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Using stochastic programming and statistical extrapolation to mitigate long-term extreme loads in wind turbines

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HIGHLIGHTS

- Stochastic programming and statistical extrapolation to mitigate long-term extreme loads.
- Formulations can be cast as large-scale nonlinear programming problems.
- Approach can identify controller settings in a more systematic manner.

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ABSTRACT

We propose stochastic programming formulations to enforce mechanical load requirements in wind turbine controller design procedures. The formulations use statistical extrapolation techniques to construct a probabilistic (chance) constraint that controls the long-term probability of exceeding an extreme load threshold (as described by the IEC-61400 standard). This approach is based on the observation that extreme loads follow a generalized extreme value distribution, which enables an explicit algebraic representation of the probabilistic constraint. We illustrate how to use the formulations to find design parameters for pitch angle and torque controllers that maximize power output while constraining long-term extreme loads. We also use the formulation to explore the ability of a hypothetical model predictive controller to mitigate extreme loads. The proposed formulations can be cast as large-scale (but structured) nonlinear programming problems that contain up to 7.5 million variables and constraints. We show that these problems can be solved in less than 1.3 h on a multi-core computer with existing optimization tools.

1. Introduction

Wind turbine optimization studies recently reported in the literature have focused on blade aerodynamic design [1] and layout design in a given spatial field [2]. From a real-time operation stand-point, recent studies have focused on the design of architectures for control and energy management that span a wide variety of techniques such as set-point optimization [3,4], pitch/torque/yaw control [5], adaptive control [6], and model predictive control [7,8]. To inform these tasks, a wide variety of models of different levels of fidelity have been used. These models range from high-fidelity finite element models that describe the mechanical structure of the turbine [9], computational fluid dynamics [10] that describe its aerodynamic properties to lower-fidelity, and lumped electromechanical models that capture aggregated dynamical features of mechanical behavior and power generation [7,11]. Incorporating models of increasing fidelity in optimization tasks is a key endeavor but it is also technically challenging due to the high computational complexity of wind turbine models. Moreover, extensive simulations often need to be performed to anticipate and certify turbine performance under a wide range of wind conditions that might also span multiple timescales. Here, wind forecasting and uncertainty quantification play a key role in characterizing potential wind conditions [12–14].

Industrial wind turbines are designed to operate through a lifetime of more than 20 years and under highly uncertain wind conditions. Strong wind conditions can compromise the mechanical integrity of the turbine if they are not properly handled through the control system. To prevent structural damage and high life consumption rates, the International Electrotechnical Commission (IEC) standards require designers to certify that the turbine and the associated control system does not exceed critical mechanical load conditions when subjected to a multiplicity of operating scenarios. Many of these critical load

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conditions are identified using statistical load extrapolation methods [15,16]. Such procedures seek to use limited short-term wind and load data to assess the long-term probability of exceeding a certain load threshold. Extrapolation techniques are based on a powerful result from statistics known as the *extreme value theorem*, which states that the maximum of a sequence of independent random variables follows a generalized extreme value distribution. The existence of such a distribution enables the estimation of probabilities of rare, long-term events.

Control of industrial turbines requires a careful trade-off between power capture and compliance with extreme load requirements. Control strategies for industrial wind turbines are typically based on control architectures that regulate power and rotor speed by operating generator torque and collective blade pitch angle. In addition, supervisory control systems are used to mitigate loads and perform shutdown procedures [17,8]. As a result, designing a viable control architecture involves extensive and time-consuming simulations with different controller settings that satisfy IEC requirements.

Recent research activity in wind turbine control has focused on model predictive control (MPC) technologies. Such strategies have been used to regulate power and speed and to enforce fatigue and load constraints. MPC is a powerful optimization-based technology that can aid standard controllers, as it can directly accommodate detailed turbine models and constraints of different forms and with this anticipate wind events and capture multivariable interactions. In particular, MPC strategies can perform simultaneous blade pitch and generator torque control while maximizing power and mitigating extreme loads. For instance, in the work of [18] it is shown that, under an extreme gust event, an MPC strategy can reduce the tower base moment by up to 15% compared to standard controllers. Similarly, the work of [19] uses an MPC formulation to demonstrate that some loads can be reduced by up to 50% under extreme gusts without negative impact on overall power production. The MPC formulation of [11] is shown to reduce the tower bending moment by up to 40%. The work in [20] uses multi-objective optimization to explore the trade-off between generated power and structural loads. MPC strategies have also been reported in the literature that seek to overcome computational complexity by using simplified model representations [21,7].

A limitation of MPC strategies reported in the literature is that they analyze robustness to diverse wind scenarios on a case by case basis and do not capture long-term extreme load constraints (as required by IEC standards). Unfortunately, computational procedures used in long-term statistical extrapolation are complex and not trivial to implement in controller design and MPC formulations. Because of this, the effect of control strategies on mechanical loads is often performed *a posteriori* and not *a priori* (by design).

In this work, we propose stochastic programming formulations that enforce extreme load constraints as required by IEC standards *directly* in controller design procedures. The formulations exploit the observation that the cumulative density function (CDF) associated to the extreme value distribution has an explicit algebraic representation. Moreover, the CDF can be easily fit to actual wind turbine mechanical load data using moment matching. We demonstrate the benefits of the proposed approach by determining optimal parameters for pitch and torque controllers and by evaluating an MPC control strategy. Our results use a medium-fidelity electromechanical wind turbine model, which allow us to perform validation against an exhaustive search procedure. We show that the optimization formulations, which are cast as large-scale nonlinear programs with up to 7.5 million variables, can be solved in less than 1.3 h by using state-of-the-art gradient-based optimization solvers.

The main contribution of this work is a methodology to handle probabilistic constraints in a scalable manner by using statistical extrapolation techniques. Notably, existing approaches to handle probabilistic constraints in nonlinear programming formulations are limited in that they rely on conservative approximations that can lead to significant performance degradation [22,23]. Our statistical extrapolation approach avoids such approximations and enables the use of powerful and scalable gradient-based optimization solvers. While in our study we focus on medium-fidelity turbine models, the proposed stochastic programming formulation is general and can accommodate higher fidelity dynamic models and provide certifiable performance guarantees in terms of mechanical loads. These developments provide unprecedented capabilities to the field of wind turbine control and also show that statistical extrapolation is a valuable tool to handle probabilistic constraints in other applications that present long-term fatigue/degradation (which is common in energy systems such as batteries and power plants).

2. Optimization formulations

In this section, we present deterministic and stochastic variants for a controller design problem. The goal of the deterministic formulation is to compute optimal parameters for pitch and torque controllers that maximize extracted power and that impose constraints on the maximum load experienced by the turbine under a known wind speed profile. In the stochastic programming formulation, the goal is to compute optimal controller parameters that maximize expected power under uncertain wind conditions and enforces the satisfaction of the maximum load using a long-term probabilistic constraint, as required by the IEC61400-1 standard. Appendix A describes all variables, parameters, and units of the physical model.

2.1. Wind turbine model

We motivate our optimization formulations using a medium-fidelity lumped wind turbine model described by the following system of differential and algebraic equations (DAEs) [7,11]:

$$\dot{w}_r(t) = \frac{1}{J}(M_z(t) - N_g T_{gen}(t)) \tag{2.1a}$$

$$\ddot{x}(t) = \frac{1}{m_{Te}}(-c_{Te}\dot{x}(t) - k_{Te}x(t) + F_z(t)) \tag{2.1b}$$

$$y_P(t) = T_{gen}(t) N_g w_r(t)(1-P_l) \tag{2.1c}$$

$$y_L(t) = H(k_{Te}x(t) + c_{Te}\dot{x}(t)) \tag{2.1d}$$

$$F_z(t) = \frac{1}{2}\rho V_{rel}(t)^2 A C_t(t) \tag{2.1e}$$

$$M_z(t) = \frac{1}{2}\rho V_{rel}(t)^2 A R_r C_m(t)/\lambda(t) \tag{2.1f}$$

$$V_{rel}(t) = V(t) - v_x(t) \tag{2.1g}$$

$$\lambda(t) = w_r(t) R_r / V_{rel}(t) \tag{2.1h}$$

$$C_t(t) = \text{ThrustCoeff}(\theta(t), \lambda(t)) \tag{2.1i}$$

$$C_m(t) = \text{TorqueCoeff}(\theta(t), \lambda(t)) \tag{2.1j}$$

Eq. (2.1a) represents the drive-train dynamics, where w_r is the rotor angular velocity, J is the total moment of inertia of the drive-train, M_z is the aerodynamic torque, T_{gen} is the generator torque, and N_g is the gear ratio. Eq. (2.1b) describes the dynamics of the tower fore-aft, where $x(t)$ is the tower top displacement, $F_z(t)$ is the aerodynamic thrust force, m_{Te} is the tower total mass, c_{Te} is the tower structural damping coefficient, and k_{Te} is the bending stiffness coefficient. The outputs of the model, extracted power, y_P, and tower base fore-aft bending moment (load), y_L, are computed using Eqs. (2.1c) and (2.1d), where H is the tower height and P_l is power loss coefficient. Aerodynamic torque and thrust are computed using Eqs. (2.1e) and (2.1f), where ρ is the wind density, A is the disk area, V_{rel} is the effective wind velocity computed using Eq. (2.1g), λ is effective tip speed ratio computed using Eq. (2.1h), and C_t and C_m are power and thrust coefficients computed with Eqs. (2.1i) and (2.1j). Eqs. (2.1i) and (2.1j) are given by: