Wind Turbine Dynamics Identification Using Gaussian Process Machine Learning

Edward Hart, Bill Leithead, Julian Feuchtwang

Wind and Marine Energy Systems CDT
University of Strathclyde,
204 George Street,
Glasgow, G1 1XW

edward.hart@strath.ac.uk , w.leithead@strath.ac.uk

University of Strathclyde Glasgow

1. 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 CQ tables and drivetrain losses from measuring generator speed and reaction torque as well as the anemometer wind speed reading.

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

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.

2. Gaussian Process Machine Learning (GPML)

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.

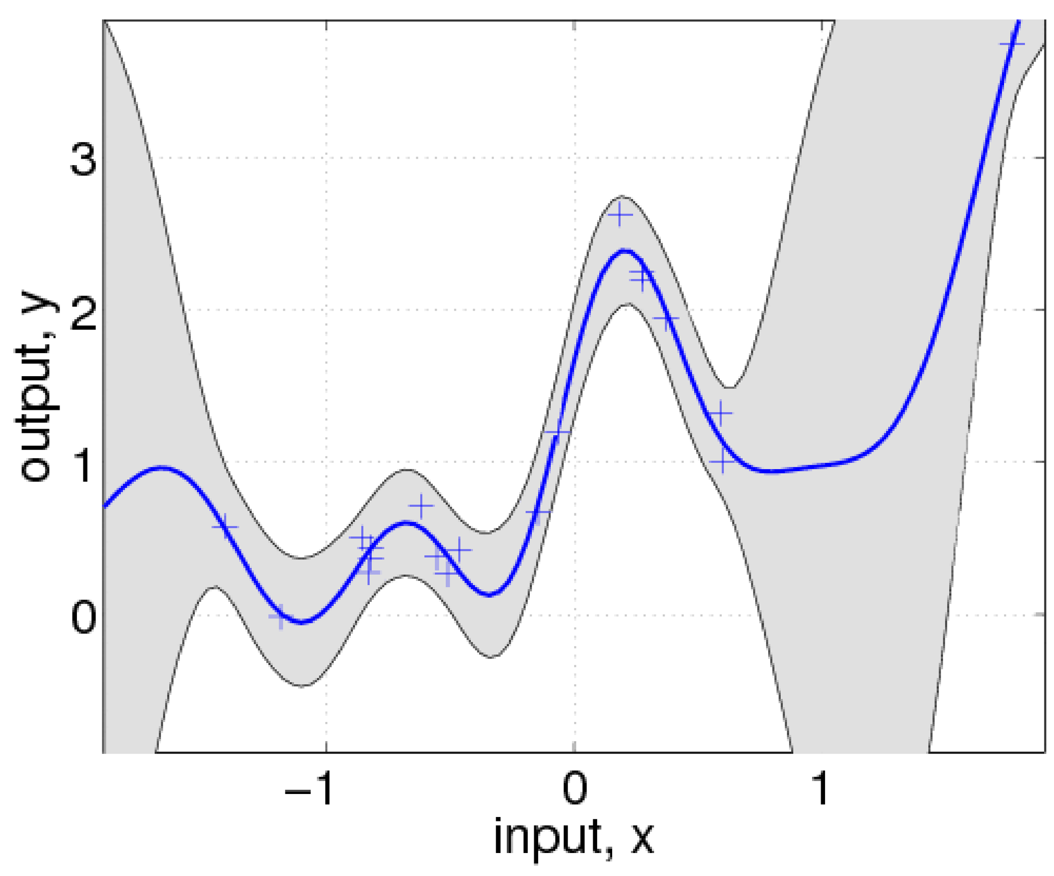

Figure 1. Mean function (blue) and 95% confidence intervals (grey) from the GP predictive distribution obtained by forming a prior and conditioning on the measured values shown by blue crosses.

3. Below Rated Dynamics

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 11mins of data sampled at 20s intervals (to avoid correlations).

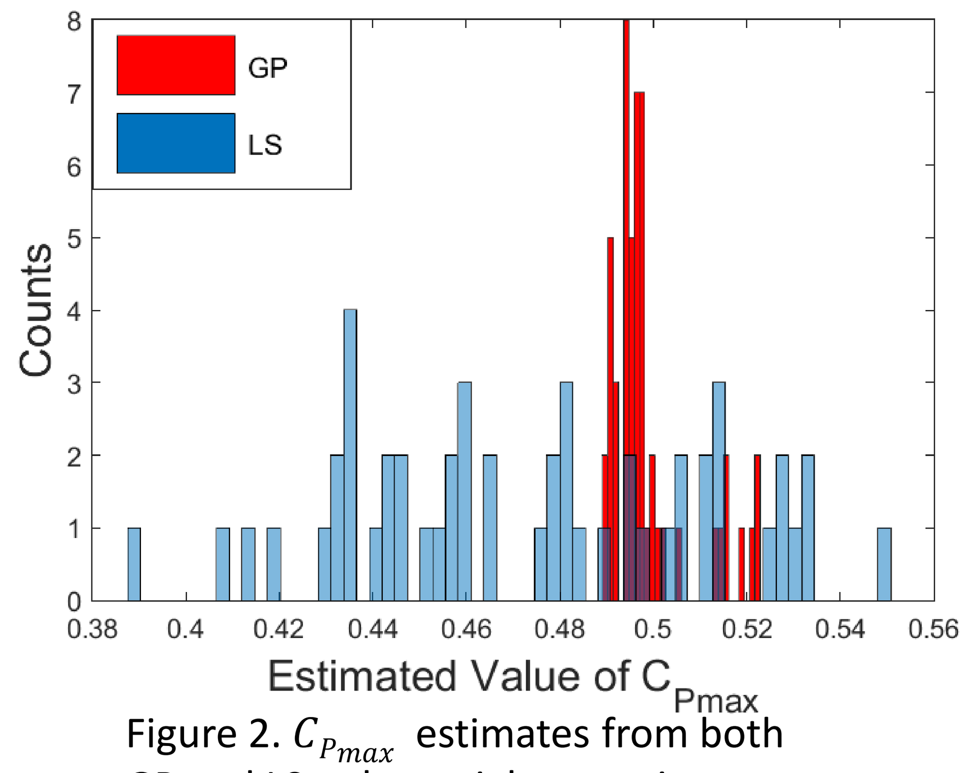

Figure 2. C_{Pmax} estimates from both GP and LS polynomial regression.

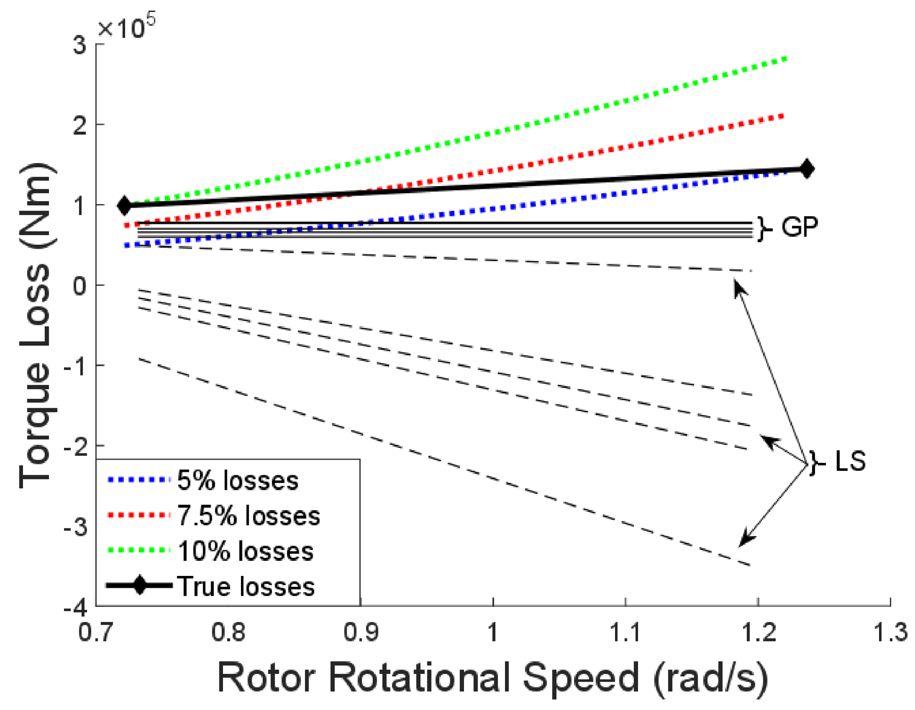

Figure 3. Losses function estimates from both GP and LS polynomial regression. The true linear losses function is also shown.

The GP predictions can be seen to have smaller error than the LS predictions. Furthermore, the GP predictions are tightly clustered, whereas the LS results show very large spreads.

4. Sufficient Subset GP (SSGP) Iteration

In order to update the predicted turbine dynamics as new data becomes available it is necessary to have an iterative GP procedure as depicted in Figure 4.

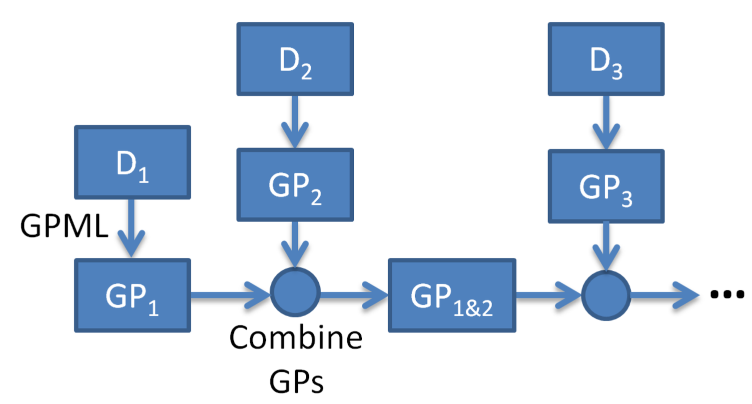

Figure 4. Schematic diagram of GP batch processing of data (D_i) into GP models.

Standard GP algorithms do not allow for this, therefore, a new form of GP regression has been developed which does allow for iterative updating of the GP model. This is called SSGP iteration.

SSGP iteration is a technique which essentially compresses the information contained in a GP model in such a way which allows for that data to be carried forward into regression on new data, without having to carry all of the original data. This results in a GP regression technique which is very fast and has iterative regression built into it.

5. Current and Future Work

Current work is focusing on further understanding the SSGP approach to GP regression and building in derivative information. Once this is complete the focus will be on implementing this regression techniques for the identification of wind turbine C_Q tables and interfacing with advanced control techniques which can take advantage of this new information.

References
[1] W. Leithead et al, 'Global Gain-scheduling Control for Variable Speed Wind Turbines' Proceedings of the European Wind Energy Conference, 1999.

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