Output Power Control of Wind Generation System using Estimated Wind Speed by Support Vector Regression

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ABSTRACT

In this paper, a novel method for wind speed estimation in wind power generation systems is presented. The proposed algorithm is based on estimating the wind speed using Support-Vector-Machines for regression (SVR). The wind speed is estimated using the generator power-speed characteristics as a set of training vectors. SVR is trained off-line to predict a continuos-valued function between the system's inputs and wind speed value. The predicted off-line function as well as the instantaneous generator power and speed are then used to determine the unknown winds speed on-line. The simulation results show that SVR can define the corresponding wind speed rapidly and accurately to determine the optimum generator speed reference for maximum power point tracking.

1. Introduction

Variable speed operation for wind turbine is desirable because of its characteristic to achieve maximum power conversion efficiency at all wind speeds. A vector-controlled induction generator is a good candidate for variable-speed wind turbine system [1]. For maximum power capture, it is advantageous to control the rotational speed of the turbine/generator according to variable wind velocities [2], [3]. The optimal tip-speed ratio (TSR) method is being used for the practical system where both wind speed and turbine speed are needed [4].

Most turbine controllers employ anemometers to measure wind speed in order to derive the desired shaft speed to vary the generator speed. In most cases, a number of anemometers at some distance away from and surrounding the wind turbine are required to provide adequate information. These mechanical sensors increase the cost and reduce the reliability of the overall system [5].

In this paper a novel implementation for SVR is proposed to predict the wind speed of a vector controlled voltage source inverter induction generator for wind power generation system. In this method, SVR estimates a continuous-valued function that plots the fundamental relation between the given inputs, which are the generator power and speed, and its corresponding output wind speed based on the training data. This function then is used to predict outputs for given inputs that were not included in the training set. The estimated wind speed is then used to calculate the optimum generator reference speed based on the optimal tip-speed ratio. Simulation results are presented to validate the proposed control algorithm.

2. Wind power generation system

The power captured by the wind turbine may be written as [6].

$$P_{rot}=\frac{1}{2}\rho\pi R^2 v^3 C_p(\lambda) \qquad (1)$$

To fully utilize the wind energy, C_p should be maintained at $C_{p,max}$ which is determined from the blade design. Then, from (1),

$$P_{max}=\frac{1}{2}\rho\pi R^2 C_{p,max} v^3 \qquad (2)$$

The reference speed of the generator is determined from (2) as

$$\omega_r^*=\frac{\lambda_{opt}}{R}v \qquad (3)$$

Once the wind velocity v is determined, the reference speed for extracting the maximum power point, shown in Fig. 1, is obtained from (3).

3. Support vector machines for regression

A regression method is an algorithm that estimates an unknown mapping between a system's inputs and outputs from the available data or training data. Once such a relation has been accurately estimated, it can be used for prediction of system outputs from the input values. The goal of regression is to select a function which approximates best the system's response.

The generic SVR estimating function takes the form [7]

$$f(x)=(w.\Phi(x))+b \qquad (4)$$

where the dot denotes the inner product, $w\subset R^n$, $b\subset R$ and Φ denotes a non-linear transformation from R^n space to high dimensional space. The goal is to find the value of x and b such that values of can be determined by minimizing the regression risk as

$$R_{reg}(f)=\frac{1}{2}\|w\|^2+C\sum_{i=1}^{n}\Gamma(f(x_i-y_i)) \qquad (5)$$

subject to

$$\begin{aligned} &y_i-(w.\Phi(x))-b\le\varepsilon+\xi_i^* \\ &(w.\Phi(x))+b-y_i\le\varepsilon+\xi_i \\ &i=1,2,3.....n \quad \xi_i^*,\xi_i\ge 0 \end{aligned} \qquad (6)$$

where $\Gamma(.)$ is a cost function and C is a constant determining the trade-off between minimizing training errors and minimizing the model complexity term $\|w\|^2$. If C

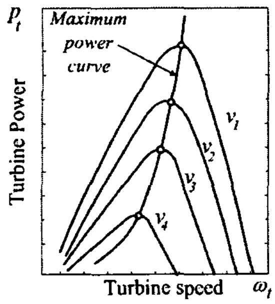

Fig. 1 Characteristic curves of wind blade

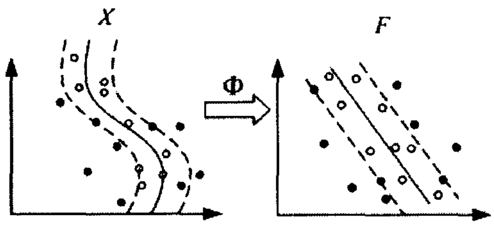

Fig. 2 A feature map from input to higher dimensional feature space

goes to infinitely large, SVR would not allow the occurrence of any error and result in a complex model, whereas when C goes to zero, the result would tolerate a large amount of errors and the model would be less complex. Everything above ε is captured in slack variables ξ_i, ξ_i^* , which are introduced to accommodate error on the input training set.

The optimization problem in (6) can be transformed into the dual problem, and its solution is given by

$$f(x)=\sum_i^n(\alpha_i-\alpha_i^*).(\Phi(x_i).\Phi(x))+b$$

subject to $0\leq\alpha_i\leq C,\ 0\leq\alpha_i^*\leq C$ (7)

In (7) the dot product can be replaced with Kernel function $k(x_i, x)$, known as the kernel function. Kernel functions enable the dot product to be performed in high-dimensional feature space using low dimensional space data input without knowing the transformation Φ as shown in Fig. 2. Using a Kernel function, the required decision function will be

$$f(x)=\sum_{i=1}^n(\alpha_i-\alpha_i^*).K(x_i,x)+b \tag{8}$$

4. Wind speed estimation using SVR

To apply SVR to estimate the wind speed, the training data for inputs and outputs and Kernel function should be firstly specified. In this model, SVR inputs are the turbine power and speed and the output is the estimated wind speed. The power-speed characteristics at different wind speeds can be used as a training data and Radial Basis Function (RBF) is used as Kernel function. Training of SVR involves the off-line adjustment (training) of Lagrange multipliers and bias α_i and b in (8), respectively.

During the off-line training, Kernel polynomial $k(x_i,x_j)$

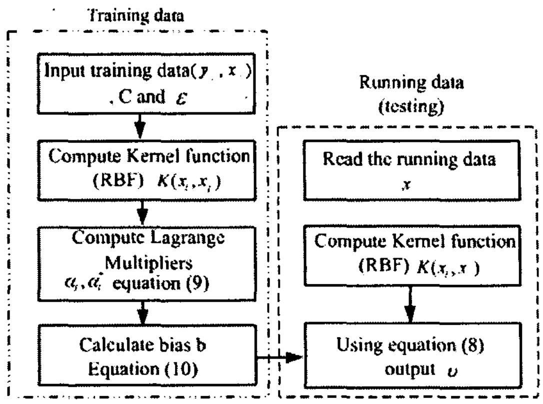

Fig. 3 Flowchart of wind speed estimation using SVR

is calculated for all support vectors. Lagrange Multipliers $\alpha_i-\alpha_i^*$ are then determined to minimize the quadratic form (9):

$$W(\alpha_i,\alpha_i^*)=\sum_{i,j=1}^n(\alpha_i-\alpha_i^*)(\alpha_j-\alpha_j^*)K(x_i,x_j)$$
$$-\sum_{i=1}^n y_i(\alpha_i-\alpha_i^*)+\frac{1}{2C}\sum_{i=1}^n(\alpha^{2_i}-\alpha_i^{*2})$$

subject to $\sum_i^n(\alpha_i-\alpha_i^*)=0,\ \alpha_i,\alpha_i^*\in[0,C]$. (9)

Only the non-zero values of the Lagrange multipliers $\alpha_i-\alpha_i^*$ are useful in forecasting the regression line and are known as support vectors. Using Kernel polynomial $k(x_i,x_j)$ and Lagrange multipliers $\alpha_i-\alpha_i^*$, the bias b can be computed as follow.

$$b=mean\left(\sum_i^n\{y_i-(\alpha_i-\alpha_i^*)K(x_i-x_j)\}\right) \tag{10}$$

In order to solve this problem, one has to choose the parameters C and the value of ε. Parameters C and ε are usually selected by users based on a prior knowledge and/or user expertise.

Now, all the parameters in (8) are computed in advance off-line. Hence, (8) is used on-line for any input x (wind speed) to compute the output $f(x)$(optimum d-axis current) as shown in Fig. 3.

5. Simulation results

The simulation study have been built in a reduced-scale using Matlab/Simulink. The squirrel cage induction generator output terminals are connected to the utility grid through back-to-back converters. In order to estimate the wind speed, SVR algorithm for was implemented. The generator controller is based on a conventional field-oriented controller, where the generator flux current is maintained constant and equal to the rated value. The speed control loop generates the q-axis current component to control the generator torque and speed at different wind speed.

In SVR, the off-line training step is performed to get Lagrange multipliers and bias values, and then the SVR model is available for the on-line mode. Equation (9) is used to estimate the wind speed value, while (3) is used to calculate the reference generator speed. The generator reference speed is calculated to extract the maximum power from the wind source.

Figure 4 shows the simulation results of wind speed estimation. It is noticeable that the estimated wind speed has a slightly different from the real value due to the trade-off between the minimizing error and the model complexity. The SVR estimation performance for wide range wind speed is shown in Fig. 5. The regression idea is to find a function which fit the observations, so the constructed function fits the observation perfectly from 7-10 [m/s].

Fig. 6(a) shows the output power corresponding to the maximum at the given wind speed. For each wind speed the rotational reference speed, Fig. 6(b), is adjusted to the value which gives the maximum power. The generator d-axis current is adjusted to its rated value while the q-axis current varies according to the wind speed. The generator torque is according to the q-axis current variation as the d-axis current is constant.

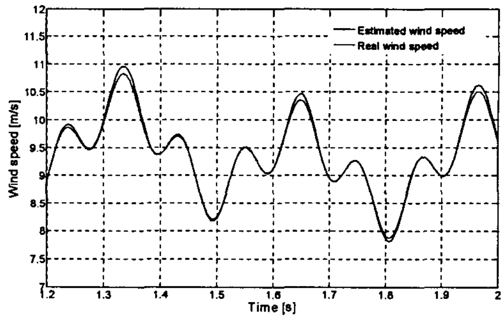

Fig. 4 Real and estimated wind speed

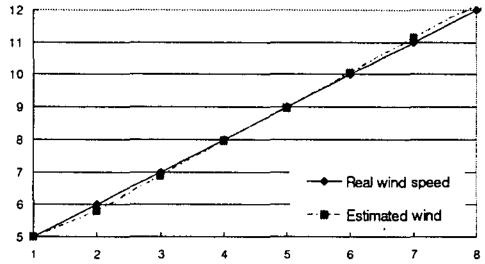

Fig. 5 Measured and SVR speed estimation

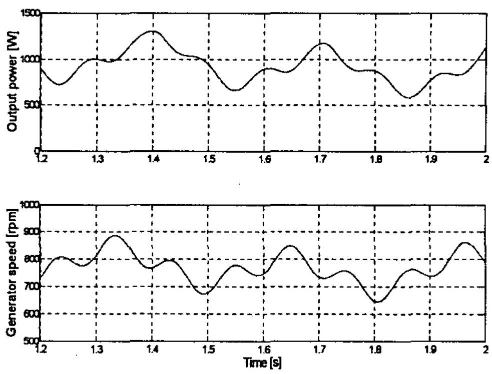

Fig. 6 Generator performance at variable wind speed

6. Conclusions

In this paper, A new support vector regression algorithm to estimate the wind speed value based on SVR. An off-line training was performed to estimate a continuos function that plots the fundamental relation between the given inputs, which are the generator power and speed, and its corresponding output wind speed based on the training data. The estimated function is then used on-line to determine the wind speed for given inputs that were not included in the training set. The presented algorithm shows a good performance in both steady state and transient operation. This algorithm can estimate the wind speed with a slight error even if the wind speed increases or decreases. SVR algorithm featured an excellent tracing for the real value. It is important to mention that SV regression models deserve to be used in control applications or short-term prediction, where they can advantageously replace traditional techniques. Matlab/Simulink has verified that the proposed algorithm is effective and advantageous for wind speed estimation either at constant or continuos variable speed.

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