HAL
open science

A machine learning approach for online IPC controller selection based on wind features

David Collet, Mazen Alamir, Domenico Di Domenico, Guillaume Sabiron

To cite this version:

David Collet, Mazen Alamir, Domenico Di Domenico, Guillaume Sabiron. A machine learning approach for online IPC controller selection based on wind features. EAWE 2018 - 14th EAWE PhD Seminar, Sep 2018, Bruxelles, Belgium. hal-01945079v2

HAL Id: hal-01945079

https://hal.science/hal-01945079v2

Submitted on 5 Dec 2018

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

A machine learning approach for online IPC controller selection based on wind features

D Collet[a,b], M Alamir[b], D Di Domenico[a], G Sabiron[a]

[a] IFPEN, rond-point de l'échangeur de Solaize, 69360, Solaize, France
[b] GIPSA Lab, 11 rue des mathématiques, 38400, Saint-Martin-d'Hères, France

E-mail: david.collet@ifpen.fr

Keywords: Control systems, fatigue, machine learning, LiDAR, O&M

1 Introduction

The wind energy production has been exponentially growing in the last decades, with about 539 GW globally installed in 2017 out of 94 in 2007. In order to achieve the COP21 objectives in terms of CO2 emissions, the growth of the wind energy industry is expected to develop even further. Thus, there is a need for reducing turbine CAPital EXpenditure (CAPEX) and OPerational EXpenditure (OPEX).
Wind turbine control aims at firstly regulating the wind turbine rotational speed and power, and secondly, minimizing wind turbine mechanical strains, and therefore the OPEX. A three bladed Horizontal Axis Wind Turbine (HAWT) is equipped with five actuators, the yaw actuator, the electrical generator, and the three blade pitch actuators which can spin the blades on their longitudinal axis. Nowadays the two most studied pitch control strategies are the Collective Pitch Control (CPC) and the Individual Pitch Control (IPC) on which the focus is set in this study.
To this day, many works have been conducted, using various control techniques going from Proportional Integral (PI) controller [1] to advanced Model Predictive Control (MPC) [2] and Nonlinear Model Predictive Control (NMPC) [3], including H_∞ [4]. The recent advances in Light Detection And Ranging (LiDAR) and Wind Field Reconstruction (WFR) have led to use its enhanced information on the inflow wind field to anticipate the control action. This makes control strategies such as feedforward [4], MPC [2] or even NMPC [3] particularly interesting.
Another research track regarding wind turbines is to predict HAWT components fatigue from wind, with statistical and machine learning solutions [5,6].
The main objective of the study is to reduce fatigue cost on the wind turbine by designing a supervisory layer which selects online the best suited controller for the current wind conditions, among a discrete set of controllers. This is performed by using machine learning regression, to predict for each controller the expected wind turbine fatigue cost under the current wind conditions.

2 Pitch control

Above rated wind speed, the generator torque is at its maximum, and the blades are pitched, in order to regulate the rotor aerodynamic torque and wind turbine power at their rated values, and thus keep the turbine in its operating range.
Usually the blades are all pitched towards the same angle, this is called CPC, but wind is not uniformly spatially distributed. Thus, wind speed and direction vary over the whole rotor area, so does the loads on each individual blade. Yet, IPC strategy allows the blade pitch angle to be varied with the blade azimuth, in order to cancel the unbalanced tilt and yaw rotor loads. A feature of IPC is the tradeoff between pitch activity increase and blade fatigue load reduction, which needs to be weighted. The IPC controllers designed in this study are usual PI controllers, similar to the one in [1], but more elaborate controllers could be used in future works.

3 Fatigue and cost function

Fatigue is usually evaluated using Palmgrem-Miner's rule, where hysteresis load cycles are counted using RainFlow Counting (RFC) algorithm. Damage Rate (DR) for one component load case can be evaluated using the following equation:

$$DR = \gamma \sum_i n_i \left(\frac{1}{2} L_i^R\right)^m$$

Where m is the Wöhler exponent whose value depends on the component material ($m = 4$ for steel and 10 for glass fiber), γ is constant for the component, n_i is the number of hysteresis cycles at range L_i^R counted by the RFC. As $m > 2$, one can see that load variance does not faithfully reflect components fatigue, which is basically used as objective function in the optimal control community.
Consequently there is a need for a more accurate fatigue based cost function derivation for control. The cost function developed here is a weighted sum of the main turbine components DR and their replacement costs. This objective function gives accurate representation of the costs induced for a wind turbine controlled by one specific controller under a given wind.

4 Machine learning based supervisory layer

In order to synthesize an efficient regression function, it is necessary to simulate the wind turbine in a wide range of meteorological conditions. 588 realistic three-dimensional wind fields are generated, and the closed loop is simulated with each controller in the set of candidate controllers. The fatigue based cost function is evaluated for each simulation. Each wind/controller combinations is associated to a scalar called target value.
The winds are defined by eleven characteristic features, that are computed with recent WFR algorithms (e.g. rotor averaged speed, direction, shear, turbulence intensity). From the wind features and target values, supervised machine learning regression algorithms will synthesize a predictive function which is able to estimate fatigue cost of the wind turbine under the current wind if it were controlled by each controller in the set. To minimize fatigue cost, this algorithm allows to take efficiently the decision to whether or not switch from one controller to another, considering a high amount of WFR data.

5 Conclusion

An innovative method combining machine learning and control systems tools is proposed to minimize a fatigue based cost function. The results are encouraging since the method allows to efficiently adapt the controller to decrease fatigue cost. Even though usual PI controllers were used, future works will aim at using advanced controllers, and achieve further fatigue reductions. Another track to be pursued is the switching strategy between controllers that needs to be smoothen in order to avoid additional switching transient induced fatigue.

Bibliography

[1] Bossanyi E A 2003 *Wind Energy* **6** 119 – 128
[2] Mirzaei M, Soltani N M, Poulsen N K and Niemann H H 2013 *Proceedings of the 2013 European Control Conference, ECC* 490 – 495
[3] Raach S, Schlipf D, Sandner F, Matha D and Cheng P W 2014 *Proceedings of the 2004 American Control Conference, ACC* 4434 – 4439
[4] Schlipf D, Schuler S, Grau P, Allgöwer F and Kühn M 2010
[5] Schröder L, Dimitrov N K, Verelst D R and Sørensen 2018 *Journal of Physics: Conf. Series* **1037** 062027
[6] Murcia J P, Réthoré P E, Dimitrov N, Natarajan A, Sørensen J D, Graf P and Kim T *Renewable Energy* **119** 910 –922