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Physics-based shaft power prediction for large merchant ships using neural networks

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ABSTRACT

There are currently over 100,000 merchant ships operating globally. To reduce emissions requires predicting and benchmarking the power they use. This is relatively straightforward for calm conditions but becomes almost impossible in larger waves. Design power predictions for ships in weather are typically derived by applying a 'margin' onto a reference 'calm water power'. This is of questionable accuracy as the techniques available to estimate these 'margins' are inaccurate. To improve the accuracy and flexibility of such predictions this paper investigates the use of neural networks. For this, 27 months of continuous monitoring data are used from 3 vessels of the same design, sampled every 5 min. Multiple network sizes are considered and evaluated to determine the quantity and quality of data required for predictions. A key aspect is determining network architectures optimised not just for accuracy, but that give close relationships between the input variables and shaft power. Predictions are compared to the results of a regression, the conventional tool to determine shaft power from measured full-scale data from ships. The predictions from this network are similar in accuracy to those of standard practices, with an error less than 10%, but the scope for further improvements is large.

1. Introduction

It is estimated that 90% of the world's trade is seaborne, due to the efficiency of shipping as a mode of transport. Despite this efficiency, the sheer volume of trade means that global shipping is responsible for 3.1% of anthropogenic CO_2 emissions (IMO, 2012), equivalent to those of a major industrialised economy such as Germany or Japan. Despite this shipping is presently outside of the United Nations Framework Convention on Climate Change (UNFCCC (United Nations, 1994)) commitments to reduce emissions. Implementation of an effective energy efficiency management (SEEMP (Register, 2012)) plan for a vessel, as mandated by IMO, requires benchmarking of its fuel usage. Therefore prediction of fuel consumption, based on its power requirement, is extremely valuable. Accurate prediction of a ship's power requirement in different weather conditions is difficult using traditional methods based on model tests and/or numerical analysis (Molland et al., 2011). Even more sophisticated methods, such as fitting high frequency operational data with regression curves (Lakshmynarayanana and Hudson, 2017) or comparing to design speeds to produce a weather margin (Kwon, 2008), (Lu et al., 2015), struggle to give accurate predictions which would allow vessels to determine the penalties for travelling a given route.

Traditional techniques for power prediction at the design stage rely on computational analysis of the added resistance due to waves, or on towing tank tests at model scale, see Molland et al. (2011). Much of the operational ship performance analysis is presently based on measured data, and focuses on trying to obtain an accurate regression curve fit to the power-speed relationship in calm water to provide a baseline performance (Carlton, 2012). It has advantages in its simplicity, but is time consuming and concentrates purely on the relationship between speed and power, ignoring fluctuations for weather. As it is the industry standard it is chosen as a means of comparison between the developed method and those in regular use for analysing ship performance. In order to derive such a regression fit, it is common to filter out performance data in waves above a certain, arbitrary, height. A choice must also be made on whether to derive the curve for the remaining data set, or whether to also filter for draught and vessel trim. It is extremely difficult to analyse ship performance data in waves using such methods shown by Lakshmynarnyanana (Lakshmynarayanana and Hudson, 2017), where the nature of the regression relationship is not known a priori. Th artificial neural network method (ANN) allows the possibility of deriving a method of predicting ship power based on all of the underlying physical parameters. This predictive model may be used in performance analysis as well as having the capability to be used for weather routing and deriving design margins for future ships.

Recorded data has historically been used for similar estimations,

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through use of the ‘noon report’ of the ship's position, wind speed, estimate of sea state and daily fuel consumption taken at noon each day during operation. This type of analysis requires a large number of voyages before the required quantity of data can be collated and also suffers from the averaging inherent in using one data point to represent the operation and weather conditions from a 24hr period. These reports are also reliant on observation and subject to human error. Despite these drawbacks noon reports are currently used to monitor vessel status and operational efficiency. Recent improvements in the ability to collect, store and transmit data allows for analysis of these different variables at a much higher frequency. The extra data can be combined with recent advances in forecasting environmental conditions using hindcast models to provide improved predictions. Dinham-Peren and Dand (2010) highlight the potential benefits and some of the problems with using these data to derive performance benefits.

Beyond Dinham-Peren and Dand (2010) there are a few other recent attempts to predict ship performance from data measured more frequently. These papers utilise a range of techniques, e.g. Trodden et al. (2015), Aldous et al. (2015) and Lu et al. (2015). Trodden et al. (2015) investigated a method for associating segments of a data-stream with its corresponding ship activity to find the fuel efficiency; the method utilises a number of filtering techniques to determine the activity being performed. To validate the methodology, results from the data analysis of speed over ground are compared to fuel consumption data measured under sea-trial conditions and found to be in close agreement. The analysis of this paper utilises one month's worth of data, constituting 43,143 data-points. Aldous et al. (2015) categorises the relevant sources of uncertainty in performance measurement. A sensitivity analysis conducted on the sources of uncertainty highlights the relative importance of each. The two major data acquisition strategies, continuous monitoring and noon reporting, are compared, using 9570 data points, after filtering, taken over 370 days. It was found that the number of observations in the data set has a significant effect on uncertainty, with more data reducing the uncertainty, with the observations taken at either 15 min (continuous monitoring) or 24 h (noon reports). Lu et al. (2015) looked at a semi-empirical addition to the method of Kwon (2008) to estimate the ship's added resistance considering the specific ship type under varying draughts, speeds, encounter angles, sea states, fouling effect and engine degradation conditions.

Despite these attempts to utilise some of the available data there are limited attempts to apply soft computing or machine learning techniques on data from operational measurements. This is despite the use of Artificial Neural Networks (ANN) in a number of other marine applications, Jain and Deo (2006) review the use of neural networks in ocean engineering. They show that the majority of applications of neural networks in ocean engineering are to predict natural variables in specific locations (wind speed and direction, wave height - Hu et al. (2016) and tide - Lee and Jeng (2002)), but that there is some use for predicting non-natural variables like predicting ship parameters - Islam (2001) and vessel location - Zissis et al. (2015). The majority of papers reviewed by Jain and Deo (2006) are simple supervised feed-forward networks with one or two hidden layers and a low number of inputs (with a few exceptions Makarynskyy (2004) and Huang et al. (2003)).

Notable exceptions - applying soft computing to operational measurements - include Pedersen and Larsen (2009), Besikci et al. (Bal Beşikçi et al., 2016) and Radonjic and Vukadinovic (2015). Pedersen and Larsen (2009) also used an Artificial Neural Network approach to ship power prediction, looking at predictions over 10min periods, they used a Bayesian learning scheme. Four variables were investigated; ship speed, relative wind speed and direction, air temperature and sea water temperature. The sampling time was every 1 s, but these measurements were inconsistent, sometimes with gaps of more than 10 s; power and speed were updated at a different time period, every 13 s. Samples with excessive variance in the heading were excluded. The relative error of the predictions was less than 2.7% for the mean propulsive power over 10 min periods. This was seen to be significantly better than empirical or data-driven methods based on towing tank tests (e.g. Holtrop (1984)). Besikci et al. (Bal Beşikçi et al., 2016) predict the fuel consumption of a vessel but use data from ‘noon reports’. The parameters considered for fuel prediction are ship speed, revolutions per minute (RPM), mean draft, trim, cargo quantity on board, wind and sea effects, in which output from the ANN is fuel consumption. Only 233 points of data are used with the best prediction being reached with 12 neurons in one hidden layer which provides better performance than multiple regression analysis. Artificial Neural Networks have also been used to predict power for two boats by Radonjic and Vukadinovic (2015) but the data used was from full scale trials, not measured from day to day use of a ship. Their results only concentrated on the ship speeds effect on power so predicting ship performance in weather is not possible from this model. The data used to train their networks includes vessel specifications such as length to beam ratio, this means a network trained on one vessels data will never be able to be used on another vessel, a vital application of this method. Importantly the focus of all of these approaches, marine or non-marine, is on the accuracy of the power prediction, but there is limited evidence of understanding how physics dependant these models are.

There are currently limited efforts to use machine learning tools to predict ship power from real data, those that do use only a few input parameters. The focus for the available attempts is on the accuracy of prediction rather than the relationship between inputs and outputs, which will be vital to make the most of these tools. This paper presents an application of machine learning tools on measured ship data to predict shaft power in a range of ship and sea conditions. The focus will be on creating networks which approximate the relationships between inputs and outputs, physics-based, and not solely on the accuracy of the results, like much of the literature. Of the six well documented applications of neural networks to ship propulsion prediction, five ((Bal Beşikçi et al., 2016) (Pedersen and Larsen, 2009) (Leifsson et al., 2008) (Petersen et al., 2012) (Radonjic and Vukadinovic, 2015)) use one hidden layer with less than 50 neurons. A two layer neural network has also been applied (Radonjic and Vukadinovic, 2015), although the number of neurons in the layers is not specified. Previous studies refer to whether a function can be found that gives high accuracy, this does not necessarily imply the network will easily be able to find the real representation as many networks suffer from poor extrapolation (Jain and Deo, 2006), perhaps indicating that they have not found the real representation. Shallow networks can memorise data but are poor at generalisation, deeper networks are capable of learning features at various levels of abstraction (Najafabadi et al., 2015) allowing explicit development of areas of the network to handle the weaker relationships between inputs and outputs. This can improve model generalisation (Lawrence et al., 1996) and so it is proposed that the use of larger networks will improve the ability to extrapolate beyond the available input data by becoming more physics-based. Guidance is given on the quantity of data required for this type of analysis and the type of architecture required to give a balance between accuracy while retaining a basis in the underlying physics of the ship's behaviour. The developed method is compared to a regression used on the same dataset, to highlight the differences in the machine learning methods and potential areas where current models might be improved. A method capable of determining the influence of weather on ship power performance allows its use in both weather routing and in providing a correction from measured data in a range of conditions back to a calm water, or reference, condition. The latter may provide more data for analysis of a range of ship operational and design effects, Dinham-Peren and Dand (2010).

2. Artificial neural networks

Artificial Neural Networks are collections of neurons that are grouped into layers with weighted connections, with a simple

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