Maximum Power Point Tracking Based on Sensorless Wind Speed Using Support Vector Regression

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Abstract – In this paper, a novel method for the 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). SVR is trained off-line to estimate the unknown mapping between the system’s inputs and outputs, and then is used online to estimate the wind speed value. The experimental results show that SVR can define corresponding wind speed instantaneously and accurately to determine the optimum d-axis current value precisely. Simulation results are shown to verify the validity of the proposed scheme.

I. INTRODUCTION

The worldwide concern about the environment has led to increasing interest in technologies for generation of renewable electrical energy. One way of generating electricity from renewable sources is to use wind turbines. It is preferable to run the wind energy generation system (WEGS) at a variable generator speed to maximize the captured wind power. Compared with constant speed operation, variable speed operation of wind turbines provides 10–15% higher energy output, lower mechanical stress, and less power fluctuation [1], [2].

Variable speed generation for wind generator is attractive because of its characteristic to achieve maximum efficiency at all wind velocities. Therefore, variable speed control of squirrel cage induction generator which applied vector control is needed [3]. For maximum power capture, it is advantageous to change the rotational speed of the turbine/generator according to variable wind velocities [4], [5]. The optimal TSR method is being used for the practical system where both wind speed and turbine speed are needed [6].

Most controller designs 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 [7].

Recently, the mechanical sensorless maximum power point tracking control method has been reported in the literature and can be categorized into three approaches. The first one is proposed by Bhowmik [8] to use a power coefficient polynomial to estimate wind velocity, an iterative algorithm is employed to determine the polynomial roots of the power coefficient online. Since the polynomial of power coefficient may be seventh order, real-time calculation of the polynomial roots will result in complex and time-consuming calculation, hence, reducing system performance. The second method has been reported by Tan and Islam [7] by applying a two-dimensional lookup table of power coefficient and power-mapping method to estimate the wind velocity directly or indirectly. The power-mapping technique may occupy a lot of memory space. If memory space is saved by reducing the size of lookup table, the control accuracy will be affected. Another issue with the power-mapping method is that only the suboptimum solution can be achieved due to the control delay caused by the inherent slow searching mechanism. The third method is presented in [3] to use the measured turbine torque and estimated rotor speed to estimate the wind speed. The disadvantage of this method is the need to design a torque observer and tune its gain to obtain accurate wind speed.

Application of Support Vector Regression (SVR) to various field of research, like pattern recognition, has shown many breakthrough and plausible performance. With SVR, the training task involves optimization of a convex cost function: there are no false local minima to complicate the learning process. The approach has many other benefits, for example, the model constructed has an explicit dependence on the most informative patterns in the data (the support vectors), and hence interpretation is straightforward. SVR estimates a continuous-valued function that encodes the fundamental interrelation between a given input and its corresponding output in the training data. This function then can be used to predict outputs for given inputs that were not included in the training set. This is similar to a neural network. However, a neural network’s solution is based on empirical risk minimization. In contrast, SVR introduces structural risk minimization into the regression and thereby achieves a global optimization while a neural network achieves only a local minimum [9]. The main feature of SVR is that they can, in principle, correctly identify the unknown samples independently of the dimensionality of the input space, i.e., of the number of elements of the array and of the number of impinging signals (after a proper learning phase).

In this paper a novel implementation for SVR is proposed to 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 interrelation between a given inputs (turbine power and speed) and its corresponding output (wind speed) based on the training data. This function 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. Experimental results are presented to validate the proposed IG control algorithm.
II. WIND POWER CONVERSION SYSTEM AND CONTROL

The power extraction of wind turbine is a function of three main factors: the wind power available, the power curve of the machine and the ability of the machine to respond to wind fluctuation. The power extracted from the wind can be expressed as the following equations [12]

\[ P_t = \frac{1}{2} \rho \pi R^2 \frac{\omega}{\lambda} C_p(\lambda) \]  

(1)

and the tip-speed ratio is defined as

\[ \lambda = \frac{\omega R}{\nu} \]  

(2)

where,

- \( \rho \): specific density of air [kg/m³];
- \( \nu \): wind speed [m/s];
- \( R \): radius of the turbine blade [m];
- \( \omega \): turbine speed;
- \( C_p \): coefficient of power conversion.

From (1), it is apparent that the power production from the wind turbine can be maximized if the system is operated at maximum \( C_p \).

Fig. 2(a) shows that the power captured in turbine blade is a function of the rotational speed and that it is maximum at the particular rotational speed. Fig. 3(b) shows that the value of \( C_p \) is a function of \( \lambda \) and it is maximum at the particular \( \lambda_{opt} \). Hence, to fully utilize the wind energy, \( \lambda \) should be maintained at \( \lambda_{opt} \), which is determined from the blade design. Then, from (1),

\[ P_{max} = 0.5 \rho \pi R^2 C_{p_{max}} \nu^3 \]  

(3)

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

\[ \omega_r = \frac{\lambda_{opt} \nu}{R} \]  

(4)

Once the wind velocity \( \nu \) is estimated, the reference speed for extracting the maximum power point is obtained from (4).

It is noticeable in Fig. 3 that generator controller consists of a wind speed estimator, speed controller and current controllers in the inner loop in the synchronous frame. The optimum generator speed is determined to extract the maximum power based on the estimated wind speed value. SVR algorithm is trained off-line and used on-line for wind speed estimation.

III. SUPPORT VECTOR MACHINE 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 [10], [11].

Considering a set of training data \( \{(x_i, y_i)\}_{i=1}^n \) where \( x_i \subset R^n \) denotes the input space of the sample and has corresponding target value \( y_i \subset R \) for \( i=1,...,n \) where \( n \) corresponding to the size of the training data. The idea of the regression problem is to determine a function that can approximate future values accurately.

The generic SVR estimating function takes the form [11]

\[ f(x) = (w \Phi(x)) + b \]  

(5)

where \((.)\) denotes the inner product, \( w \subset R^n \), \( b \subset R \) and \( \Phi \) denotes a non-linear transformation from \( R^n \) space to high dimensional space. The goal is to find the value of \( w \) and \( b \) such that values of \( x \) can be determined by minimizing the regression risk as
In (10) the dot product can be replaced with Kernel function $K(x_i, x_j)$, known as the kernel function. Kernel functions enable dot product to be performed in high-dimensional feature space using low dimensional space data input without knowing the transformation $\Phi$ as shown in Fig. 5. Using a kernel function, the required decision function will be:

$$f(x) = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*) K(x_i, x) + b \quad (9)$$

At present the kernel functions using most are mainly [11]:

1. **Polynomial Kernel Function**
   
   $$K(x_i, x_j) = [(x_i \cdot x_j + 1)^q]$$

2. **Radial Base Function (RBF)**
   
   $$K(x_i, x_j) = \exp\left(-\frac{|x_i - x_j|^2}{\sigma^2}\right)$$

3. **Sigmoid function**
   
   $$K(x_i, x_j) = \tan(v(x_i, x) + c)$$

**IV. WIND SPEED ESTIMATION BASED ON SVR**

To apply SVR for estimating 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 while the output is the estimated wind speed, so the relation between the three quantities turbine power, speed and wind speed can be used as a training data and Radial Basis Function (RBF) is used as the kernel. Training of SVR involves the off-line adjustment (training) of Lagrange Multipliers and bias $a_i$ and $b$ (9) respectively.

During the off-line training, Kernel polynomial $K(x_i, x_j)$ is calculated for all support vectors. Lagrange Multipliers $\alpha_i$ are then determined to minimize the quadratic form (10):

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

$$- \sum_{i=1}^{m} \alpha_i (a_i - \alpha_i^*) - \frac{1}{2} \sum_{i=1}^{m} \alpha_i^2$$

Subject to

$$\sum_{i=1}^{m} (\alpha_i - \alpha_i^*) = 0, \alpha_i, \alpha_i^* \in [0, C]$$

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

$$b = \text{mean} \left( \sum_{i=1}^{m} (\alpha_i - \alpha_i^*) K(x_i, x_j) \right)$$

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

Now, all the parameters in (9) are already off-line computed. Hence, (9) is used online for any input $x$ (wind speed) to
compute the output \( f(x) \) (optimum d-axis current) as shown in Fig. 6.

V. SIMULATION RESULTS

The simulation setup has been built in a reduced-scale using Matlab/Simulink. A 3[kW] squirrel-cage induction generator is mechanically coupled to the dc motor without a gear box. The ratings and parameters of the cage-type induction generator are listed in Table I in Appendix. Also, the specification of the wind turbine blade modeled for the simulator is given in Table II. The generator output terminals are connected to the utility grid through back-to-back converters and a transformer. The ratings and parameters of the system are listed in the Appendix. 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 IG 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 (4) is used to calculate the reference generator speed. The generator reference speed is calculated to extract the maximum power from the wind source.

Figure 7 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. 8. 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. 9(a) shows the output power corresponding to the maximum at the given wind speed. For each wind speed the rotational reference speed, Fig. 9(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 as shown in Fig. 9(c). The generator torque
VI. CONCLUSIONS

In this paper, a wind speed estimation scheme for wind driven squirrel cage induction generator was proposed. The generator speed was regulated to extract the maximum wind power and to either in constant or variable wind/generator speed. The generator reference speed was adjusted based on the optimum tip-speed ratio and the estimated wind speed.

A new support vector regression algorithm to estimate the wind speed value based on the training data from previous off-line training was presented. 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. This method is based on the wind turbine characteristics and independent of the generator turbine constants or torque measurements, it results a fast estimation for the wind speed value even though the wind speed is changing continuously. It is important to mention that SV regression models deserve to be used by in control applications or short-term prediction, e. g. wind speed estimation, where they can advantageously replace traditional techniques.

APPENDIX

The specification of the induction machine used for test is three-phase, four poles, 230[V], 50[Hz], 3[kW], and 1435[rpm], of which parameters are listed in Table I. The parameters of the wind turbine used are shown in Table II.

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<thead>
<tr>
<th>TABLE I PARAMETERS of INDUCTION MACHINE</th>
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<tr>
<td>Parameters</td>
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<tr>
<td>Stator resistance</td>
</tr>
<tr>
<td>Rotor resistance</td>
</tr>
<tr>
<td>Iron loss resistance</td>
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<tr>
<td>Stator leakage inductance</td>
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<td>Mutual inductance</td>
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<tr>
<th>TABLE II PARAMETERS of TURBINE BLADE MODEL</th>
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<td>Parameters</td>
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<tr>
<td>Blade radius</td>
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<td>Max. power conv. coeff.</td>
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<td>Optimal tip-speed ratio</td>
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<tr>
<td>Gear ratio</td>
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<td>Cut-in speed</td>
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REFERENCES