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Estimation of the wind turbine yaw error by support vector machines

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Abstract: Wind turbine yaw error information is of high importance in controlling wind turbine power and structural load. Normally used wind vanes are imprecise. In this work, the estimation of yaw error in wind turbines is studied using support vector machines for regression (SVR). As the methodology is data-based, simulated data from a high fidelity aero-elastic model is used for learning. The model simulates a variable speed horizontal-axis wind turbine composed of three blades and a full converter. Both partial load (blade angles fixed at 0 deg) and full load zones (active pitch actuators) are considered. The validation step is done under different conditions of wind shear, speed and direction, giving good estimation results.

Keywords: Wind turbine, support vector machines, regression.

1. INTRODUCTION

Renewable energy techniques are nowadays widely spread in different regions. Among these techniques appears wind technology that represents an alternative of oil for the production of electricity at competitive cost and reduced gas emissions.

In horizontal-axis wind turbines, yaw manoeuvres allow the rotor and nacelle to be aligned towards the wind direction. Wind misalignment (or yaw error) reduces power capture and may increase load on the blades and therefore turbine fatigue (Jeong et al. 2013). In large turbines, these rotations are to be optimized due to the heavy structure mass, and therefore one needs to have a precise estimate of the wind direction relative to the rotor (deviation of the yaw from the wind direction, or wind misalignment). However, the wind parameters (speed and direction) are usually measured using sensors, such as anemometers, that give the local measurements on the top of the nacelle and these measurements might be disturbed by the rotor wake of the turbine itself.

Different methods were proposed in the literature to estimate the wind direction by combining different sensors' information or models. Since misalignment of the yaw affects the aero-elastic response of the blades, information about the blades can be used to estimate the wind direction felt by the rotor. For instance, Battasso et al. (2014 and 2015) developed a data-based observer using the blade bending moments to estimate wind misalignment. They indicated that the lowest harmonics of the blade loads are the most affected by misalignment. It is important to point out that data based approaches do not require a precise model of the system, which allows faster implementation.

The estimation of the wind direction in data learning approaches is a regression problem. In this work, the statistical data-based method called support vector machines for regression (SVR) are used. This method have been used in wind turbines for the estimation of the power coefficient (Shamshirband et al., 2004), the probability distribution of wind speed (Petkovic et al., 2014) and the wind speed (Salcedo-Sanz et al., 2011, Chen and Yu, 2014, Yu et al. 2014). The support vector machines method (SVM) was previously used by our group for fault detection of sensors and actuators in wind turbines, which is a classification problem (y=+/-1) (Sheibat-Othman 2013, Laouti et al. 2014).

The objective of this paper is to use SVR for the estimation of the yaw error. In Section 2, the considered wind turbine and simulation conditions are discussed. Then, basic information about support vector machines for regression is presented. This is followed by the implementation of SVR for the case of wind direction estimation. In Section 5, simulation results are presented and discussed under different operating and tuning conditions.

2. WIND TURBINE

The wind turbine data used in this work has been obtained using a Vestas proprietary high fidelity aero-elastic wind turbine model. The operation conditions expected to influence the estimation of the wind direction were varied in the simulations:

- Wind speed mean values υ = 8 and 14 m/s (see Fig. 1).
- Wind direction mean values y = - 30 to 25 deg (Fig. 2).
- Wind shear S = 0.1, 0.16, 0.18, 0.20.

Different measurements are assumed available at a measurement frequency of Δt = 10 ms, over a time period of 750s. These measurements are:

1. Wind speed υ [m/s]
2. Wind direction y

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3. Azimuth angle ϕ
4. Generator speed, w_g [tr/min]
5. Generator power, P_g [W]
6. Blade 1 pitch angle/position, β_1 [deg]
7. Blade 2 pitch angle/position, β_2 [deg]
8. Blade 3 pitch angle/position, β_3 [deg]
9. Flapwise root bending moment of blade τ_1^f [kN.m]
10. Flapwise root bending moment of blade τ_2^f [kN.m]
11. Flapwise root bending moment of blade τ_3^f [kN.m]
12. Edgewise root bending moment of blade τ_1^e [kN.m]
13. Edgewise root bending moment of blade τ_2^e [kN.m]
14. Edgewise root bending moment of blade τ_3^e [kN.m]

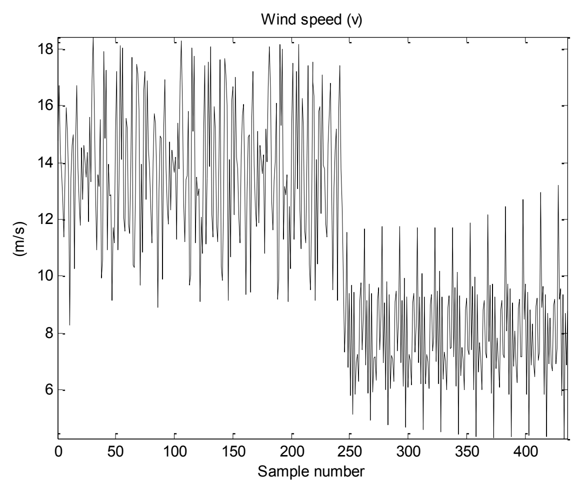

Fig. 1. The used wind speed data (υ ≈ 8 or 14 m/s)

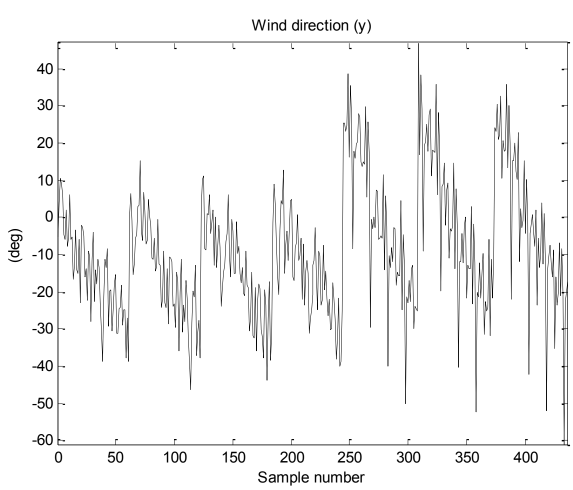

Fig. 2. The considered wind direction domains (y ≈ -40 to 40 deg)

3. FUNDAMENTALS OF SVR

The ε-support vector regression method is a kind of machine learning technique that is based on the structural risk minimization concept. The objective in SVR minimization is to search for a function as flat as possible matching data with the most ε deviations from the real vector. For more details about SVR see Vapnik (1997).

Consider N training vectors $x_i \in \Re^p$ characterized by a set of p descriptive variables/observations $x_i = \{x_{i1}, x_{i2}, \dots, x_{ip}\}$ and by the class response $y_i \in \Re$. In order to use nonlinear functions for regression of the data x, a nonlinear map $\phi : x \to \phi(x)$, into a high dimensional space, is proposed to allow linear regression in that space ($f(x) = \langle w, \phi(x) \rangle + b$). Dot products of <x_i,x> appearing in the calculations in linear SVR are in the nonlinear case replaced by the dot products <$\phi(x_i)$, $\phi(x)$>. This is a symmetric function in $\mathbf{x_i}$ and $\mathbf{x}$ that should satisfy Mercer's condition, and is called a kernel: $K(x_i, x) = \langle \phi(x_i), \phi(x) \rangle$. SVR is formulated as a minimization of the following function:

$$\min_{w,b} \frac{1}{2}\|w\|^2 \tag{1}$$

Subject to:

$$\Bigg\| \underbrace{f(x_i)}_{\langle w, \phi(x_i)\rangle + b} - y_i \Bigg\| \le \varepsilon , \; i = 1, \dots , N \tag{2}$$

The optimization problem is solved using the Lagrange function to find an ε-insensitive loss function, described by the following decision function:

$$f(x) = \sum_{i=1}^{N} \left(\alpha_i - \alpha_i^*\right) K(x_i, x) + b \tag{3}$$

with the property:

$$w = \sum_{i=1}^{N} \left(\alpha_i - \alpha_i^*\right) \phi(x_i) \tag{4}$$

Where b is the bias term (a scalar) and α_i and $\alpha_i^* \ge 0$ are the Lagrange multipliers. The sample points that appear with non-zero coefficients α_i are called support vectors. The Gaussian kernel (a Radial Basis Function) with the variance σ is used in this work for data mapping:

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

A slack variable C can be introduced into (1) to relax the margin constraints and allow neglecting a controlled part of data, which transforms the optimization problem into the following one:

$$\min_{w, b, \xi^-, \xi^+} \frac{1}{2}\|w\|^2 + C \sum_{k=1}^{N} \left(\xi_k^- + \xi_k^+\right) \tag{6}$$

Subject to:

$$y_i - w^T \phi(x_i) - b \le \varepsilon + \xi_k^- , \; i = 1, \dots , N$$