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What is This?

Data-driven estimation of the inertia moment of wind turbines: A new ice-detection algorithm

Alexander Stotsky and Bo Egardt

Abstract
Turbine blades accumulate ice under certain atmospheric conditions, such as low temperature and high humidity. This implies additional loads that might damage the turbine. A reliable ice-detection algorithm is required to shut down the turbine and prevent damages. A simple sensorless technique is proposed in this article for detection of both icing and ice shedding events. The technique is based on the estimation of the turbine inertia moment using generator speed measurements, turbine model and robust and fast convergent data-driven algorithms. Estimated inertia moment can be used for both ice detection and adaptation of the parameters of the control system. Implementation of this technique allows a stable turbine operation during hazardous ice conditions via adjustment of the control system parameters or turbine shut down in the extreme icing conditions.

Introduction

Wind turbines accumulate ice under certain atmospheric conditions. Additional hundreds of kilograms (up to 600 kg per blade) might be accumulated on the blades (see Figure 1) that implies reduction of the aerodynamic performance and turbine power output.[1,2] Besides, an occurrence of the ice shedding events due to increase in ambient temperature introduces a risk of injuries. Moreover, ice shedding events course additional drive train loads that might damage the turbine. The turbine should be shut down in order to prevent damages in the extreme icing conditions. This in turn motivates the development of a reliable ice-detection mechanism.[1,3] In addition, the parameters of the control system might be adjusted for load mitigation, based on the detected amount of ice in light and moderate icing conditions.

Traditional ice-detection techniques based on measurements of atmospheric parameters are unsuitable for detection of the mass of the blade ice. Optical strain sensors, developed recently, could be mounted inside each blade for detection of the blade ice. A high cost, long installation times and unreliable instrumentations are the main obstacles to practical implementation of this sensing technique.

A simple sensorless technology is proposed in this article for ice detection. The technique is based on estimation of lumped inertia, which changes significantly with ice accretion on the turbine blades and ice shedding events. Generator speed measurements and one-mass turbine model are used for estimation of the turbine inertia.

Ice accumulation is dependent on the turbine rotational speed. Small turbines with high rotational speeds are less liable to ice accretion compared to large turbines with low rotational speeds. Ice-detection method, described in this article, is more suitable for large wind turbines.

A data-driven algorithm is proposed in this article for estimation of the prediction error via explicit solution of the discretized one-mass turbine model. (Data-driven approach is associated with accumulation of input–output data, which are used directly for control, estimation and change detection.[4,5]) A standard least

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Figure 1. Turbine blades accumulate ice under certain atmospheric conditions.

squares estimator, then, can be used for calculation of the inertia moment. Smoothing of the regressor variable, achieved via summation of the difference between aerodynamical and generator torques guarantees robustness of this estimator with respect to measurement noise.

The article is organized as follows. Drive train model is presented in section "Drive train model." Data-driven algorithm for estimation of the inertia moment and simulation results are described in section "Data-driven algorithm for estimation of inertia moment." Finally, section "Conclusion" contains some concluding remarks.

Drive train model

A one-mass lumped model of the drive train is described as follows[6]

$$\omega = N\omega_r \qquad (1)$$

$$J\dot{\omega} = \frac{P}{\omega} - T_g \qquad (2)$$

where ω_r and ω are turbine and generator speeds, $J = (J_r + N^2 J_g)/N^2$ is a lumped rotational inertia of the system, where J_r and J_g are turbine and generator inertias, respectively; P and T_g are turbine power and generator torque, respectively, and N is a gear ratio.

Note that low temperature and icing have impact on aerodynamics of the blades, turbine friction torque and others. However, the amount of ice accumulated on the blades has the most significant impact on the turbine performance. Ice accumulation and shedding events have the most significant impact on the turbine inertia, which in turn depends on the mass of the blades. Changes in lumped inertia, arising from icing are accounted only in model (2), whereas all other factors are neglected. The moment of inertia is equal to the rotating mass multiplied by the square of the distance to the rotational axis. Estimation of the inertia moment is equivalent to estimation of the mass of the blade ice since a nominal blade mass is known.

It is observed that changes in operating conditions result in changes in rotational inertia for a wide class of machines, such as rotating electrical machines, automotive drive trains and others. Inaccuracy in the inertia moment has a direct impact on the performance of control system. Changes in rotational inertia due to a change in operating conditions might be used in diagnostic applications. A simple data-driven technique that is described in section "Data-driven algorithm for estimation of inertia moment" for estimation of lumped inertia can be applied to a wide class of rotating machines.

Data-driven algorithm for estimation of inertia moment

Prediction error estimation

Euler discretization of one-mass turbine model (2) with the step Δt yields

$$\omega_k = \omega_{k-1} + \varphi_k\theta_* \qquad (3)$$

where $\varphi_k = ((P_{k-1}/\omega_{k-1}) - T_{gk-1})\Delta t$ is a regressor and $\theta_* = 1/J$ is unknown inverse of the inertia moment to be estimated.

Note that a simple Euler discretization method for nonlinear one-mass turbine model (2) leads to simplified estimator of the inertia moment. However, a sufficiently small discretization step Δt is required for trajectories of continuous and discrete time systems to be close to each other. Deviation of the trajectories of continuous time system (2) from the trajectories of discrete time system (3) due to improper choice of Δt has essential impact on the estimation performance.

The sequence (3) can be written as follows

$$\omega_1 = \omega_0 + \varphi_1\theta_*$$
$$\omega_2 = \omega_1 + \varphi_2\theta_*$$
$$\cdots$$
$$\omega_k = \omega_{k-1} + \varphi_k\theta_*$$

In order to estimate the prediction error, the sequence (3) should be properly initialized. The performance of data-driven algorithm strongly depends on the initialization. This initialization is performed via equating the initial value of the rotational speed to 0, that is, $\omega_0 = 0$. This can be implemented in any step via subtracting the value of the measured generator speed and initialization of the counter.

Therefore equation (3) can be presented in the following form

$$\omega_k = \sum_{j=1}^{k} \varphi_j\theta_* \qquad (4)$$

Note that model (4) is the data accumulation model with initialization events associated with forgetting of the past regressor data. Fast forgetting of the regressor data is achieved via frequent initialization events.

Introducing the model that is driven by the adjustable parameter θ_k as follows

$$\hat{\omega}_k = \sum_{j=1}^{k} \varphi_j \theta_k \qquad (5)$$

where $\hat{\omega}_k$ is the output, the model mismatch can be presented as

$$e_k = \hat{\omega}_k - \omega_k = \psi_k \tilde{\theta}_k \qquad (6)$$

where $\psi_k = \sum_{j=1}^{k} \varphi_j$. The term $\psi_k \tilde{\theta}_k$ represents a prediction error, that is, the error that is directly proportional to the parameter mismatch $\tilde{\theta}_k = \theta_k - \theta_*$.

Least squares estimation algorithm

Least squares estimate θ_k of unknown parameter θ_* in a window of a size w, which is moving in time, can be written as follows

$$\theta_k = \left[\sum_{i=k-w+1}^{k} \psi_i^2 \right]^{-1} \sum_{i=k-w+1}^{k} \psi_i \omega_i \qquad (7)$$

where ω_i is a measured generator speed, $k = w, w+1, \ldots$.

The sum $\sum_{i=k-w+1}^{k} \psi_i^2$ is bounded away from 0 in the turbine transient operation that allows estimation of the inertia moment. As it was mentioned above, icing has a direct impact on aerodynamics of the blades and hence on the turbine power P_k, which is used in estimation algorithm as a known quantity. Deviation between actual and estimated turbine power might have a negative impact on the performance of estimation of the inertia moment. The model for the turbine power might be updated via measurements of the generator torque T_{gk} at steady state, where $\omega_k = \omega_{k-1}$. Updated model for the turbine power can be used subsequently for estimation of the inertia moment under the turbine transients.

Note that the regressor ψ_i, used in estimation algorithm (7), reduces the noise that is present in the generator speed measurements due to the smoothing properties of summation. Also, note that the least squares algorithm (7) becomes a Kaczmarz algorithm[7] with $e_k = 0$, if the window size is equal to 1, that is, $w = 1$.

Simulation results

The performance of the ice-detection algorithm is illustrated in Figures 2 and 3. The estimation performance is verified using one-mass drive train models (1) and (2) driven by the generator torque control, as described in Stotsky and Egardt,[6] and upwind speed measurements from the Hönö turbine located outside Gothenburg,
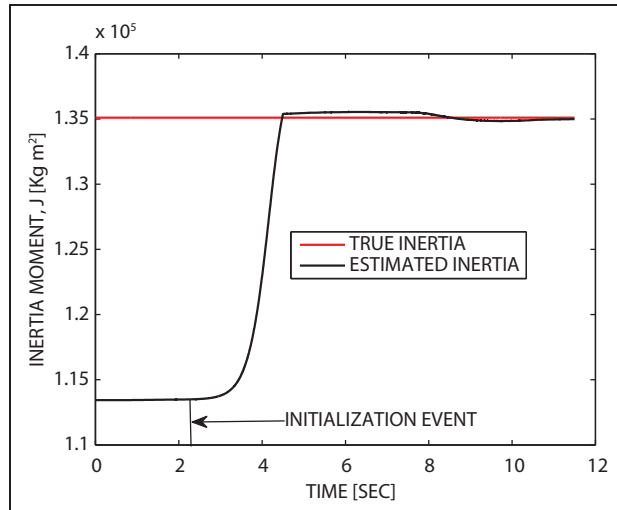

Figure 2. Estimation of the inertia moment $J = (J_r + N^2 J_g)/N$ with ice accretion.
Simulation was performed on the model of 2-MW turbine with the parameters described in Stotsky and Egardt.[8] The wind speed measurements made on the Hönö wind turbine outside Gothenburg, Sweden, are directly used in simulations. Inertia moment was estimated in the closed-loop system with the turbine speed controller described in Stotsky and Egardt.[6] The simulations were performed with a wind speed record shown in Stotsky and Egardt[6] and disabled collective pitch controller.
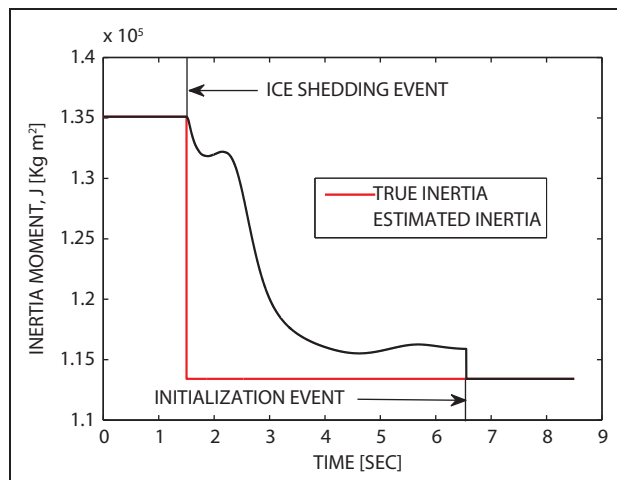

Figure 3. Detection of the ice shedding event via estimation of the inertia moment.

Sweden. Ice accumulation and shedding events are modeled via a change in the turbine inertia moment. Figure 2 shows estimation of the inertia moment in the case of ice accretion, and Figure 3 shows the detection performance of the ice shedding event. Data-driven estimator shows fast convergence and robustness with respect to the generator speed measurement noise. Both icing and shedding events can be detected.

However, the performance of the estimation depends on the initialization events. Therefore data-driven algorithm should be periodically initialized and/or

combined with other ice-detection methods. For example, a video detection of ice shedding events can be used for initialization of data-driven algorithm, which can estimate the amount of ice shed from the blades more precisely. In addition, data-driven estimation algorithms might be sensitive to unmodeled dynamics that is the main obstacle to application of this technique to drive trains with essential flexibility of the drive shaft.

Conclusion

A new ice-detection technique based on data-driven algorithm for estimation of the inertia moment is described. It is shown that data-driven algorithm (despite the dependence on the initialization events) provides high-quality estimate of the turbine inertia moment, using generator speed measurements only. This is turn allows exact estimation of the mass of the blade ice that guarantees safe and stable turbine operation in cold climate.

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Declaration of conflicting interests

The authors declare that there is no conflict of interest.

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