D1.5 Paper: System identification ROM trained on LES

[Version 1.0]

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1. Overview

This report presents a short description of the scientific publication (**Title paper: Probabilistic surrogate modeling of offshore wind-turbine loads with chained Gaussian processes**) related to this report. This paper presents a novel approach to modelling site-specific loads on wind turbines using chained Gaussian processes. The results will be presented at the Torque conference in Delft in June 2022. The accompanying paper has been accepted to be published in the Journal of Physics: conference series.

This present document provides a general overview of the publication and its conclusions. The reader is directed to the journal publication for further details. As noticed, the title deviates from the paper's title due to new research developments during the process.

2. Abstract

Heteroscedastic Gaussian process regression, based on the concept of chained Gaussian processes, is used to build surrogates to predict site-specific loads on an offshore wind turbine. Stochasticity in the inflow turbulence and irregular waves results in load responses that are best represented as random variables rather than deterministic values. Moreover, the effect of these stochastic sources on the loads depends strongly on the mean environmental conditions - for instance, at low mean wind-speeds inflow turbulence produces much less variability in loads than at high wind-speeds. Statistically this is known as heteroscedasticity. Deterministic, and most stochastic surrogates do not account for the heteroscedastic noise, giving an incomplete and potentially misleading picture of the structural response. We draw on the recent advancements in statistical inference to train a heteroscedastic surrogate model on a noisy database to predict the conditional probability density function (pdf) of the response. The model is informed via 10-minute load statistics of the IEA-10MW-RWT subject to both aero- and hydrodynamic loads, simulated with OpenFAST. Its performance is assessed against the standard Gaussian process regression. The predicted mean is similar in both models, but the heteroscedastic surrogate approximates the large-scale variance of the responses significantly better.

3. Objectives

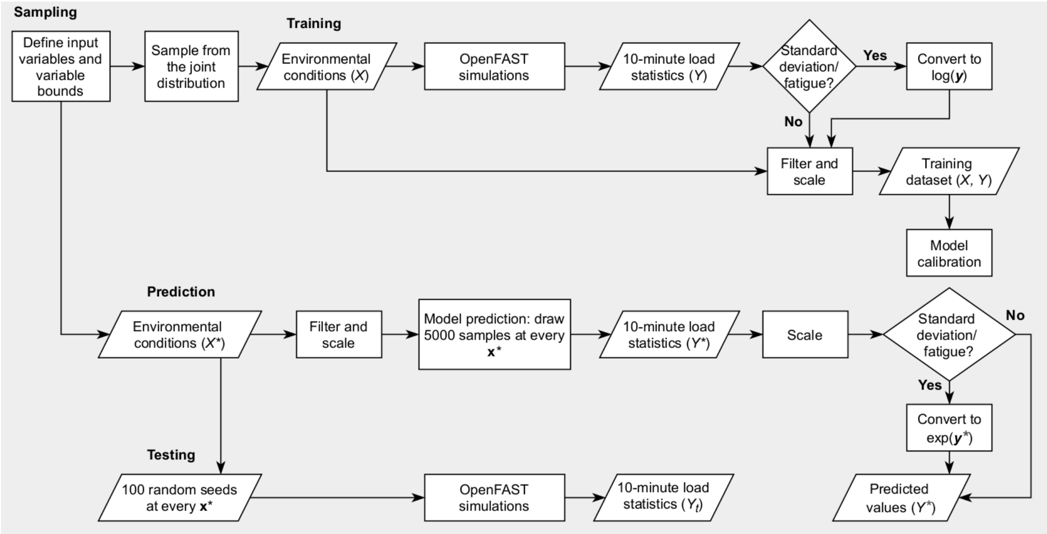

Figure 1 Probabilistic machine learning framework

The main objective is to develop a probabilistic framework that accurately predicts the 10-minute load statistics, given a set of site conditions. A schematic of the framework is shown in figure 1. The surrogate is modeled on the responses of the aero-hydro-servo-elastic code, OpenFAST. The inflow turbulence is generated using TurbSim. The model is trained on data sampled from a joint distribution of average wind speed, power law coefficient, turbulence intensity, wave significant height, wave period and wave direction. The stochasticity in wind and wave inputs is emulated in OpenFAST by means of random seeds.

The standard way of dealing with the stochasticity in the loads is to reduce them to their average over a very long time period or their average over several repetitions of the 10-minute simulations with different random seeds before training the surrogate. The IEC61400-1 standard recommends a 60-minute long time signal or six 10-minute simulations. However, 60 minutes of data has also been shown to be insufficient to fully characterize the uncertainty in the fatigue loads. Alternative approaches, such as those investigated in the paper, model the distribution (e.g., via the probability density function (pdf)) from which the training samples are drawn directly. The stochastic machine learning models approximate the conditional distribution of the response, given the data. They can infer the underlying hyper-parameters of the pdf directly from a noisy data set within the bounds of assumptions specified by the user.

4. Conclusions

The work presents a Bayesian approach to modeling the probability distribution function of offshore wind turbine loads. On account of the heteroscedasticity observed in the 10-minute load statistics calculated using a stochastic simulator, the sparse heteroscedastic Gaussian process regression's performance, modeled within the chained Gaussian process framework, is assessed for a specific test case. The results are compared against the standard Gaussian process regression for reference. Overall, within the limits of the number of training points and the assumptions in modeling, H-GPR can reproduce the conditional distributions at various inflow conditions with low error, quantified by the normalized Wasserstein distance. While the expected value of the distribution is not affected by the heteroscedastic model, the prediction of the variance shows a significant improvement over GPR. The method suffers from the curse of dimensionality and is unable to model very high gradients in the variance, especially those driven by hydrodynamic loads (at low wind speeds) or controller actions, presumably due to insufficient training points. However, the excellent predictions at mid to high wind speeds provide the user with a useful tool, should they be interested in uncertainty quantification of site-specific fatigue or extreme loads in offshore wind turbines. From an industrial point of view, future research includes determining the value of probabilistic surrogates in estimating extreme events using the statistical information from the predictions rather than using very conservative design safety factors. The extension of the model to a high-dimensional problem such as floating offshore wind turbines is also of particular interest.

References

[1] Singh D, Dwight RP, Laugesen K, Beaudet L, Vire A. Probabilistic surrogate modeling of offshore wind-turbine loads with chained Gaussian processes. IOP Journal of Physics: conference series. (Accepted, March 2022).