Energy Conversion and Management 81 (2014) 520–526

Contents lists available at ScienceDirect

Energy Conversion and Management

journal homepage: www.elsevier.com/locate/enconman

Wind turbine power coefficient estimation by soft computing methodologies: Comparative study

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ARTICLE INFO

Article history:
Received 28 October 2013
Accepted 24 February 2014
Available online 18 March 2014

Keywords:
Wind turbine
Power coefficient
Blade pitch angle
Support vector regression
Soft computing

ABSTRACT

Wind energy has become a large contender of traditional fossil fuel energy, particularly with the successful operation of multi-megawatt sized wind turbines. However, reasonable wind speed is not adequately sustainable everywhere to build an economical wind farm. In wind energy conversion systems, one of the operational problems is the changeability and fluctuation of wind. In most cases, wind speed can vacillate rapidly. Hence, quality of produced energy becomes an important problem in wind energy conversion plants. Several control techniques have been applied to improve the quality of power generated from wind turbines. In this study, the polynomial and radial basis function (RBF) are applied as the kernel function of support vector regression (SVR) to estimate optimal power coefficient value of the wind turbines. Instead of minimizing the observed training error, $SVR_{\_poly}$ and $SVR_{\_rbf}$ attempt to minimize the generalization error bound so as to achieve generalized performance. The experimental results show that an improvement in predictive accuracy and capability of generalization can be achieved by the SVR approach in compare to other soft computing methodologies.

1. Introduction

Due to global environmental pollution emergence, trends towards the sustainable energy and green power sources such as wind energy have risen. Wind energy is one of the economic renewable sources and a feasible alternative to conventional energy sources. The common goal of the wind turbine is to maximize favorableness by maximizing energy extraction, and therefore the power output of the wind turbine often varies with vacillating winds. Until recently there have been no requirements or market motivators for wind turbines to control their power output [1]. Higher wind insight levels have increased the interest for wind turbines to provide additional services that are critical to grid dependability by controlling their power output through power control [2,3]. Development of control solutions is a valuable approach to reduce reduction of operations and maintenance costs of wind turbines [4].

Modern large wind turbines can be classified into three different types, including the constant speed type, variable pitch control type and variable speed type. Variable speed wind turbine power generation system is more superior to others because of its high power extraction efficiency and high power quality [5–7]. In the operating wind speed range, in order to achieve the maximum power point tracking of wind turbine, the turbine shaft rotational speed should be adapted optimally with respect to the variable wind speed [8]. Such turbine rotor speed control should base on the real-time information of wind speed. When the wind speed is lower than the rated wind speed, the rotational speed of the wind turbine is controlled according to the variable wind speed by the rotational speed control of the generator for keeping the optimal power coefficient C_p of the wind turbine. The variable pitch control of the wind turbine blade generates the optimal electric power when the wind speed is higher than the rated wind speed.

The wind systems are nonlinear power sources that need accurate on-line identification on the optimal operating point [9–11].

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http://dx.doi.org/10.1016/j.enconman.2014.02.055
0196-8904/

Since it is nonlinear function a soft computing techniques are preferred for its estimation and prediction. Aiming at optimizing such systems to ensure optimal functioning of the unit, many soft computing techniques are used today such as the fuzzy logic (FL) [12–14], artificial neural network (ANN) [15,16], neuro-fuzzy [17–22] and support vector machines (SVM) [23–25]. The basic idea behind the soft computing methodology is to collect input/output data pairs and to learn the proposed network from these data.

Artificial neural networks (ANNs) are being extensively applied to various areas to overcome the problem of nonlinear relationships and predictions [26–30]. Recently, improved version of ANNs which is called support vector machines (SVMs) has gained importance in forecasting problems related to environment [31–34]. There are two main categories for support vector machines: support vector classification (SVC) and support vector regression (SVR). SVM is a learning system using a high dimensional feature space [35–39]. The support vector regression algorithms (SVR) specifically developed for regression problems are appealing algorithms for a large variety of regression problems, since they do not only take into account the error approximation to the data, but also the generalization of the model, i.e., their capability to improve the prediction of the model when new data are evaluated by it [40–46]. SVR is based on statistical learning theory and a structural risk minimization principle, which has been successfully used for nonlinear system modeling [47–51]. The accuracy of a SVM model is largely dependent on the selection of the model parameters. However, structured methods for selecting parameters are lacking. Consequently, some kind of model parameter calibration should be made.

The SVR scheme for estimation of the optimal values of wind turbine power coefficient was used in this article. The SVR_rbf and SVR_poly were examined: the first one is radial basis function and the next is polynomial function. These functions represent kernel functions which are utilized to form qualified function for SVM. Hence, the RBF and polynomial function are applied for estimation of wind turbine power coefficient in this study. The traditional ANN and adaptive neuro-fuzzy inference system (ANFIS) [52–55] were also investigated for comparison.

The objective of this article investigation is to establish an SVM for estimation of the wind turbine power coefficient (C_p). An attempt is made to retrieve correlation between power coefficient C_p in regard to blade pitch angle and tip-speed ratio of the wind turbine. That system should be able to forecast the power coefficient in regards to the main turbine parameters and wind speed as well.

2. Wind turbine power

The major components of a typical wind energy conversion system include a wind turbine, a generator, interconnection apparatus, and control system. Therefore, the design of a wind energy conversion system is complex. The most important part of a wind energy conversion system is the wind turbine transforming the wind kinetic energy into mechanical or electric energy. The system basically comprises a blade, a mechanical part and an electric engine coupled to each other. The kinematical energy of wind is the function of wind speed, the specific mass of air, the area of air space where the wind is captured and the height at which the rotor is placed. The power available in a uniform wind field can as expressed as

$$P_w = \frac{1}{2}\rho A v^3 \tag{1}$$

where P_w is the power (W) of the wind with air density ρ (kg/m^3) and wind speed v (m/s) is passing through the swept area A (m^2) of a rotor disk that is perpendicular to the wind flow. The wind turbine can only capture a fraction of the power available from the wind. The ratio of captured power to available power is referred to as the power coefficient

$$C_p = (\beta, \lambda) \tag{2}$$

which is a function of the collective blade pitch angle β and the tip-speed ratio λ. The tip-speed ratio is defined as the ratio of the tangential velocity of the blade tips divided by the effective wind speed, or

$$\lambda = \frac{R\Omega_r}{V_e} \tag{3}$$

where R is the rotor radius, Ω_r is the rotor speed, and V_e is the effective wind speed perpendicular to the rotor plane. The value of C_p can be expressed according to [27] as:

$$C_p(\beta,\lambda) = 0.5176\left(\frac{116}{\frac{1}{\lambda-0.08\beta}-\frac{0.035}{\beta^3+1}} - 0.4\beta - 5\right)e^{\frac{-21}{\frac{1}{\lambda-0.08\beta}-\frac{0.035}{\beta^3+1}}} + 0.0068\lambda \tag{4}$$

3. Input parameters

As a data-driven model, the ability of the SVR to make reasonable estimations is mostly dependent on input parameter selection. Adequate consideration of the factors controlling the system studied is therefore crucial to developing a reliable network. According to the experiments [27], the inputs parameters (blade pitch angle and tip-speed ratio) are collected in wind turbine are to be defined as input for the learning techniques. The wind turbine rotor radius is R = 75 m and relationship between wind speed and rotor speed has been presented in [20]. The experimental data was acquired three months to cover all wind speed fluctuations. For the experiments, 70% of the data was used to train samples and the subsequent 30% served to test samples. A summary of the statistical properties of the wind turbine database is provided in Table 1. The standard deviation in the tables represents the distribution of the responses around the mean. It indicates the degree of consistency among the responses.

4. Supervised machine learning

SVMs are a type of supervised machine learning technique that is part of a generalized linear classifier family. The formulation contains the structural risk minimization (SRM) concept, as a contrary to the empirical risk minimization (ERM) approach that is widely employed in the statistical learning methods. SRM mitigates an upper bound on the generalization error, unlike the ERM which makes the error minimal on the training data. It is this difference that lends support to the SVMs with a greater potential to generalize. Furthermore, the solutions offered by the classical neural network models may be prone to fall into a local optimal solution, whilst a global optimum solution is assured for SVM. SVMs

Table 1
Statistical properties of wind turbine database.

Wind turbine				
Input parameters	Average value $\bar{x}$	Standard deviation (σ)	Maximum value (x_{max})	Minimum value (x_{min})
Tip-speed ratio	7.94	4.47	21	0.5
Blade pitch angle (deg)	11.56	9.08	30	0