

Wind Turbine Dynamics Identification Using Gaussian Process Machine Learning

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Introduction

Huge amounts of data are available to a wind turbine control system, unfortunately this data is usually composed of several additive components, plus noise.

This project seeks to apply machine learning techniques to extract these component parts, this will allow for improved control and a deeper understanding of wind turbine aerodynamics.

The first focus of this project is determining wind turbine C_Q tables and drivetrain losses from measuring generator speed and reaction torque as well as the anemometer wind speed reading.

Regression Equations

Above Rated: $\hat{H} = \hat{\lambda}^{-2} C_Q(\hat{\lambda}, \hat{\beta}) + L^*(\hat{\omega}_r^{-1}) + \eta_H(\hat{\omega}_r^{-2})$

These values can be measured using data available to the controller

Aerodynamic terms

Drive train losses related term – linear in $\hat{\omega}_r^{-1}$

Noise

Below Rated: $\hat{G} = \hat{\lambda}_{max}^{-3} C_{Pmax} + L^*(\hat{\omega}_r^{-1}) + \eta_G$

The noise term in the above rated regression equation is driven by the difference between the true rotor effective wind speed and the anemometer wind speed measurement.

In the below rated regression equation the noise term stems from the tip speed ratio deviating from λ_{max} . This equation is also a polynomial regression equation.

In both cases the noise term depends directly on the wind field characteristics and so stationarity can only be assumed for 5-10mins at a time. This implies that an iterative process of dynamics identification is required.

Gaussian Processes

Gaussian process (GP) machine learning is a robust and flexible regression technique which results in probabilistic predictions for the underlying function.

For the below rated case, fast and efficient algorithms have been developed which have allowed for a deeper understanding of GPs. The theory developed here has also shown the correct way to build these techniques into an iterative learning algorithm.

The next stage of work in terms of GP theory will be to extend the iterative GP processes to work for general nonlinear functions.

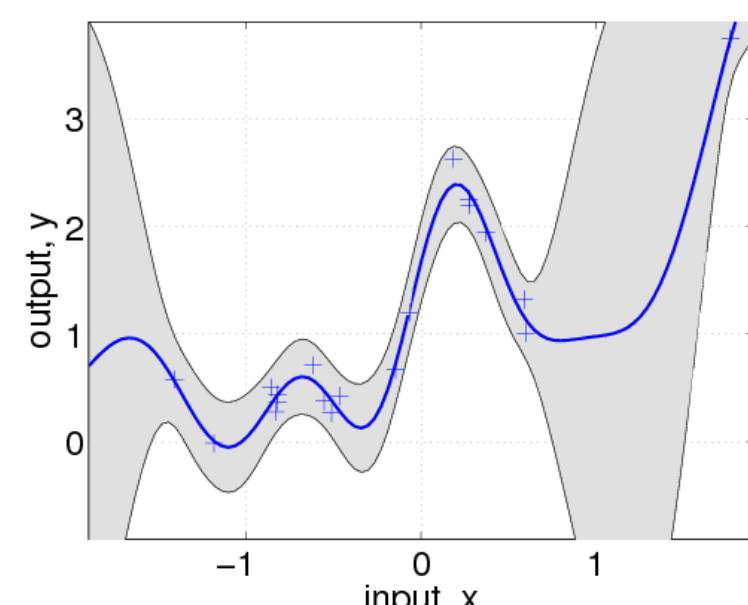


Figure 1. Mean function (blue) and 95% confidence intervals (grey) from the GP predictive distribution obtained by forming a prior and conditioning on the measured values shown by blue crosses.

Below Rated Regression Results

Figures 2 and 3 show predictions of C_{Pmax} and the drivetrain losses function respectively for both the GP polynomial regression algorithms developed in this work and Least Squares (LS) regression. Regression data was obtained from simulations using the Supergen Exemplar 5MW wind turbine model. Each prediction is made from regression on a single dataset containing roughly 11 mins of data sampled at 20s intervals (to avoid correlations).

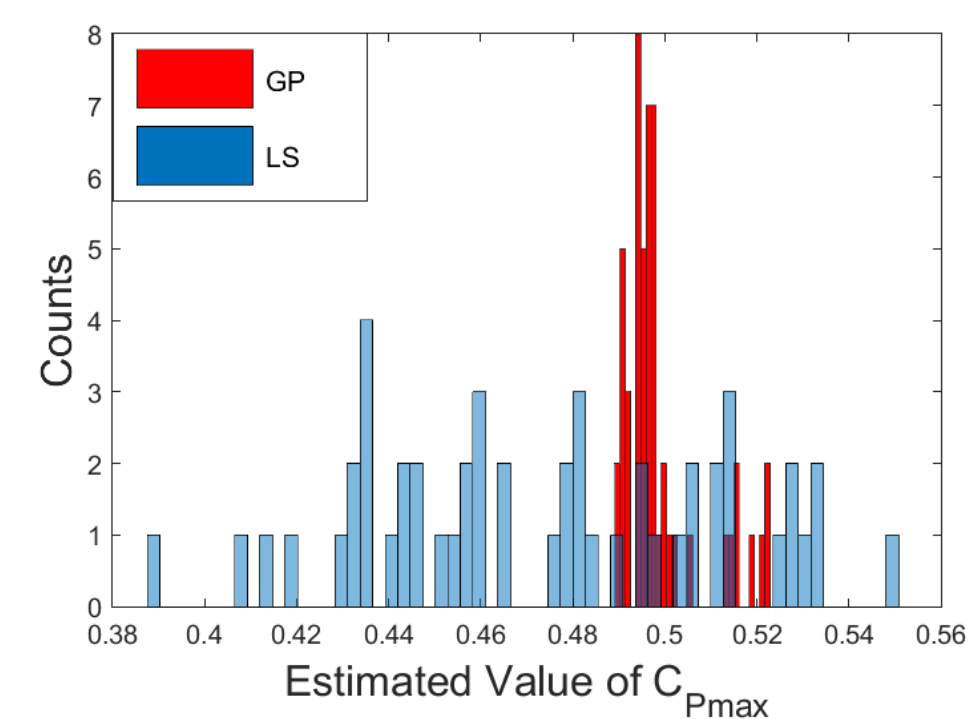


Figure 2. C_{Pmax} estimates from both GP and LS polynomial regression. The true value is 0.4885.

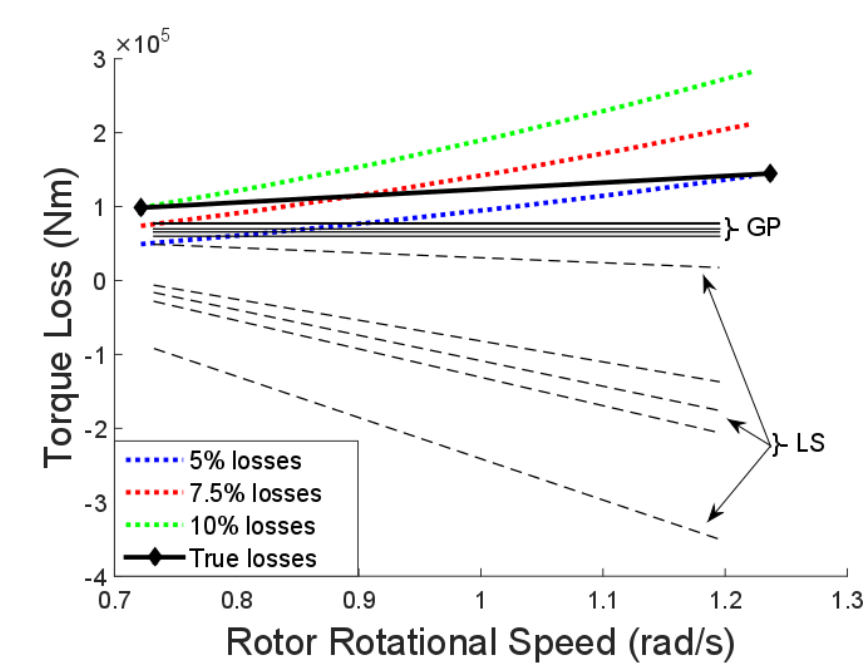


Figure 3. Losses function estimates from both GP and LS polynomial regression. The true linear losses function is also shown.

As the above results show the GP algorithms outperform LS in these cases. Current work is focussing on the iterative learning processes for the below rated (polynomial) regression case as applied to wind turbine data.

Future Work

- Finish developing and testing iterative GPs for polynomials
- Explore nature of noise terms in both below rated and above rated regression equations
- Investigate performance of GPs applied to above rated regression equations
- Develop iterative GPs for general case
- Investigate applications to wind turbine controller updating.