that the pitch angle and the generator torque can be controlled to maximize the energy capture from the wind and enhance the quality of the power produced by the wind turbine with a DFIG generator. These improvements are in the presence of reactive power remedies used in modern wind turbines. The concepts proposed in this paper are illustrated with the data collected at an industrial wind farm.

1. Introduction

Distributed energy generation is becoming prevalent in the energy market, especially with the rapid expansion of alternative energy [1,2]. This newly distributed generation creates challenges related to power quality [3–5]. The power quality issue can be addressed at the wind turbine or the wind farm level. This paper focuses on a single generator, which is fundamental to power quality improvement at the aggregate level.

Numerous metrics are used to measure the power quality of a wind turbine, the most common of which are power factor, reactive power, and harmonic distortion. As the generation of wind energy on an industrial scale is relatively new, the area of improvement in power quality remains open. Tapia et al. [3] presented a control strategy for reactive power control of a wind farm, including double-fed induction generators, and thus the voltage level control of distribution network was improved. Harmonics generated by the interactive wind and photovoltaic hybrid power system were investigated by Giraud and Salameh [6]. Muljadi and McKenna [7] analyzed the power quality issues in a hybrid power system involving wind turbines and diesel generators. Ko and Jatskevich [8] discussed modeling and control of a wind-hybrid power generation system to enhance power quality. In their simulation study, a fuzzy-LQR (linear-quadratic regulator) controller was shown to be effective against disturbances caused by the wind speed and load variations.

Maximizing the power capture from the wind is one of the main drivers in the design of the wind turbine control system. Boukhezzar et al. [9] proposed a non-linear approach to control a variable-speed turbine to maximize power in the presence of generator torque considerations. Datta and Ranganathan [10] developed a search algorithm to track the peak power points for variable-speed wind turbines. Munteanu et al. [11] applied a linear-quadratic stochastic approach to solve the power optimization model, and tested it using an electromechanical wind turbine simulator. A trade-off between the efficiency of energy conversion and input variability was studied in the simulation experiments. Muljadi and Butterfield [12] developed a pitch control strategy to maximize power and minimize turbine loads for different wind speed scenarios.

Data mining is an emerging science that has found successful applications in various areas including manufacturing [13,14], marketing [15,16], medical informatics [17], and energy [18–21]. Evolutionary computation is a powerful tool for solving complex optimization models. Successful applications of evolutionary

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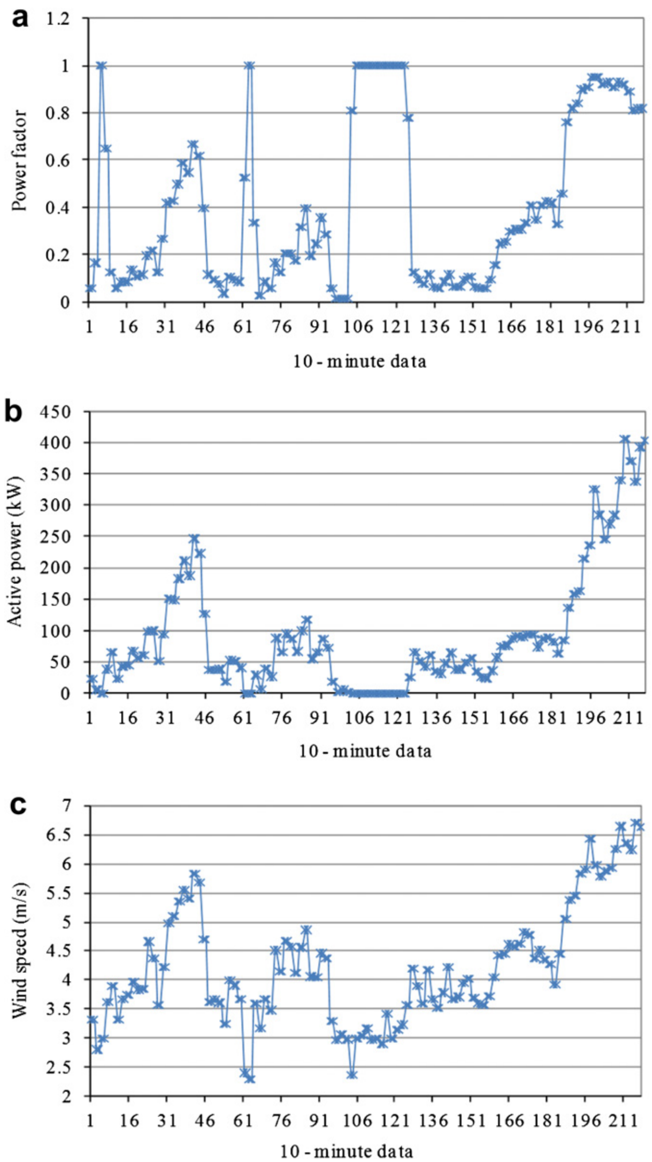

Fig. 1. Active power, power factor, and wind speed plot for a wind turbine: (a) power factor, (b) active power, (c) wind speed.

computation algorithms have also been reported in a variety of domains [22–25].

In this paper, data mining and evolutionary computation are integrated to optimize the power factor and the amount of power produced by a wind turbine. Data-mining algorithms identify dynamic models from a large volume of the SCADA (Supervisory Control and Data Acquisition) wind farm data collected, and an evolutionary computation algorithm is then applied to solve the bi-objective power optimization model.

As most wind farms are relatively new, it is natural that their performance has not been adequately studied. Prediction of the power produced by a wind farm at different time scales is of interest to the electricity grid.

2. Problem formulation and methodology

2.1. Power optimization problem formulation

The theoretical wind energy captured by the rotor of a wind turbine is computed from Eq. (1) [9,26]:

Table 1
Variables used for dynamic modeling of wind turbines.

Variables	Description	Unit
v	Wind speed	m/s
x_1	Blade pitch angle	°
x_2	Generator torque	%
y_1	Active power	kW
y_2	Power factor	No unit
y_3	Rotor speed	rpm

$$P_r = 0.5\rho\pi R^2 C_p(\lambda,\beta)v_b^3 \tag{1}$$

where P_r is the wind energy captured by the rotor, ρ is the air density, R is the rotor radius, and v_b is the wind speed before passing the rotor. The parameter C_p is the power coefficient that depends on the blade pitch angle β and the tip-speed ratio λ determined from Eq. (2) [10,27]:

$$\lambda = \frac{\omega_r R}{v_b} \tag{2}$$

where $\omega_r$is the rotational speed of the rotor.

The literature on optimization of the power coefficient C_p is quite extensive. The values of β_{opt} and λ_{opt} maximize the power coefficient $C_{p,opt}$. Since λ is a function of ω_r, it is obvious that there exists an optimal rotor speed $\omega_{r,opt}$.

Maximization of the power extracted from the wind calls for optimal control settings of the wind turbine parameters. However, optimization of the power alone does not necessarily guarantee the quality of the power generated by the wind turbine. Power quality is measured by different metrics, e.g., power factor, harmonic distortion, and transient overvoltage. In this paper, the definition of the power factor provided in Eq. (3) [26,27] is used as the primary metric of power quality.

$$\begin{aligned} PF &= \frac{P}{S} \\ S^2 &= P^2 + Q^2 \\ P &= S|\cos\phi| \end{aligned} \tag{3}$$

where PF is the power factor, P is the active power measured in Watts (W), S is the apparent power measured in volt-amperes (VA), Q is the reactive power measured in reactive volt-amperes (VAr), and ϕ is the phase angle between the current and the voltage and measured in degrees (°).

True power factor measures the efficiency of electric power utilization, and the goal for wind turbine control is to maintain a power factor of 1. However, the power factor of wind turbines is difficult to control, and thus its value is frequently lower than 1 for individual wind turbines and wind farms.

In this paper, optimization of the active power and the power factor by supervisory control of a wind turbine is pursued. The plots of active power, the power factor, and the wind speed of a turbine over a 36-hour time period are shown in Fig. 1(a) through Fig. 1(c). The wind speed during this time period is in the range of 2–7 m/s (considered here as a low wind speed scenario). At times the value of the power factor and the active power are low. A well designed

Table 2
Description of the data set.

Data Set	Start Time Stamp	End Time Stamp	Description
1	7/01/08 12:00 AM	7/31/08 11:50 PM	Total data set; 4466 observations
2	7/01/08 12:00 AM	7/24/08 12:00 PM	Training data set; 3457 observations
3	7/25/08 12:10 AM	7/31/08 11:50 PM	Test data set; 1009 observations