Data-Driven Methods for Prediction of Fuel Consumption

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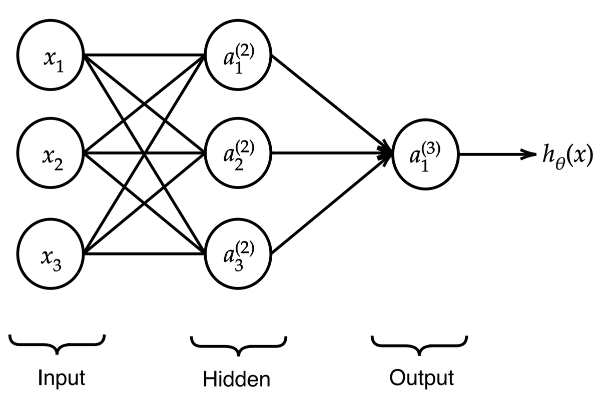
Problem

Due to increasing fuel prices and focus on the environmental impact from the shipping industry, there is a greater need for control and evaluation of the ships real time energy performance.

General empirical hydrodynamic methods can estimate the resistance of a ship given its main dimensions and thereby the required fuel to obtain a certain speed. Since these methods are general and applicable for most type of vessels, the result is a less accurate prediction. However, powerful data-driven methods allows tailor suited prediction of fuel consumption, accounting for the influence of wind, waves and ocean currents.

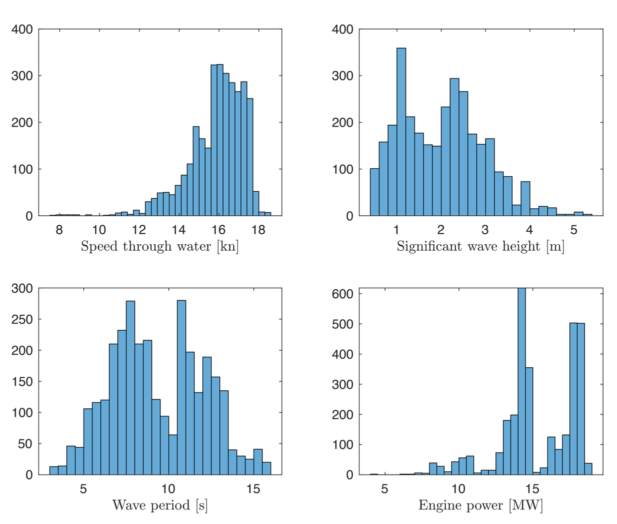
Machine Learning

One of the main branches within the field of data-driven methods is supervised machine learning, where the main objective is to train a predictive model. Among the methods within supervised learning is artificial neural networks, deep learning, Gaussian process regression, where the latter is a stochastic model. These models are capable of quantifying the change in i.e. ship resistance due to wind, waves and current without knowing the physics involved.



Data

Four sister cruise vessels with their onboard performance monitoring system make up most of the data used in this thesis. The system measure and distribute real time data and are available by the use of an API, allowing the prediction model to continuously learn, update and improve its performance. Weather data comes from three different sources: ECMWF, Tidetech and Norkyst800 (Havforskningsinstituttet). A thorough pre-processing study of the data were conducted and a running median filter [2] were found to be applicable for most cases.



Methodology

By isolating well known and established physics in the system such as resistance due to friction and wind, a machine learning algorithm detects and expose how and which other factors contribute to the total resistance. Quantification of the residual resistance (wave resistance) is commonly performed with empirical methods such at with Hollenbach's method, while frictional and wind resistance are found from

$$C_T = \frac{T}{\frac{1}{2}\rho V_s^2 S}, \quad C_f = \frac{F_f}{\frac{1}{2}\rho V_s^2 S} = f(R_n), \quad C_{AA} = \frac{F_{wind}}{\frac{1}{2}\rho V_{rel}^2 A_x}$$

Thus, one of the main point in this thesis is to explore different data-driven methods that serve the purpose of accurately predicting the residual and thereby total resistance in the best manner.

$$C_r = ML(H_s, T_p, \gamma_{rel}, STW, T_{AP}, T_{FP})$$

With an accurate model of how the total ship resistance responds to environmental factors such as wind, waves and current, prediction of the total fuel consumption on a specific voyage can exploit the weather forecast for optimal route planning.

Results

A neural network with two hidden layers and a total of 31 neurons with a Bayesian learning algorithm [1] results in what seems to give a fairly accurate representation of the total resistance. Hence the prediction of fuel consumption[a] seems to be accurate. The Gaussian process regression with exponential kernel function shows a more varying performance in Fig. 1, but have the ability to predict the consume within an confidential interval.

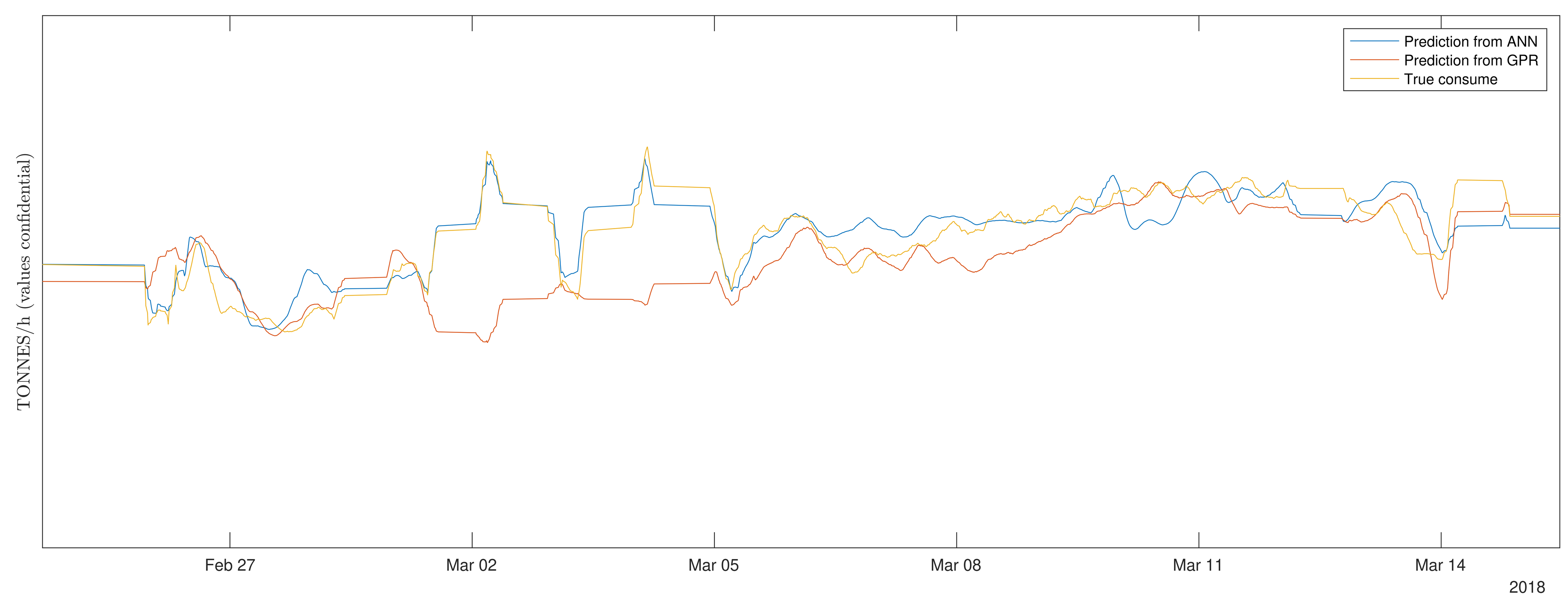


Figure 1: Time series of fuel consumption predicted by an ANN, GPR and true consume.

[a]For propulsive purposes only

Conclusion

The prediction of total resistance and fuel consumption for a ship in transit by use of data-driven methods, shows promising results. Both artificial neural networks and Gaussian process regression are applicable for the purpose, but are sensitive for extrapolation beyond the training sample space. Bayesian regularization learning algorithm and logistic sigmoid function seems to be most accurate for the ANN, whereas for the GPR an exponential kernel function is suitable. A sensitivity analysis of length scaling in GPR is recommended for further work.

References

[1] Frank Burden, Dave Winkler: *Bayesian Regularization of Neural Networks*, Artificial Neural Networks: Methods and Applications (2009)

[2] Gonzalo R Arce: *Nonlinear signal processing: a statistical approach* (2005)

Acknowledgements

The author would like to thank Professor Sverre Steen and Sigbjørn Rudaa for guidance . The project is carried out in collaboration with Wilhelm Wilhelmsen which provide in-service data from their fleet, as well as their outstanding domain knowledge within the shipping industry, operation of ships and digital services.