An Artificial Neural Network based decision support system for cargo vessel operations

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There is increasing interest in understanding fuel consumption from the perspective of increasing energy efficiency on a vessel. Thus the aim of this paper is to present a new framework for data-driven estimation of fuel consumption by employing a combination of (i) traditional statistical analysis and (ii) Artificial Neural Networks. The output of the analysis is the most frequently occurring fuel-speed curves corresponding to the respective operational profile. The inputs to the model consider important explanatory variables like draft, sea current and wind. The methodology is applied to a case study of a fleet of 9000 TEU vessels, in which telemetry data on the fuel consumption, vessel speed, current, wind direction and strength were analysed. The performance of the method is validated in terms of error estimation criterion like R^2 values and against physical phenomena obtained from the data. The results can be used to study the economic and environmental benefits of slow-steaming and or fuel levies, or by extending this part of the model into exergy analysis for a more holistic review of energy saving initiatives.

Keywords: Fuel consumption in vessels, Artificial neural networks, telemetry data

1. Introduction

1.1. *Aim of study*

Fuel efficiency of ships have, in recent years, been of interest due to the volatility of fuel prices and environmental considerations. The volatility of the fuel prices, especially when it is high, have become significant economic driving forces to optimise each voyage, as fuel costs can exceed 50% of a carrier's cost when sailing speeds and fuel costs are high (Stopford, 2010; Ronen, 2011).

In terms of environmental concerns, the IMO set up a goal of 50% reduction of GHG emission by 2050 (compared to the 2008 levels) (International Maritime Organisation, 2018) in order to reduce the footprint of ships significantly. As of 1 Jan 2019, ships greater than 5000 tonnes are required to have continuous monitoring on fuel consumption (International Maritime Organisation, 2018), this sets up an environment encourgaing a more holistic research with access to realtime information and fuel consumption, and with a legal requirement driving the push for improved emissions control.

The paper proposes to process telemetry data in a data-driven model to analyse the optimal speed, and weather effects to optimise fuel consumption. It also combines port-port vessel journey to predict the fuel consumption given the desired vessel speed, current, average draft, wind direction and wind strength.

1.2. *Literature review*

Fuel consumption of a ship is of interest as an important piece of information for several decision-making points on its operation profiles. It has a direct impact on the fuel cost, and emission goals.

The ship's power vs ship curve that is prepared during the delivery sea trials are usually the first point of reference, but these are usually based on a limited range of sea-states, thus this is not representative of the sea-faring scenario most of the time.

The prediction of fuel-speed functions can be classified in three ways (i) data-based (which includes statistical methods and machine learning techniques) (ii) naval architecture principles (iii) hybrid (of methods (i) and (ii)). In recent years, methods steer towards methods (i) and (iii), either as a full data-based or a combination of naval architecture principles and data-based methods. This is largely due to numerical or theoretical methods which have to be extensively complicated to replicate the results measured under operation conditions. The goal of this paper is also to use telemetry data present onboard a vessel to estimate its fuel consumption, thus the literature review is focussed on either data-based or a combination of data-based and naval architecture principle models.

Regardless of the methods used to derive fuel-speed curves, Adland et al. (2020), in particular, highlight that the assumption of constant fuel-speed consumption elasticity needs to be re-evaluated. Few researchers have focussed on that aspect with the exception of Wang and Meng (2012), who also reported that the coefficient of fuel-speed curves of container ships varies from 2.7 to 3.3. Tsitsilonis and Theotokatos (2018) also proposed a method to capture propeller curves under different operational profiles (which in principle recognises that a constant curve in either a fuel-speed or power-rpm curve is not representative of the actual operational conditions).

Tsitsilonis and Theotokatos (2018) proposed to use Kernel Density Estimates (KDE) to identify shaft power as a function of the density bins the data belongs to. Each shaft power data bin, together with the respective vessel speed (of the said data bin) forms an operational profile. The most frequently occurring profile is the highest peak demonstrated on the KDE plot. However the method, applied on cargo vessels, bulk carriers and VLCCs, only yielded differentiating power-speed curves for VLCCs which travel on ballast and laden journeys. The power-speed curves for container ships and bulk carriers only had 1 such curve after the analysis, which does not reflect true conditions.

Thus, the method proposed in this paper method aims to combine data categorisation from Bialystocki and Konovessis (2016), and simplification of the KDE method to group fuel-speed data groups and the addition of a Artificial Neural Network(ANN) to identify operating profiles not discerned in the methods described above. This paper attempts to shed light on the variances in the fuel-speed data and draw relationships between the variances in the ship resistance, by using an analytical and systematic method to come up with more accurate, updated fuel-speed curves according to the operational profile.

This article is divided into several parts. In Section 2, the statistical treatment of data is introduced. Section 3 discuss the theory and set-up of the ANN. Section 4 identifies how the parameters (average draft, current, wind strength and direction) relate to fuel consumption estimation. The results from several realistic case studies are presented in Section 5 including a discussion of validation of results. Section 6 discusses the application of the model. The conclusions of this study are presented in Section 7.

2. Methods and data

2.1. *Modelling of ship fuel consumption*

The data comes from the telemetry system on board a fleet of two sister vessels of 9000 TEU capacity. The main characteristics of the analysed ship are listed in the table below (Table 1):

Table 1.: Main characteristics of fleet of ship.

Type	**9000 TEU container ship**
Built	2013
Length LOA (m)	328.2
Width (m)	45.2
Moulded depth (m)	27.1
Summer Draft (m)	14.5
Deadweight (ton)	108,600
Shaft Power @ MCR (kw)	51,070

Fuel consumption of a vessel is linked to the resistance that a ship encounters. The main idea of methods outlined in the literature review is to relate resistance of a ship to its fuel consumption. Bialystocki and Konovessis (2016) highlighted three parameters in their statistical analysis of fuel consumption as : (i) increased draft and displacement (ii) worsening of weather conditions and (iii) worsening of hull and propeller roughness.

For this analysis, there is no access to hull condition thus the five factors that could relate to item (i) and (ii) and are accessible as telemetry data, are identified below:

- Average draft
- Current
- Wind direction and wind speed
- Vessel journey :High seas vs sheltered water

First and foremost, vessel speed has a major impact on fuel consumption, and this relationship is characterised by a power function, suggesting that at higher speeds, there is a non-linear (higher) increase in fuel consumption if other conditions remain constant.

Average draft is used as an indication of the intended cargo weight and arrangement in the cargo holds.

The sea-state can be used to classify the subsequent three parameters.

Current can act as an aid or impediment to a vessel depending on the direction of current and the vessel's travelling direction. If current is against the vessel, the vessel experiences greater resistance. Current is recorded as knots (kn) based on telemetry data on the difference between the water speed and vessel speed-over-ground.

The weather a ship faces during voyage has significant influence on her fuel consumption, in particular relating to prevailing wind and waves. Normally, a 10 - 15% weather margin (Watson, 1998) is taken into account in design calculations. Head wind requires more power for the ship to advance; therefore more fuel is consumed by the main engine. A tail wind, on the other hand, decreases the amount of fuel consumed. Depending on the cargo load, a beam wind, with the windex effect can also have significant influence on the fuel consumption. The forces of the wind are classified according to Beaufort scale, while the wind direction is based on relative angle range from 0 - 180 degrees, which are then filtered into 3 categories : Head (0 - 60 degrees), Beam (60-120 degrees), Tail wind (120-180 degrees). The method on classifying wind speed and direction is based on Bialystocki and Konovessis (2016)'s method.

Vessel leg is used to confine random effects to a journey leg, as the cargo load does not change during the journey from Port A to Port B, and also the local weather or journey conditions (such as close sea) can have a significant effect on the ANN modelling accuracy.

2.2. *Data treatment*

2.2.1. *Overall flow of data analysis*

The first part of data analytics involves the use of the appropriate data for the analysis. This refers to cleaning the data of erroneous values, for e.g. sensors cannot cover every operational profile and may register negative values which do not make sense in the physical world. Data is also categorised according to vessel journey as reported in (Tsitsilonis and Theotokatos, 2018). In a typical vessel journey, the cargo load is expected to remain the same in the leg of the journey, and the decision behind the vessel speed would be dependent on the schedule to meet at the upcoming port or the weather conditions. Segmenting the data in to vessel journey would reflect the clustering of data, roughly according to the decision-making time frame along a payload journey and, the local-regional weather condition.

The data entries corresponding to the engine steady state operation are identified.

(1) The engine power versus speed data set is split into individual data sets corresponding to each vessel voyage. One voyage is defined as the travel from the origin to the destination port (i.e. the one leg of a round voyage).
(2) The fuel consumption data (in tonnes/day) from each voyage is then expressed as a Kernel Density Function (KDF) in order to identify the most frequently occuring operational profile. Each peak is classified as an vessel operational profile.
(3) The specific kernel probability distributions of the fuel consumption bins (from 1 minima to the next minima) are extracted together with the corresponding parameters (vessel draft, sea-state conditions).
(4) Using the categorised engine power data, an ANN model is trained according to the current direction and strength, wind direction and strength, average draft of vessel and speed of vessel. The output of the model is the fuel consumption in tonnes/day.
(5) Upon a satisfactory learning of the ANN (based on error criteria and model validation on physical phenomena), simulation is carried out according the desired operational profile to predict the fuel consumed for the operational profile of interest.

2.3. *Kernel density estimation*

Kernel density estimation (KDE) is a non-parametric way to estimate the probability density of a random variable. The random variable of interest is the fuel consumption of the vessel in tonnes/day. A plot of the fuel probability density functions demonstrates that parametrised models (such a Gaussian distribution) would not accurately describe the multimodal fuel data. Kernel density estimates are closely related to histograms and can have properties such as smoothness or continuity by using a suitable kernel (see Figure 1). The benefit of using this method to describe the probability distribution is the ability to separate the data into bins which reflect different operation decisions or conditions of travel.

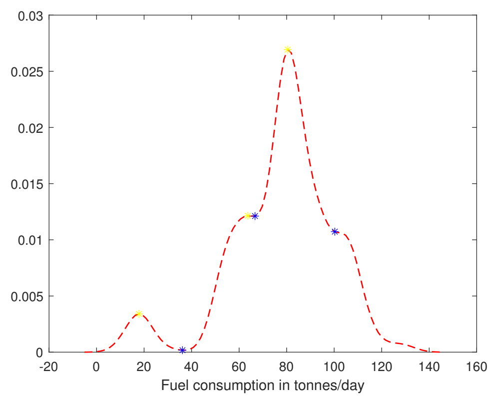

Fig. 1.: A kernel density estimate constructed using the data of fuel consumption in tones/day for a vessel journey, usually defined as a Port A to Port B journey.

Let $(x_1, x_2, \ldots, x_n)$ be independent fuel consumption samples, within a voyage V, drawn from a distribution with an unknown density f at any given point x. The shape of the function is estimated through a kernel density estimator (see Eq.(1)) and is described below:

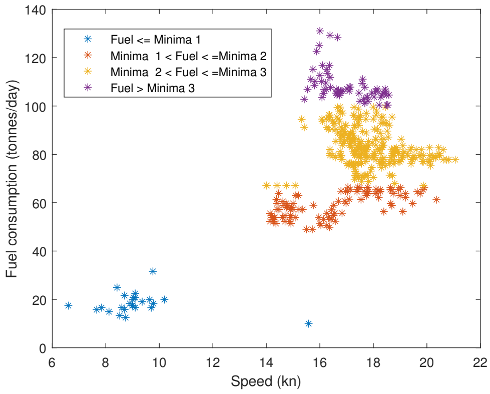

Fig. 2.: Fuel-speed plot as as clustered and colour coded according to the KDE of fuel consumption for vessel journey between two ports. The KDE with 2 maximas in Figure 1 shows the respective clustering of data in the middle of this figure (Fuel consumption vs Speed plot). The 2 clusters plotted geographically also could indicate different sea states that resulted in difference in fuel consumptions

$$\hat{f}_h(x) = \frac{1}{n}\sum_{i=1}^{n}(x - x_i) = \frac{1}{nh}\sum_{i=1}^{n}K\frac{(x - x_i)}{h} \tag{1}$$

where K is the kernel and h is a smoothing parameter called the bandwidth. K_h is is the scaled kernel and defined as $K_h(x) = 1/h \cdot K(x/h)$. Both K and h are non-negative functions. The selection of the bandwidth, h, has to be optimal in terms of the trade-off between over-smoothing the kernel density function, which does not yield extra information or having a distribution that is overly noisy with too many minima/maxima for the data to be conclusive. With reference to the optimisation of bandwidth, the Silvermans reference bandwidth is used. Tsitsilonis and Theotokatos (2018) also utilised the same bandwidth estimator for ship operation data. The Silvermans reference bandwidth can be described below:

$$h_I = 0.9[min(\frac{IQR(x)}{1.34}), \sigma)] \cdot n^{(-1/5)} \tag{2}$$

where IQR is the interquartile range of the random variable, fuel consumption, x and σ the standard deviation of the sample. This is a rule-of-thumb estimator where the underlying goal is to select a bandwidth that minimises the mean integrated squared error. Having determined a bandwidth and filtered the fuel consumption data into bins from the KDE, the most frequently occurring values corresponding to the local maxima is determined and sorted into operational profile I of the voyage:

$$k_x = argmax(\hat{f_{h_I}}(x)) \tag{3}$$

where k_x denotes the bin i.e. the operational profile it is filtered into.

3. Design of ANN model

In general, an ANN consists of three segments, an input layer, an output layer and a hidden layer (see Figure 3). In the input layer, each neuron receives inputs $a_{j=1}, a_{j=2}, ..., a_{j=n}$ attached with a weight a_j which indicates the connection strength for a particular input for each connection. Then it multiplies every input by the corresponding weight of the neuron connection. At the input layer, there is also a bias neuron, which can be described as a type of connection weight with a constant non-zero value added to the summation of inputs and corresponding weights. In between the input and output layer, is the hidden layer where a transfer/activation function creates the output. The activation functions can be stepwise to reflect binary outputs or sigmoid to produce a range of values. Generally there could be more than one hidden layer. The number of hidden layers and the number of neurons in each hidden layer need to be identified and are usually optimised by trial and error; the initial weights are randomised to start the training process. During the different trials, the data was divided into three different subsets: training, cross validation and testing. Cross validation set is used as a signal to stop the training and prevent over training. Determination coefficient (R^2) is used for measuring ANNs performance.

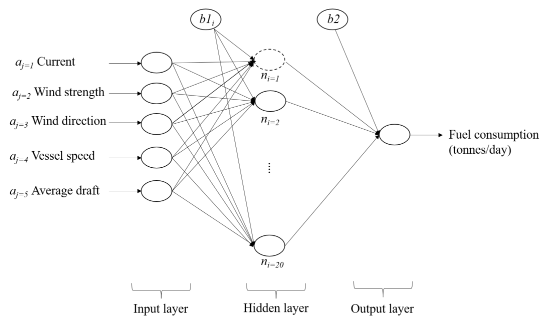

Fig. 3.: General structure of an ANN with five inputs and one output, and twenty hidden layers

4. Performance of the ANN Model

Fuel consumption of the ship is measured in tonnes/day and is the output of interest in the ANN model. The inputs to the ANN model are current(kn), wind strength (Beaufort scale), vessel speed (kn), wind direction (beam, head, tail wind). The inputs are refined according to literature review such as that of Bialystocki and Konovessis (2016). The following equations which demonstrate the mechanism of a neuron are described below:

The transfer function used is the hyperbolic tangent function (see Eq. 4) :

$$f(u_i) = tanh(u_i) = \frac{1 + e^{-u_i}}{1 - e^{-u_i}} \quad (4)$$

where u_i refers to the net inside activity level of the i-th neuron in the hidden layer and has its corresponding weights W_{ij} and biases $b1_j$ based on the inputs a_j which can be described below (see Eq. (5)).

$$u_i = \sum_{i=1}^{n=5} \sum_{j=1}^{n=20} W_{ij} a_j + b1_i \quad (5)$$

With respect to the five inputs, Eq. (5) can be written as:

$$\begin{aligned} u_i &= W_{i,1} \cdot current + W_{i,2} \cdot windstrength \\ &+ W_{i,3} \cdot vesselspeed \\ &+ W_{i,4} \cdot winddirection \\ &+ W_{i,5} \cdot avg.draft + b1_i \end{aligned} \quad (6)$$

The output from the hidden layer is then used as inputs to the output layer. Each hidden layer node n_i has its own weights (identified as $lw_2 i$), This is passed through the transfer function as expanded in the equation below

$$f(k) = tanh(k) = \frac{1 + e^{-k}}{1 - e^{-k}} \quad (7)$$

where k_i refers to the net output activity level of the i-th neuron in the hidden layer and has its corresponding weights lw_{2i} and biases b_2.

$$\begin{aligned} k &= \sum_{i=1}^{n=20} f(u_i) \cdot lw_i + b2 \\ &= \sum_{i=1}^{n=20} \frac{1 + e^{-u_i}}{1 - e^{-u_i}} \cdot lw_i + b2 \end{aligned} \quad (8)$$

where n refers to the number of hidden layers (20, in the case of this paper).

The model yielded an overall R^2 value of 0.8800 (see Figure 4). The training set (70% of the data) obtained a R^2 value of 0.9048, while the validation and testing set (15% of the data respectively) had a value 0.8501 and 0.8411 respectively.

The weights and biases in the ANN are summarised below (see Table 6):

5. Validation and benchmarking

The model is validated through two ways, one, by looking at the goodness-of-fit for the model and two, by simulating the results and comparing with the behaviour according to the situations which may affect the overall ship resistance and hence the derived propeller curve. Literature review suggest that many researchers utilising ANN validate models in terms of the R^2 values or other error indices such as RMSE (Abdel Naby et al., 2008; Leifsson et al., 2008; Adland et al., 2020). The goodness of fit (R^2) values are deemed to be of satisfactory value. Similar applications of ANN to different ship operations demonstrate that 'acceptable' R^2 values are 0.744 to 0.834 for fuel prediction for oil tankers (Bal Beikçi et al., 2016). In addition to using R^2 values as a benchmark between the original data and predicted values, the results corresponding to the physical phenomenon can also be used to assess the performance of the model.

The simulated data (see Figure 5 and 6) demonstrates that the ANN model can derive results according to the steepest propeller curve (Profile 1) and the most gentle propeller curve (Profile 2) in accordance to the different operating conditions stemming from the sea-state and thus the overall resistance to the vessel. In Figure 5, Leg 1: Profile 1 refers the sea state conditions that suggests the highest resistance the ship might face, such as high current against the vessel, head wind of strength, Beaufort scale 7 (which is considered as high wind, near gale strength) and at an average draft of 14 m. The histograms (see Figure 7) show that the current, wind strength and associated draft from cargo load experienced is in the upper end of the distribution of sea state conditions of the vessel experience. Leg 1: Profile 2, which reflects a much gentler propeller curve indicates that the resistance a ship is experiencing is much lesser. Current is significantly lesser at almost zero. While the ship experiences headwind, it is a Beaufort strength 5, it is 2 states lower and is considered a 'fresh breeze' as compared to Leg 1: Profile 1. In addition, the average draft is at 13 m, implying lesser cargo load. Leg 1: Profile 3 has conditions in between that of Leg 1: Profile 1 and 2. The current against the vessel is lesser at -0.8 kn, and the average draft is of a lower value than Leg 1: Profile 1. Wind conditions remain at headwind and at Beaufort strength 7, similar to Leg 1: Profile 1. Overall Leg 1: Profile 1 reflects a scenario where the sea-state conditions suggest that the ship would experience high resistance, and Leg 1: Profile 2 reflects a scenario where the sea-state conditions is more conducive for a lower ship resistance. Leg 1: Profile 3 refers to a sce-

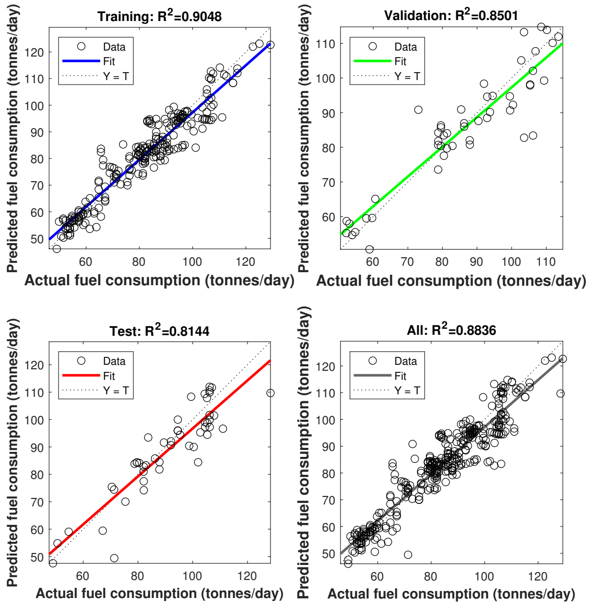

Fig. 4.: Plot of the actual and predicted fuel consumption in Leg 1 withing a channel using the ANN model, broken down into training, validation, test and overall results.

Table 2.: Weights and biases in the ANN. See Eqs (6) & (8)

n	W_{i1}	W_{i2}	W_{i3}	W_{i4}	W_{i5}	l_w	$b1$	$b2$
1	0.3182	-0.1767	-0.9280	3.959	0.6833	0.156	-3.603	0.0448
2	1.0129	0.8684	-1.7210	3.3834	-2.0642	-0.3224	5.0481	
3	-0.7675	1.5010	1.0198	0.6436	-1.8524	0.6949	-0.5875	
4	-4.6135	-1.7680	-4.3690	-1.5216	3.1281	0.2176	3.0596	
5	-1.0453	-3.0860	-2.4904	-1.5757	3.5233	-0.1618	3.2163	
6	-0.5871	-0.3435	-5.6738	3.3350	1.0151	-0.1683	3.0262	
7	-0.0034	-0.7860	2.6684	-0.8905	1.1342	0.2061	2.9490	
8	-2.2038	-0.6202	0.4561	2.6423	-0.2203	-1.2714	-1.1539	
9	0.3652	1.2574	-2.5649	-1.0541	0.9890	-0.1365	-1.6418	
10	-3.3971	0.3049	0.7089	-1.1972	0.2492	-0.1810	0.2392	
11	-0.7620	-2.8466	-0.5012	0.5669	0.3166	0.3740	-1.9342	
12	-3.8127	-1.4858	-1.1629	1.3434	0.9851	0.1149	0.5971	
13	-1.7807	-0.2802	0.4893	1.7727	0.0218	1.7326	-0.7216	
14	1.6415	-0.8688	-4.6067	-1.0624	-2.6141	0.2545	2.1147	
15	2.6458	-2.2624	0.3082	-2.4584	-2.9388	-0.1428	4.3786	
16	2.0198	0.1407	-0.3368	1.1250	4.7158	0.4616	2.8408	
17	3.6052	1.2295	-0.2614	0.8858	-1.8925	-0.0457	2.6464	
18	-1.8330	-2.8262	1.6702	-1.9683	1.6982	-0.2329	-3.6153	
19	0.9197	-4.9122	-3.5518	0.2605	3.3848	0.2245	1.7562	
20	0.2493	2.6183	0.4218	-2.2200	-4.5869	0.1746	-1.9334	

nario in between them. A similar plot to Figure 5 except with fuel-speed power curves plotted from the simulated results demonstrate that the power coefficients are in the range of 2.21 to 3.13, which agree with literature review of container ships by Wang et al. (2019) and Adland et al. (2020).

It can be observed that the first ANN presented reflects the environment within rather closed waters as there is another island that simulates travelling within a channel.

6. Design of decision support system for improving ship energy efficiency

It is generally understood that most research on optimising vessel operations attempt to predict or have snapshots, as accurately as possible, the ship resistance. The summary of the proposed method in this paper is attempting to provide snapshots of the ship resistance under different sea-state conditions. One novelty of this paper is the derivation of propeller curves (fuel - speed curves in Figure

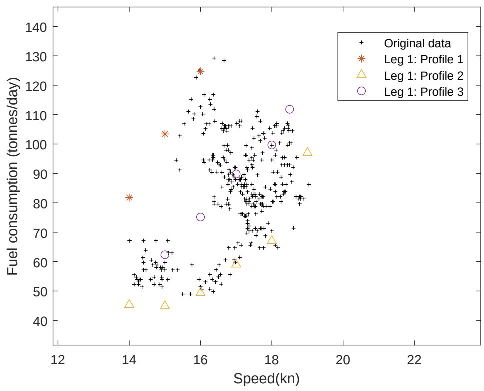

Fig. 5.: A plot of the original data demarcated in black and 3 fuel-speed curves simulated from 3 differing profile. Profile 1 suggests sea-state conditions which will results in higher ship resistance, while Profile 2 suggest sea-state conditions resulting in lower ship resistance. Profile 3 suggests sea state conditions that are in between that of Profile 1 and 2.

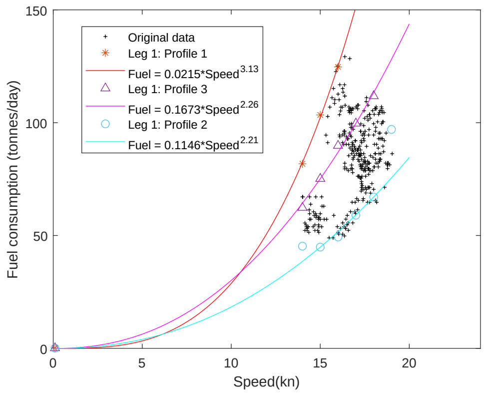

Fig. 6.: A similar plot to Figure 5 except with fuel-speed power curves plotted from the simulated results. The power coefficients are in the range of 2.21 to 3.13, which agree with literature review of container ships by Wang et al. (2019) and Adland et al. (2020).

6) through actual data. These propeller curves are superior to design propeller curves as there are elements captured that the design propeller curves do not.

6.1. *Impact on optimal speed*

Adland et al. (2020) investigated and demonstrated that the elasticity of fuel consumption of oil tankers varies across speeds and sea-states. The article suggests that the 'cubic law' is only true near the design speed of vessels and conditions set out in the speed trial analysis. In the same way that engine load diagrams have different curves (for e.g. one may refer to Figure 3.10 of the report by MAN Energy Solutions (2018)) for recommended operations or heavy operations, the derived fuel-speed curves from the telemetry data indicated that within a vessel leg where the cargo remains constant, the different sea-state affect the fuel consumption of the vessel.

For a given voyage, the fuel consumption is not just affected by the speed of the vessel. Figure 5 shows that while travelling at 17 kn, the vessel may consume between 85 tonnes/day to 115 tonnes/day due to the sea-state that affects the overall ship resistance. If considering the impact of slows-teaming on CO_2 emissions simply based on design propeller curves, there could be an over-estimation in the reduction of CO_2 emissions.

7. Conclusion

In this paper, a systematic methodology for deriving vessel and journey specific fuel-speed curve from ship telemetry data has been carried out. Kernel densities estimation is used to categorise operational profiles, and then an ANN is used to derive the relationship between fuel consumed and vessel speed, vessel average draft and sea-state conditions. The method demonstrated that it was able to deduce fuel-speed curves in close-sea conditions such as within a channel. The fuel-speed curves varied according the sea-state thus highlighting that the different working loads experienced by the vessel can be captured by the model. In addition, the model is validated by comparable R^2 values with other statistical/machine learning methods, as well as by analysis of the physical phenomena (i.e. based on domain knowledge) of the conditions that affect the ship resistance. In summary, the method allowed a more accurate prediction of fuel consumption, and a vessel specific understanding of what is considered optimal speed. It is thus inferred that the method on analysing telemetry data demonstrates consistent results, and benefiting the industry with improved maritime practices or streamlined vessel operation. This encourages better data collection practices in the industry which will become a valuable big data push for the maritime industry.

References

Abdel Naby, M. M., H. W. Leheta, A. A. Banawan, and A. H. Elhewy (2008). Investigation of various artificial neural networks techniques for the prediction of inland water units' resistance. *Ships and Offshore Structures 3*(3), 247–254.

Adland, R., P. Cariou, and F. C. Wolff (2020). Optimal ship speed and the cubic law revisited: Empirical evidence from an oil tanker fleet.

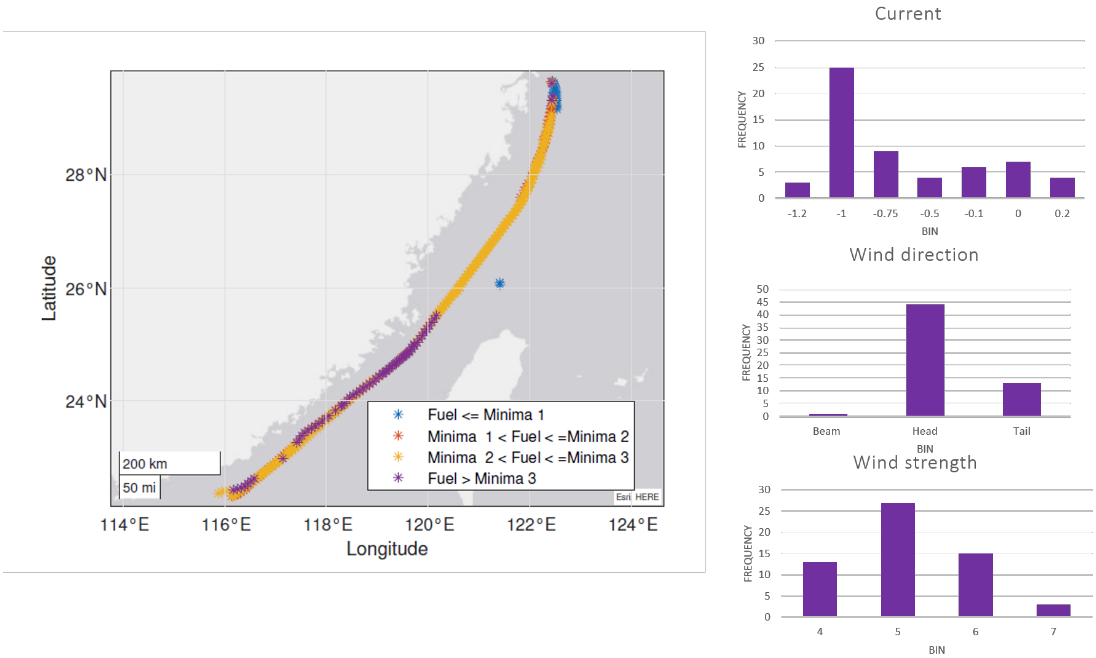

Fig. 7.: A geographical plot of the original data. The histograms in the right of the figure refer to the sea-state conditions of the journey demarcated in purple within a channel. The purple plots in the geographical plot indicate where the fuel consumption is the highest. The minimas refer to the KDE probability density plot in Figure 1.

Transportation Research Part E: Logistics and Transportation Review 140(May), 101972.

Bal Beikçi, E., O. Arslan, O. Turan, and A. I. Ölçer (2016). An artificial neural network based decision support system for energy efficient ship operations. *Computers and Operations Research 66*(January 2013), 393–401.

Bialystocki, N. and D. Konovessis (2016). On the estimation of ship's fuel consumption and speed curve: A statistical approach. *Journal of Ocean Engineering and Science 1*(2), 157–166.

International Maritime Organisation (2018). Reducing greenhouse gas emissions from ships.

Leifsson, L., S. Hildur, S. Sigurasson, and A. Vesteinsson (2008). Simulation Modelling Practice and Theory Grey-box modeling of an ocean vessel for operational optimization. *16*, 923–932.

MAN Energy Solutions (2018). Basic principles of ship propulsion - Future in the making. Technical report.

Ronen, D. (2011, jan). The effect of oil price on containership speed and fleet size. *Journal of the Operational Research Society 62*(1), 211–216.

Stopford, M. (2010). *Maritime economics* (3rd ed.), Volume 47. New York: Taylor and Francis.

Tsitsilonis, K. M. and G. Theotokatos (2018). A novel systematic methodology for ship propulsion engines energy management. *Journal of Cleaner Production 204*(August), 212–236.

Wang, S., S. Gao, T. Tan, and W. Yang (2019). Bunker fuel cost and freight revenue optimization for a single liner shipping service. *Computers and Operations Research 111*, 67–83.

Wang, S. and Q. Meng (2012). Sailing speed optimization for container ships in a liner shipping network. *Transportation Research Part E: Logistics and Transportation Review 48*(3), 701–714.

Watson, D. G. M. (1998). *Practical Ship Design, Volume 1*, Volume 1.

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