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Wind-turbine collective-pitch control via a fuzzy predictive algorithm

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ABSTRACT

This paper proposes a new fuzzy predictive algorithm for collective pitch control of large wind turbines. Collective pitch controllers operate in region three to harvest the rated power and maintain the rated speed. The wind turbine model is represented by a Takagi–Sugeno (T–S) fuzzy model. The number of T–S fuzzy rules is reduced based on a gap – metric criterion. A model predictive controller is designed based on the fuzzy model taking into consideration the pitch actuator constraints. The proposed controller is coupled with conventional PI controllers for individual pitch control so as to minimize the moments on the turbine blades. A Kalman observer is designed to estimate the immeasurable states. The performance of the proposed fuzzy-predictive controller is compared to a gain schedule PI controller and a mixed H2/H∞ controller. Simulation results, based on a typical 5-MW offshore wind turbine, demonstrate the superiority of the proposed fuzzy-predictive controller.

1. Introduction

The installed wind-energy capacity reached 336 GW in the mid of 2014 [1]. The expected annual growth rate in 2014 is 13.5%. It was 12.8% in 2013. The steady growth of the installed wind power is due to its economic and environmental advantages. Control systems can play a pivotal role in enhancing the economic performance of the wind energy systems [2]. This can be achieved by increasing power extraction, alleviating mechanical stresses, and improving power quality.

The operation modes of a wind turbine depend on wind speeds. Typically, there are three main regions of operations. Region 1 is defined by wind speeds up to the cut-in value. In this region, the wind is utilized merely to accelerate the rotor for startup. Wind speeds higher than the cut in value and lower than the rated value define Region 2. In this region, the turbine should operate to extract the maximum power [3]. Wind speeds higher than the rated value and up to the cut-out value specify Region 3. Typically, wind turbines are controlled using decentralized controllers to take care of the operations in regions 2 and 3. This study focuses on Region 3. In Region 3, wind turbines are usually subject to undesirable high structural loading. As a result, the control objectives are to reap rated power, maintain rated speed, and alleviate the mechanical loads. Designing a pitch controller, taking into consideration the restrictions on the pitch angle limits and rates of change, is our target. The pitch angle of a wind turbine is controlled individually and collectively. The target of collective pitch control (CPC) is to regulate the generator power at the rated value by maintaining the rated generator speed. On the other hand, individual pitch control (IPC) aims at attenuating the flap-wise moments on the blades [4].

Many researchers have focused on controlling variable-speed variable-pitch wind turbines. In Ref. [5], an adaptive neural network controller is introduced. The objective is to control all operating regions of the turbine. In Ref. [6], the pitch angle is controlled utilizing the artificial neural network. The operation of the turbine is observed by utilizing the back propagation learning algorithm. In Ref. [7], a CPC is designed based on mixed H2/H∞ control with pole placement. In Ref. [8], the objective of the pitch control is to achieve different load reduction criteria. In Ref. [9], a linear quadratic Gaussian controller is proposed. Both CPC and IPC are designed based on a single linear model. The main disadvantage in Refs. [5–9] is that the proposed algorithms do not take into account constraints on the pitch angles. This may lead to the wind up phenomenon and significant degradation of performance if the control signal hits the saturation limits.

In Refs. [10–12], different IPC strategies are discussed to reduce the flicker emission on the turbine blades. In Ref. [13], a non-linear pitch control strategy is proposed to damp the tower oscillations, regulate the rotor speed, and compensate the phase-lag introduced by the pitch actuator. In Ref. [14], pitch faults, due to pitch

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asymmetry and pitch implausibility, are analyzed. In Refs. [15,16], the effects of short-duration wind variations on the output power of a wind turbine, under pitch control, are studied.

Model Predictive Control (MPC) is a control algorithm that depends on a system's model for predicting the future output over a selected horizon. At every sampling instant, an optimization problem is solved on-line over the prediction horizon to get the control action. Several authors have used MPC to implement different wind turbine controllers. In Refs. [17–19], an MPC is used to extract the maximum power from the wind turbine (region 2). In Ref. [20], a multiple MPC strategy is represented for the full operating regions of the turbine. The generator torque and pitch angle are controlled simultaneously to maximize energy capturing, smooth the generator power, and reduce the transient loads. The main disadvantage in Ref. [20] is the use of a large number of models which increases the computational complexity of the algorithm. Abrupt switching between models could result in sluggish transient responses. In this paper, a fuzzy model predictive algorithm for CPC is investigated. The fuzzy rule-base is reduced by using a gap metric criterion. The fuzzy model is employed to construct the predictor. Fuzzy models represent nonlinear mappings. So, they can effectively represent the nonlinearities of wind turbine models. MPC is used to obtain the CPC action taking into account the allowed pitch-actuator limits and rates of change.

There are four main contributions in this research. First, it introduces a gap metric measure as a tool to determine the number of fuzzy rules that adequately model a system. Second, it utilizes a fuzzy model to mimic the nonlinear behavior of wind turbines in region 3. The resulting model has a simple form amenable to predict the future response. Third, the use of a predictive control algorithm allows us to include the input constraints explicitly while deducing the optimal control action. Explicit inclusion of the constraints is a fundamental difference in predictive control design compared to traditional PI controllers. Fourth, the proposed controller significantly reduces the mechanical stresses applied to the wind turbine. This has a definite economic benefit as it reduces the maintenance cost.

This paper is organized as follows. In Section 2, the wind model is discussed. The procedure to emulate the nonlinear behavior of a wind turbine using a fuzzy model is proposed. A gap metric criterion is applied to these linearized models to determine which of them should be included. Furthermore, the procedure to write a simplified fuzzy model for design purposes is discussed. The design of MPC for collective pitch control is discussed in Section 3. Simulation results, comparing the proposed controller to different controllers, are depicted in Section 4. Conclusions are derived in Section 5.

2. Developing the fuzzy model

A large wind turbine can be modeled by up to 24 degrees of freedom (DOF). Table 1 summarizes the main degrees of freedom of a 3-blade horizontal-axis wind turbine [4]. Detailed wind-turbine models are available via specialized software packages like HAWC2 [21], FAST [4], and Cp-Lambda [22]. FAST (Fatigue, Aerodynamics, Structures and Turbulence) is employed in this work to simulate the operation of a 5-MW, three-blade, variable-speed variable-pitch offshore wind turbine. FAST is developed by the US National Renewable Energy Laboratory. It is provided with a tuned gain schedule PI controller for CPC. The gain schedule PI controller supplied with FAST is considered the baseline controller and used for comparisons with the proposed CPC controller. The 5-MW wind turbine specifications are stated in Ref. [4].

Table 1
The degrees of freedom of a 3-blade horizontal-axis wind turbine.

Element	Number of DOF	Description
Blades	2	Flap modes per blade
	1	Edge mode per blade
Nacelle	1	Yaw bearing
Derive-train	1	Generator azimuth
	1	Shaft torsion
Furl	1	Rotor-furl hinge between nacelle and rotor
	1	Tail-furl hinge between nacelle and tail
Tower	2	Fore-aft modes
	2	Side-to-side modes
Platform	3	Translational modes (surge, sway, heave)
	3	Rotational modes (roll, pitch, yaw)

For a CPC design, the enabled DOFs are the generator and the drivetrain. The DOFs are considered as the dominant dynamics of the turbine [4]. Although our control design is based on a reduced order model that represents 2 DOF, the resulting controller will be tested based on the full order nonlinear model. The states of the design model are the perturbations in the drivetrain torsional speed, drivetrain torsional displacement, and rotor speed.

This section discusses three main points:1) the linearized models that cover the operating region, 2) the gap-metric measure to select the effective linearized models, and 3) the procedure to write a simplified fuzzy model.

2.1. FAST linearized models

In order to design a CPC, linearized models are derived. Each of the resulting models relates the perturbations of the collective pitch to those of the generator speed. FAST can produce these linear models around a specific operating point in the form of (1). Generator speed, azimuth angle of the rotor, the hub height wind speed, and the pitch angle are the main variables that specify an operating point. In Region 3, the generator speed should be at the rated value. Linearized models are calculated at different azimuth angles for a given wind speed. Then, an average model is derived, for design purposes, using Multi-blade Coordinate Transformation [23]. Moreover, at steady state, FAST will give a nominal pitch angle that is associated with a given average wind speed. Hence, the main variable that characterizes the linearized models is the wind speed. The resulting model takes the standard state-space form

$$\begin{aligned} \dot{x} &= A_c x + B_c u_{cpc} \\ y &= C_c x \end{aligned} \tag{1}$$

where A_c, B_c, and C_c are constant matrices with appropriate dimensions. u_{cpc} and y are the perturbations in the collective pitch and generator speed, respectively. x is the perturbation in the states. The state vector, x, includes the perturbations in the drivetrain torsional speed, drivetrain torsional displacement, and rotor speed. In a FAST model, the generator torque is based on the generator speed. If the generator speed is greater than or equal to the rated value, then the generator torque is constant at its rated value. Otherwise, the generator torque is proportional to the square of its speed while the generated power is proportional to the cube of the speed. Hence, the generator speed is the fundamental quantity that we measure and rely on to obtain our results [4].

2.2. The gap-metric concept

The gap metric criterion can be used to check the proximity of linear models [24,25]. The idea is that the distance between the two selected models should be larger than a prescribed level, otherwise, one model is enough to describe them both.

In this section, a gap metric criterion is defined. Then, it is used to determine the linearized models that can adequately represent