Letters to the Editor

MPPT Control of Wind Generation Systems Based on Estimated Wind Speed Using SVR

Ahmed G. Abo-Khalil and Dong-Choon Lee

***Abstract*—In this paper, a novel algorithm for wind-speed estimation in wind-power generation systems is proposed, which is based on the theory of support-vector regression (SVR). The inputs of the SVR wind-speed estimator are chosen as the wind-turbine power and rotational speed. During the offline training, a specified model, which relates the inputs to the output, is obtained. Then, the wind speed is determined online from the instantaneous inputs. The experimental results have verified the validity of the proposed estimation algorithm.**

***Index Terms*—Maximum-power-point tracking (MPPT), support-vector regression (SVR), wind-speed estimation, wind turbine.**

I. Introduction

In most of wind-energy generation systems, anemometers are used to measure the wind speed for the maximum-power-point-tracking (MPPT) control [1]. The anemometer installed on the top of nacelle may be a source of inaccurate measurement of the wind speed. In wind farms, several anemometers are often placed at some locations to measure the average wind speed [2]. The use of anemometers raises a problem of calibration and measurement accuracy, as well as increasing the initial cost of the wind generation systems. For these reasons, it is desirable to replace the mechanical anemometers by the digital wind-speed estimator based on the turbine characteristics.

Recently, the wind-speed estimation methods have been reported in the literature, which can be categorized into two approaches. The first method is to use a power equation as a function of power coefficient C_p and tip-speed ratio λ [1]. Since the polynomial order of power coefficient may be higher than the seventh order for accurate estimation, the real-time calculation of the roots of the polynomial is a time-consuming task. The other one is to use a lookup table of power mapping [2]. This method may require external memory for highly accurate estimation. In addition, the execution time and estimation accuracy depend on the size of the lookup table.

In this paper, a novel wind-speed estimation scheme for the MPPT control of wind-power systems is proposed, which is based on the support-vector-regression (SVR) theory. The effectiveness of the proposed algorithm has been verified by experimental results.

II. Support-Vector Regression

A regression method is an algorithm to estimate a relationship between the system input and output from the available samples or training data. It is desirable that the relationship should be determined so that the system output matches the real value as closely as possible [3].

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Once such a relation is accurately estimated, it is used for predicting the system output with the input values.

Let us consider a set of training samples of $(x_i, y_i)|_{i=1}^{n}$, $i = 1, \ldots, n$, where x_i and y_i denote the input and output spaces, respectively, and n is the dimension of training data. The general function of SVR estimation takes the form as [4]

$$f(x) = (w \cdot \Phi(x)) + b \tag{1}$$

where w is a weighting matrix, b is a bias term, Φ denotes a nonlinear transformation from n-dimensional space to a higher dimensional feature space, and the dot represents the inner vector product. Equation (1) can be solved by minimizing the regression risk as

$$R_{\text{reg}}(f) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\Gamma\left(f(x_i) - y_i\right) \tag{2}$$

subject to

$$|y_i - w \cdot \Phi(x_i) - b| \le \varepsilon + \xi_i, \qquad i = 1, 2, \ldots, n \quad \xi_i, \xi_i^* \ge 0 \tag{3}$$

where $\Gamma(\cdot)$ is a cost function, ε is the permissible error, and C is a constant which determines the tradeoff between minimizing training errors and minimizing the model-complexity term $\|w\|^2$. Every vector outside ε-tube is captured in slack variables ξ_i, ξ_i^*, which are introduced to accommodate unpredictable errors on the input training set.

Using a kernel function, the required decision function can be expressed as [4]

$$f(x) = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*) \cdot K(x_i, x) + b. \tag{4}$$

The radial-basis function (RBF) has been used in this paper as a kernel [4]

$$K(x_i, x) = \exp\left\{-\frac{|x_i, x|^2}{\sigma^2}\right\} \tag{5}$$

where the σ is called as kernel parameter.

III. Wind-Speed Estimation Based on SVR

For the application of the SVR to estimate the wind speed, the training samples for input and output, kernel function, and parameters of C and ε should be first decided. Thereafter, training samples are obtained from the turbine-power equation with prespecified rotor speed ω_m and wind speed υ samples as [5]

$$P_t = \frac{1}{2}\rho\pi R^2 \upsilon^3 C_p(\lambda) \tag{6}$$

where ρ is the specific density of air, and R is the radius of the turbine blade.

For each sample, the rotor speed and the corresponding turbine power are combined as a pair for the inputs of the SVR estimator. It is well known that, for the fixed-pitch turbine, the power–speed characteristics are fixed for each wind speed without intersection, as shown in Fig. 1 [6]. Hence, if the turbine power and the rotor speed are known for any operating condition, the wind speed can be calculated. The RBF as a kernel with $\varepsilon = 0.001$, $\sigma = 23$, and $C = 400$ is used,

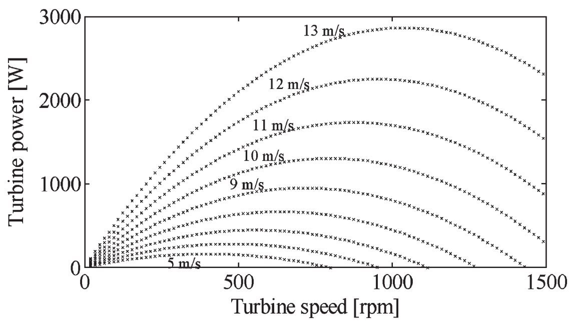

Fig. 1. Power–speed characteristics for 3-kW wind turbine.

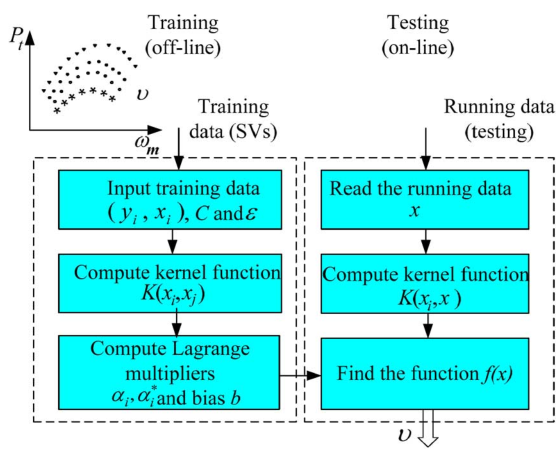

Fig. 2. Flowchart of wind-speed estimation.

which are usually selected based on *a priori* knowledge or user expertise. Thereafter, Lagrange multipliers $(\alpha_i - \alpha_i^*)$ are decided by using MATLAB, and the wind speed is calculated online, as depicted in Fig. 2.

During online operation, the turbine power is calculated as

$$P_t = J\omega_m \frac{d\omega_m}{dt} + B_t\omega_m^2 + P_g \tag{7}$$

where P_g is the generator power, J is the system moment of inertia, and B_t is the friction coefficient. The control-block diagram of the cage-type induction generator can be found in [6].

IV. Experimental Results

The wind-turbine simulator has been built with a torque-controlled dc-motor drive, which emulates the characteristics of the wind turbine, as shown in Fig. 1. The dc motor is mechanically coupled with a 3-kW squirrel-cage induction generator, which is connected to the utility grid through the back-to-back pulsewidth-modulation converters and a transformer.

Fig. 3(a) shows the estimated and measured wind speeds, which match each other with a slight delay. This delay occurs not only because the system-dynamic characteristic is not included in the training process but also because the generator-speed-control response is not instantaneous. For varying wind speeds, the generator speed through the MPPT control is shown in Fig. 3(b). Each turbine power corresponding to the measured and estimated wind speeds is shown in Fig. 3(c). The difference between the two waveforms of the turbine power is negligible. The SVR estimation accuracy of wind speed is shown in Fig. 4. It has been found that the estimation error is less than 3.3% for the range between 5 and 13 m/s. This small error results in a high accuracy in wind-speed estimation.

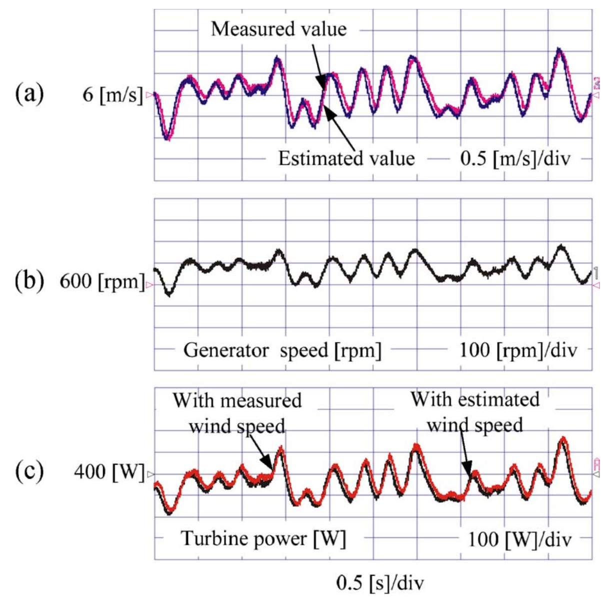

Fig. 3. Experimental results using SVR. (a) Measured and estimated wind speed, υ and $\hat{\upsilon}$. (b) Generator speed ω_m. (c) Turbine power P_t.

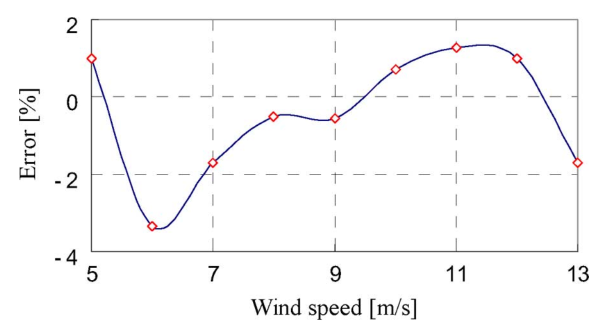

Fig. 4. Wind-speed-estimation error.

V. Conclusion

A novel wind-speed estimator using the SVR algorithm has been proposed for wind-power generation systems that is based on offline training of the input–output samples. The main advantages of the proposed estimation algorithm are the high accuracy and the fast transient performance, since a relevant function between system input and output is deduced by offline training, and the output can be calculated directly with the inputs.

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