

Estimating fuel consumption in maritime transport

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ABSTRACT

Growth in technology has accelerated in the last few decades, and therefore demand for energy has dramatically increased. This has also brought about a major problem called global warming. The scarcity of resources, indeed, have been compelling us to sustain energy with the adoption of cleaner energy practices and alternative ways that can help us reduce energy consumption and carbon dioxide emissions. With the pressure due to increasing global environmental consciousness, the international shipping industry has thus been exposed to some challenges and energy-related problems it needs to wisely deal with. To reduce fuel consumption and greenhouse gases, ship owners and operators need to find an efficient fuel economy with the control and alteration of some related factors. In this study, several determinants of fuel consumption in maritime transport were considered and alternative models were built employing the Response Surface Methodology using data obtained from the noon reports of a bulk carrier. Since the model building process is relatively tedious in the Response Surface Methodology, a guideline was also provided. The results indicate that as their speed increases up to a certain point, ships consume less fuel; however, after such a threshold, fuel consumption begins to increase. In addition, even though its main effect was found insignificant, revolution per minute's interaction with other inputs was found to affect the output. Thus, adopting the Response Surface Methodology, which allows for quadratic terms and higher order interactions, is critical to build a predictive model that performs well so that ship operators and shipping companies can make economic and environment-friendly decisions better. This study serves the literature by estimating the fuel consumptions of cargo ships using statistical models so that carbon dioxide emissions from fuel consumption can be estimated. Even though specific types of fuel and ships were considered, the approach adopted here can be extended and applied to other cases as long as there is accurate data.

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1. Introduction

In today's highly globalized world, governments and various associations need to introduce new regulations related to carbon dioxide (CO₂) emissions that derive from maritime transport. Ships generally use fossil fuels that is derived from crude oil, a non-renewable natural resource, and the behavior of its cost over time is not always stable as it often steadily increases. To save money and overcome the drawbacks associated with its price and overuse, research has focused on the prediction of fuel consumption. Burning fossil fuels has a prominently negative effect on the

environment. They cause air pollution and damage the ecosystem polluting a variety of natural resources. Fortunately, due to increasing social consciousness propelled by the means of our digitized world, some governments and nations have been working together to avoid the negative impacts of fossil fuels, conducting projects related to global warming, climate change and sustainable energy. Fuel consumption in maritime transport has thus become a vital research topic due to its potential to incite environmental issues.

According to a report by the International Energy Agency (IEA), approximately 80% of total energy demand in the world was met by fossil fuels in 2018 (IEA, 2019). However, combustion of these fuels for energy generation have several consequences in means of environmental impacts such as climate change due to air-borne emissions (Vidadili et al., 2017) even though energy produced by

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utilizing them is relatively high and very cost-effective.

The environmental problem caused by shipping emissions is well investigated especially in the last two decades and these emissions were judged to cause damaging effects both on human health and the environment (Cullinane and Bergqvist, 2014; Dulebenets, 2016; Psaraftis and Kontovas, 2013; Wang et al., 2019).

The International Maritime Organization (IMO) stands in a central position for regulating air pollution caused by ships, regularly publishes regulations and reports focusing on emission estimations, emission abatement technologies and emission restrictions. The International Convention for the Prevention of Pollution from Ships (MARPOL) is the primary international treaty that is concerned with pollution caused by ships. Particularly, MARPOL Annex VI (Prevention of Air Pollution from Ships) focused on limiting the emissions from ship exhausts.

Based on a report published in 2014 by the IMO, ships released 1016 million tons of CO₂, on average, between 2007 and 2012, which accounts for approximately 3.1% of worldwide CO₂ emissions. With the tripling of world trade, if no action is executed, it is anticipated that emissions from shipping will have increased by 50–250 percent by 2050. In addition, the increase in average ship sizes has been the leading propellant of this change (Asariotis et al., 2010). Accordingly, energy demand for ships and emissions incurred may cause problems that are more serious in the near future. Thus, realistic estimations of fuel consumption, which varies depending on the dynamic conditions, using various operational models, can guide ship owners to take some measures such as applying route optimization or implementing other alternative energy saving methods.

In this study, we aim to construct a statistical model for fuel consumption rate in maritime transport considering several factors that are illustrated in Fig. 1. Utilizing noon reports, the main and interaction effects of these factors were measured employing the Response Surface Methodology (RSM). A noon report is a data sheet prepared by the ship's chief engineer on a daily or activity-basis. It provides information on weather conditions, machinery, fuel consumption, fuel level, and so on. We constructed alternative models for the fuel consumption rate and chose the best one considering several theoretical and practical issues. Estimating a ship's fuel consumption rate accurately in intended conditions can assist one in easily answering some specific questions. For instance, the average fuel consumption rate can be estimated given a specific cargo quantity. Fuel economy and emissions incurred by maritime transport are issues that IMO is working on continuously and comprehensively. As of January 1, 2020, the maximum rate of mass sulfur in fuel content is reduced from 3.5% to 0.5%. Therefore, the prediction of fuel consumption has become extremely important in terms of controlling ship emissions.

Speed can affect fuel consumption both directly and indirectly (Prpić-Oršić and Faltinsen, 2012; Leloup et al., 2016; Lindstad et al., 2015; Cariou, 2011; Gusti and Semin, 2016). The effects of revolution per minute (RPM), draught and cargo load, and the direction of sea waves were well investigated by Arapatsakos et al. (2011), Schembari et al. (2012), and Thomson et al. (2015), respectively.

As the most authoritative institution operating internationally in the reduction and control of emissions from ships, the IMO updates regulations on emissions systematically. Within the framework of the latest regulation, went into effect on January 1, 2020, the amount of sulfur contained in ship fuels must be decreased to reduce emissions. Despite these efforts, the climb in the number and size of ships due to increasing global trade necessitates models for the prediction of emission and fuel consumption. Thus, it is essential to determine what measures should be taken by predicting fuel consumption in particular routes.

This study aims to contribute to this growing area of research

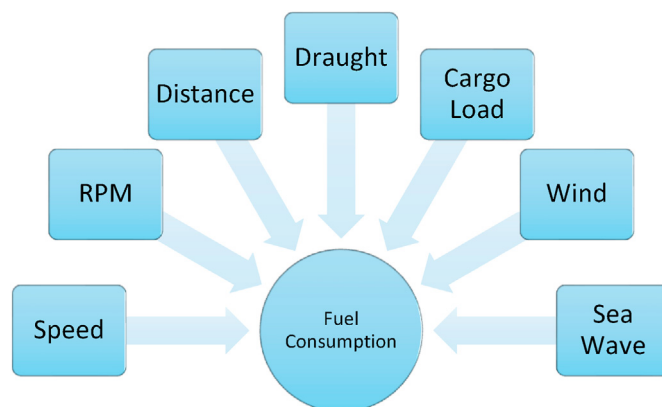


Fig. 1. An Illustration of Factors that can Affect Fuel Consumption.

exploring the effect of factors mentioned above when constructing an effective fuel consumption model. Evaluating the effect of each factor and comparing their effects, a ship's fuel consumption rate can be reduced at the outset. The study proceeds as follows. Section 2 provides a brief review of the related literature, followed by a detailed explanation of the methodology adopted and data and variables collected. Section 4 discloses the experimental results followed by a discussion and possible avenues for future research.

2. Literature review

Some research in the related literature focused only on the sailing speed of ships since it is believed to be the core cause of fuel consumption rate. An increase in the speed of a ship may cause an important increase in fuel consumption. To uncover the quantitative relation between speed and fuel consumption rate and to find a way to optimize the speed, along with some important marine companies, researchers delved into much deeper. MAN Diesel and Turbo (2011) made important definitions for the optimization of the speed. They considered numerous factors such as frictional, hull, air, and some residual resistances, which were believed to affect the speed. Besides, they used efficiency ratios such as hull, propeller, shaft efficiencies along with some forces to uncover the quantitative relation between ship's power and speed. They suggested that the exponent of the speed could be chosen as 3.5 ($x^{3.5}$, x :sailing speed) for feeder container ships and as 4 (x^4 , x :speed) for larger container ships. According to the same study, if one doubled the speed, fuel consumption would increase 16 times for large container ships that were used in shipment of large amounts of containers. Wang and Meng (2012) also empirically showed that this exponent should be between 2.7 and 3.3 when the ship's speed was less than 20 knots.

Furthermore, Kontovas and Psaraftis (2011) emphasized that emissions from commercial shipping were currently a subject of intense investigation. They added that among the most fuel-consuming ship categories, container vessels polluted air the most. The authors also stated that speed reduction techniques had become very popular as an operational measure to reduce fuel consumption rate and actually, these techniques could be used to decrease greenhouse emissions (GHGs) and other types of pollutants incurred by ships. They proposed some ways such as lowering the speed while reducing the hoteling time. Hence, there would be no need for high speed in maritime transport. While implementing these techniques, an exponent of four or greater was shown to provide a better performance when the sailing speed of vessels was greater than 20 knots. Using data on 2259 container ships,

Notteboom and Carriou (2009) also reported that this exponent was around 3.3 among these vessels.

Although speed optimization is an important aspect in maritime transport, reducing the speed is not sufficient for optimization. In fact, higher speed generally means a shorter transit or travel time and fewer ships require to maintain a fixed service frequency. Therefore, some researchers suggested the use of shipping network analysis to reduce fuel consumption and the emissions related to it. Shipping network analysis mainly consists of network design, service frequency determination, fleet deployment, schedule design, container assignment, and routing and booking of cargos. Agarwal and Ergun (2008) constructed a network design to perform shipment activities as efficiently as possible. They presented an integrated mixed integer linear program for solving ship scheduling and cargo routing problems. They considered 20 ports and 100 ships using real-life simulation. Furthermore, Meng and Wang (2011) focused on service frequency determination for a long-haul liner service route. The network problem was formulated as a mixed integer nonlinear program and solved using the branch-and-bound technique, which gives a close approximation to the optimum solution after a limited number of iterations. Alvarez (2009) made some suggestions related to ship fleet deployment. For cost efficiency, Qi and Song (2012) proposed an efficient schedule design. Bell et al. (2011) exhibited some solutions regarding the container assignment problem. In addition, Song and Dong (2012) employed several techniques to find effective solutions for cargo, booking, and routing activities. Notteboom and Vernimmen (2009) and Ronen (2011) proposed cost models to determine the relation among fuel price, sailing speed, service frequency and the number of ships on the shipping route. Using discretized arrival times within a shortest path problem framework, Fagerholt et al. (2010) asserted that extensive computational results from the solutions confirmed the superiority of the shortest path approach and these computations would construct the potential for fuel savings on shipping routes.

All of these studies were particularly successful at the optimization of speed and shipping network; however, they fell in short considering environmental effects of ships' fuel consumption. Although some authors noted the influence of severe environmental conditions, they were not able to construct a quantitative relation between them and fuel consumption. As a result, some studies dealt with the environmental routing problem, and more specifically the weather routing problem. Such problems may not answer to our needs since environmental conditions are changing continuously and therefore uncertainty is unavoidable. Emphasizing the importance of considering the effect of weather conditions on fuel consumption rate, Lin et al. (2013) employed the three-dimensional modified isochrones method; however, they assumed that the revolution speed of propeller along the route was constant. Therefore, speed would have no effect on fuel consumption.

Although weather conditions and speed have important effects on fuel consumption, there are some other factors such as cargo load, trim, and mean draught that must be considered as well. Numerous studies in different disciplines have attempted to predict fuel consumption using various models while considering such factors rather than only weather conditions and speed. Beşikçi et al. (2016) provided an artificial neural network (ANN) based decision support system (DSS) for the prediction of fuel consumption. Considering many factors such as speed, RPM, draught, trim, weather and sea conditions, they constructed an ANN using statistical methods such as multiple regression and experimental design. They estimated a regression model for fuel consumption and validated it on a different sample of ships. Finally, they suggested creating a DSS that could help ship operators or ship owners

to be proactive regarding fuel consumption levels so that the efficiency of energy consumption could be improved. Although the authors made a thorough review of factors that were believed to have an effect on fuel consumption, they did not provide a sufficient explanation for how each factor would affect fuel consumption. The authors developed a neural network model to estimate fuel consumption using various variables and validated it with an application. The weight of each factor affecting fuel consumption was named as a hidden layer, and the weights were unknown at the beginning. Thus, the result of changing a parameter in the equation was not certain. However, the regression model on fuel consumption was predicted using an inexact approach. Besides, the complexity of such a DSS can limit the involvement of ship operators, ship personnel, or workers in improving fuel efficiency. Furthermore, Jalkanen et al. (2012) developed an emission estimation model called Ship Traffic Emission Assessment Model (STEAM), which was based on data obtained via Automatic Identification System (AIS). STEAM could estimate shipping emissions accurately using abatement technologies, engine load, ship speed, fuel sulfur content and wave effect as inputs. Bilgili and Celebi (2018) developed some formulae based on deadweight ton (DWT) and block coefficient (C_B) values for emission estimation. Yan et al. (2020) developed a model to predict fuel consumption and reduction with the aid of random forest regression. Speed, total cargo weight, sea and weather conditions were used as inputs. The authors compared five regression models and found out that random forest clearly provided the best results. A ship optimization model was then developed based on random forest regression using data on two voyages. The mean absolute percentage error (MAPE) was obtained as 7.91%. Choosing the best route, the model could reduce fuel consumption by 2–7%. Similarly, Bui-Duy and Vu-Thi-Minh (2020) developed a fuel consumption model for route optimization based on deep learning that utilized average velocity, sailing time, ship's capacity, wind speed, and wind direction as inputs. The authors indicated that the MAPE of the model was around 5.89%. Uyanik et al. (2020) tried to estimate the fuel consumption of a container ship adopting machine learning and concluded that RPM, main engine cylinder values, scavenge air and shaft indicators had significant effects on fuel consumption. Wang et al. (2019) developed fuel consumption prediction method based on least absolute shrinkage and selection operator (LASSO) regression using a dataset that contains numerous ship characteristics. The results indicated that speed was highly correlated with fuel consumption. Gkerekos et al. (2019) compared several methods that considered various ship characteristics obtained from noon reports and found that extra trees regressors and random forest regressors performed better. Utilizing data obtained from 418 noon reports, Bialystocki and Konovessis (2016) asserted that harsh weather and sea conditions increased fuel consumption for car and truck carriers. Yuan and Nian (2018) developed a Gaussian process metamodel and concluded that each of the seven factors they considered, including both operational and weather conditions, had a significant effect on fuel consumption. Furthermore, Meng et al. (2016) emphasized the importance of fuel efficiency and fuel efficiency management programs since the cost of fuel oil incurs the highest cost that companies have to face nowadays. Using empirical data covering a period of six months, they desired to demonstrate the influence of weather conditions and the displacement of water. They constructed a regression model aiming to obtain an optimum level of ship fuel efficiency. They also analyzed their results using score-based evaluation for outliers to reach better solutions.

In summary, a thorough review on the related literature reveals a gap between academic research and comprehensive statistical fuel consumption modeling. Primarily, all of the methods

mentioned above require a great deal of time and effort to implement. Besides, the lack of statistical approaches is obvious and cannot be overlooked. When studying fuel consumption, various parameters such as wind power, cargo load, and speed should definitely be considered. Research so far has aimed to find the effects of all possible factors when fabricating fuel consumption models; however, the literature still lacks a single model that explains how the combinations of these factors affect fuel consumption. Moreover, conducting this kind of research is costly since it requires many parameters and different modeling approaches. Since statistical experimentation targets to describe or clarify the variation of information under pre-determined conditions, its use in maritime transport can be highly beneficial.

3. Methodology

Due to limited space and the fact that the RSM is a well-developed approach in statistical experimentation that has been applied in a wide range of areas, its description further provided in the supplementary material. In this section, we rather explain the data and variables obtained from noon reports, followed by the procedure for finding the best predictive response surface model given this data.

3.1. Data and variables

Data used in this study was extracted from the noon reports of a bulk carrier with a length of 190 m and a beam of 35 m. The DWT of the ship is 55,000 tons. A noon report is a data sheet prepared by the ship's chief engineer on a daily basis. Such a report is used to assess the performance of a ship and its tracing activities and contains information on ship and port name, report type, date and time of the report, the distance taken by the ship, RPM value, speed, the remaining amount of fuel in the ship's tanks, weight of cargo, weather and sea conditions, the angle of sea wave, draught forward and aft, ballast/laden condition.

In noon reports, draught forward and draught aft correspond to the distance between bottom of the ship and the sea level for both aft and forward of the ship. For draught level, there are three possible situations:

- Trimmed Aft: If draught aft is bigger than draught forward, the ship will be inclined backward.
- Normal: If draught aft for the ship is equal to draught forward, the ship will remain straight on the sea.
- Trimmed Forward: If draught aft is lower than draught forward, the ship will be inclined forward.

A ship in the sea can be either in the ballast condition or in the laden condition:

- Ballast: When the ship has no cargo, it takes on some extra weight to increase draught since it is unsafe to travel given low draught.
- Laden: A ship will be in the laden position if it has cargo.

In noon reports, the direction of wind and sea waves relative to the ship are also provided. When the direction of wind is north, it is blowing into the front of the ship; when it is west, it is blowing straight over the portside of the ship.

A summary of data considered for modeling is given in [Tables 1 and 2](#). Note that since weather and sea conditions are not controllable factors, details on them are not provided. There are no missing cases in the data. We only considered the consumption of high sulfur intermediate fuel oil (HSIFO) since it is the most

commonly used type of fuel by such vessels and information on other types of fuel such as marine gas oil (MGO), marine diesel oil (MDO), and low sulfur intermediate fuel oil (LSIFO) was insufficient. Speed is measured in knots, draught forward and draught aft measures are given in meters, and cargo load is given in tons.

For design purposes, we also binned each continuous input factor and named them by adding the suffix “_CAT” to the corresponding variable name. The leveled data are provided in [Table 3](#).

3.2. Model building and selection

The steps followed to find the most suitable response surface model can be summarized as follows:

Data extraction and pre-processing: Data is retrieved from noon reports and examined to detect missing values. If there are no missing values, data is apportioned into training and validation sets, with a 70%–30% random split. Next, the response and the continuous inputs in both of these sets are examined to detect unusual observations, and the discrete inputs are examined whether there are very uneven splits in their categories. Using normal probability plots, the quantitative factors are transformed to avoid such observations hindering model interpretation.

Model estimation and refinement: Once it becomes suitable for model estimation, alternative models can be fitted to the training data. It is advised to build the first alternative with no constraints and the second one considering main-effect and interaction-effect plots. If a model returns insignificant parameters, extremely high variance inflation factors (VIFs), and/or unusual patterns in the residuals, it needs to be refined. In this case, transforming the output is the first thing to consider. When violation to normality and homoscedasticity assumptions in the residuals is resolved, but VIFs highlight multicollinearity as an issue and there are also insignificant parameters, stepwise regression should be employed. It is up to the practitioner to adopt the hierarchy principle, which suggests the incorporation of insignificant main effects into the model when their interaction is significant. VIF of a controllable variable shows how much the coefficient estimate for that variable is inflated when it is correlated with other controllable variables in the analysis. VIFs greater than 10 indicates that the model is clearly suffering from multicollinearity. The variance inflation factor for input X_i is given by the formula

$$VIF_i = \frac{1}{1 - R_i^2} \quad (\text{Eq. 1})$$

where R_i^2 is the coefficient of determination obtained by regressing X_i on the remaining inputs.

Model evaluation: The performance and predictive ability of a model is decided using adjusted R^2 and R^2 -predicted in the training and validation data sets, but residuals in the validation set should also be examined carefully.

4. RESULTS and DISCUSSION

The data was first split into a training set consisting of 134 observations and a validation set consisting of 59 observations. As seen in [Fig. 2](#), the original response and the quantitative inputs in the training set do not seem to be normally distributed and each of them contains at least one potential outlier. Since the violation to normality assumption for the quantitative factor TOTFUEL is not severe, it was not transformed; however, the negatively skewed SPEED was transformed by the formula $\ln(\max(\text{SPEED} + 1) - \text{SPEED})$. RPM and RESPONSE were not transformed at this stage, but the outliers they contained were removed. CARGO_CAT was

Table 1
Summary of categorical inputs.

			BALLAST		
			Shows the direction and angle of the sea waves.		
			YES	NO	TOTAL
DRAUGHT	Indicates if the ship is inclined forward or backward, or if it remains straight.	AFT	34	147	181
		STRAIGHT	0	12	12
		TOTAL	34	159	193

Table 2
Descriptive statistics for the response and the input factors.

Variables	Mean	Standard Deviation	Median	Description
RESPONSE	0.107	0.0256	0.1045	Consumption of HSIFO per mile
RPM	114	6.01	115	Number of the rotations of a machine in 1 min
SPEED	12.86	1.28	13.1	Speed of the ship in terms of nautical mile or knots when it goes along its direction
TOTFUEL	937.5	375.6	911.5	The sum of all types of fuel in the ship such as marine gas oil, marine diesel oil, high sulfur fuel oil, low sulfur fuel oil
CARGO	33767	18610	42000	Weight of the load the ship is carrying (in tons)

Table 3
Levels of the categorized inputs.

Input Factor	Low Level	Medium Level	High Level
RPM_CAT	88–99	100–111	112–122
SPEED_CAT	2.7–6.8	6.9–11.1	11.2–15.4
CARGO_CAT	0–20,000	20,001–40,000	40,001 and more
DRAUGHT_CAT	Inclined Backward	Normal	Inclined Forward
TOTFUEL_CAT	230–780	781–1330	1331–1840

preferred over CARGO to include in the models, but RPM was not categorized since, unlike the case with CARGO, the values it takes on do not form clearly distinguished groups as seen in Fig. 3.

Next, we examined the main effects and interaction effects provided in Figs. 4 and 5 to decide which factors should be included in the models. Fig. 4 shows how the mean of HSIFO consumption per mile changes with different levels of the inputs and suggests that the effect of RPM, SPEED_LN and TOTFUEL is quadratic rather than linear. Mean fuel consumption per mile (RESPONSE) decreases up to a certain point in each of these inputs and then starts increasing. It seems that categorizing CARGO is favorable and DRAFT_BALLAST should also be considered. According to Fig. 5, the interactions between RPM and other inputs except TOTFUEL are significant. The interaction between SPEED_LN and DRAFT_BALLAST also appears to be significant. Note that the more parallel the lines in each of these subplots, the less the effect of the interaction between those inputs on RESPONSE.

Since the quantitative inputs are not linearly related with RESPONSE, we only considered their quadratic effects along with the main effects of the qualitative inputs. Note that higher order interactions were also ignored to keep the model as practically useful as possible. At this point, running a stepwise regression, which simply adds and removes variables based on a pre-determined threshold of Type I error (α), is suggested; however, when the output requires transformation, most statistical packages do not allow using the stepwise option and finding the optimal parameter for transformation at the same time. In general, α is automatically set at 0.15; however, this could be changed based on experience or some rationale. For more on this matter, please refer to Draper and Smith 1998, (p.342).

Table 4 provides the RSM estimation results for the transformed output, which is the 1.6^{th} power of the original response. This exponent was estimated using Box-Cox transformation in Minitab.

Note that the initial model containing the inputs given in Table 4 produced a couple of standardized residuals that are greater than 3.00 in absolute value. This model was revised by removing these potential outliers and named as the “final training model”. Its R^2 and adjusted- R^2 were calculated as 89.28% and 87.82%, respectively, suggesting that the model fit the training data fairly well. Its R^2 -pred being equal to 80.37% also indicates that the model has a strong predictive power. The final training model was reached after three revisions, employing stepwise regression without ignoring the information obtained from the main effects and interaction effects plots.

Note also that the quantitative inputs were modified by coding the original inputs as follows:

$$\begin{aligned} C_RPM &= \frac{RPM - 105}{122 - 105}, \quad C_SPEED_LN \\ &= \frac{SPEED_LN - 2.0149}{2.7213 - 2.0149}, \quad C_TOTFUEL = \frac{TOTFUEL - 170}{1174.6 - 170} \end{aligned}$$

The quantitative inputs in the final training model were not found to be causing multicollinearity; however, the parameter estimates for RPM^2 and the interaction between RPM and SPEED_LN were found to be insignificant at $\alpha = 0.05$ at some instances before concluding the procedure. They were not discarded from the model when (1) VIFs did not indicate that multicollinearity among inputs was present, (2) goodness-of-fit measures and R^2 -predicted were sufficiently high, and/or (3) residual plots as given in Fig. 6 did not show any patterns to suspect non-normality of residuals or heteroscedasticity. The hierarchy principle was not adopted at any of these instances. The quadratic effect of SPEED_LN appears to be higher than that of any other inputs (F -value = 84.07), whereas the effects of qualitative inputs CARGO_CAT (F -value = 51.51) and DRAFT_BALLAST (F -value = 46.13) are also notable. RPM does not contribute to the final training model singly, but its interactions with SPEED_LN and the qualitative inputs are all found significant at $\alpha = 0.05$.

Fig. 6 suggests that the distribution of residuals produced by the final training model can be assumed normally distributed with zero mean and constant variance even though it seems slightly right-skewed. They also appear to be random. Thus, parameter estimates for the regression equation can be reliably used for the prediction of RESPONSE.

Fig. 7 exhibits the contour plots of the first-order and second-order response surfaces which help us find the direction that

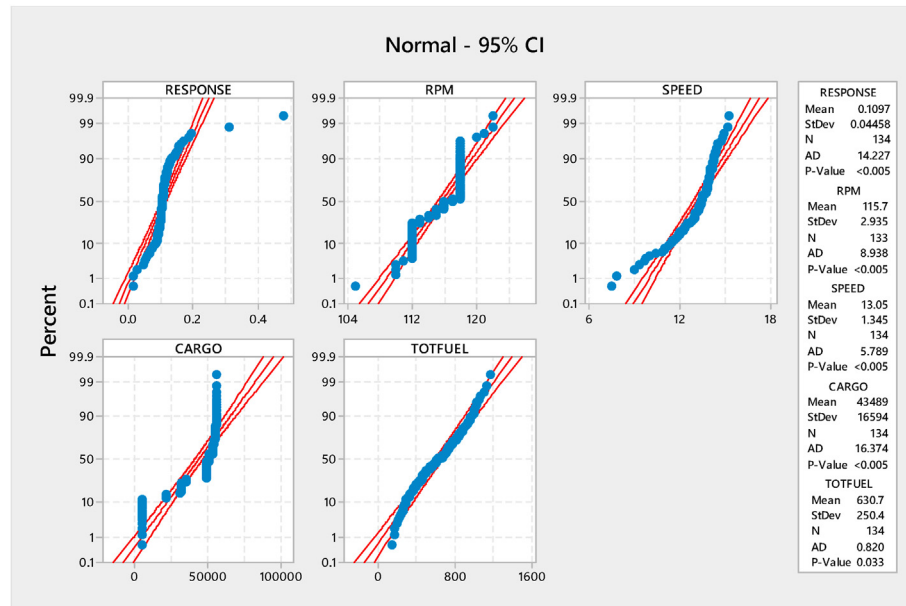


Fig. 2. Probability plot of the original response and the quantitative input factors (training data).

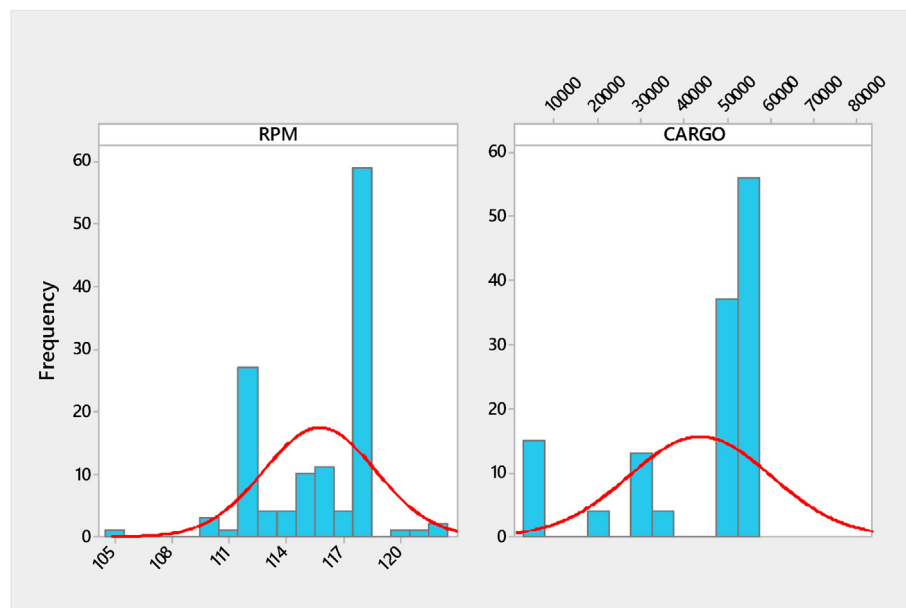


Fig. 3. Histograms of RPM and cargo (training data).

allows us to maximize or minimize the response. The optimal response, in each subplot, can be found in the region colored in extra light green. Thus, the HSIFO consumption per mile (RESPONSE) decreases when the input factor TOTFUEL decreases but SPEED_LN increases, whereas it appears to increase as TOTFUEL becomes greater than 600 tons but RPM remains less than 115. Note that the hold values are the values of inputs that are kept constant when calculating the fitted values for RESPONSE.

For such a bulk carrier that is neither inclined forward nor backward but carrying a high load of cargo (more than 40,000 tons), RESPONSE can be expected to be minimized when RPM is kept at 122, SPEED is around 12 knots, and TOTFUEL is approximately equal to 667 tons.

The predictive equation of the final training model can be

written as follows:

This equation was later used to predict RESPONSE in the validation set and it produced an R^2 of 86.08% and an adjusted R^2 of 80.64%, which are sufficiently high. Fig. 8, on the other hand, indicates no signs of violation to the model assumptions. Thus, the model can be used for the prediction of the HSIFO consumption per mile given data obtained from noon reports.

In conclusion, after splitting data into two sets, several alternative models for the HSIFO consumption per mile were fitted to the training set and the best ones were determined based on R^2 , VIFs, and residual plots. Only two-way interactions were incorporated into the models along with the main effects to avoid complicating the model. Some alternatives returned adequate R^2 's with inputs having VIFs greater than 10 or with parameter

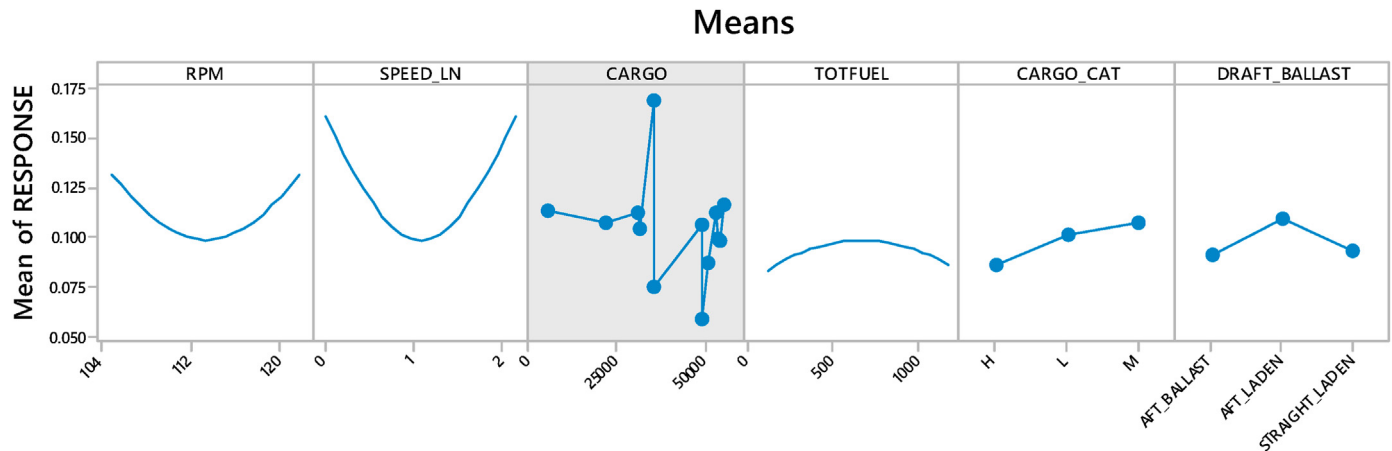


Fig. 4. The relation between the inputs and mean response.

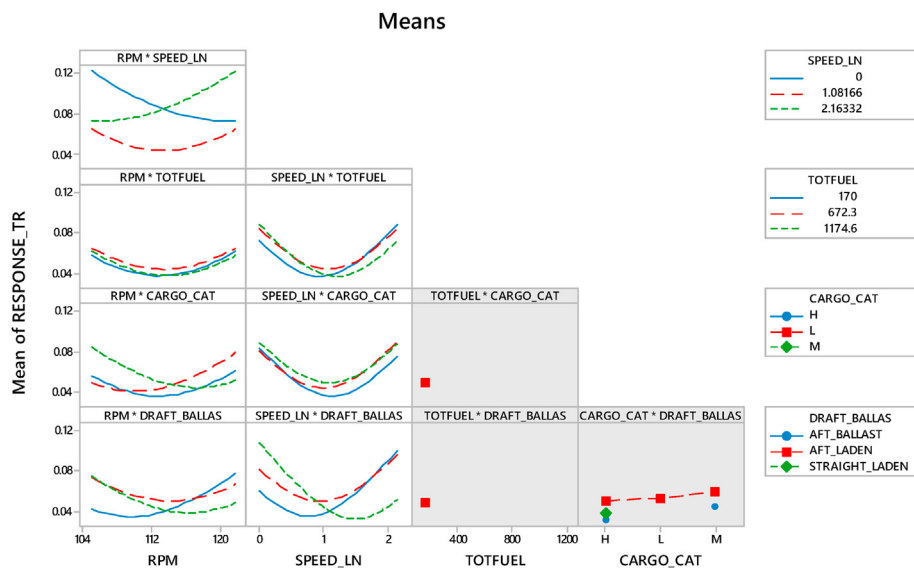


Fig. 5. Mean response levels estimated at interaction levels of inputs.

estimates that were insignificant. Some also produced standardized residuals greater than 3.00 in absolute value. Due to all these inadequacies coupled with the possibility that these models were suffered from non-normality and heteroscedasticity, they were improved adopting various statistical solutions. To obtain a better model, first of all, the Box-Cox transformed HSIFO consumption per mile was used as response. Complete results for the initial models are not reported here but they are available upon request. For diagnostic checking, four-in-one graphs produced by MINITAB were used. The normal probability plot for the final training model indicated that there was no violation to the normality assumption and there were no outliers. There was also no reason to suspect heteroscedasticity or autocorrelation; the data appeared to be random. The results showed that how a tedious approach such as the RSM can help practitioners better understand how an input affects the output. SPEED was found to have the most prominent effect on the HSIFO consumption per mile. However, this effect appeared to be non-linear rather than linear. On the other hand, even though its main effect was found insignificant, RPM's interaction with other inputs had a significant effect on the response. Conventional approaches could have easily failed to consider such

relationships. Additionally, the RSM can be employed as an initial step that can lead one to better designed experiments as it would greatly assist in determining the number of factor levels and in specifying these levels. In other words, noon reports can be utilized within the RSM framework to decide on what type of statistical experiment should be preferred and how pre-determined experimental conditions should be picked. Note also that, in a designed experiment, it is possible to fail at monitoring the output at precise factor levels. Regression-like methods such as the RSM are especially advantageous when the experimenter has been unable to obtain the required factor levels (Montgomery, 2013, p.460).

5. Conclusion and further suggestions

Having been used for various purposes all over the world, ships are responsible for the consumption of substantial amounts of fuel oil. They also emit millions of tons of GHGs, which are causing a growing public environmental concern worldwide. Due to unsteady fuel prices and pressure from environmentally conscious global citizens, international shipping industry has been recently faced with substantial challenges and energy-related problems. To

Table 4
Coded coefficients for the final training model.

Term	Effect	Coefficient	Standard Error	t-value	p-value	VIF
Constant		0.02259	0.00124	18.22	0.00	
TOTFUEL	0.00529	0.00264	0.00160	1.65	0.10	7.76
CARGO_CAT						
H	−0.01051	−0.00525	0.00056	−9.37	0.00	2.47
L	−0.00097	−0.00048	0.00072	−0.67	0.50	1.92
DRAFT_BALLAST						
AFT_BALLAST	−0.00929	−0.00464	0.00181	−2.57	0.01	7.58
AFT_LADEN	0.01495	0.00747	0.00110	6.82	0.00	3.82
C_SPEED_LN ²	0.04408	0.02204	0.00240	9.17	0.00	2.81
C_TOTFUEL ²	−0.01013	−0.00506	0.00129	−3.93	0.00	1.34
C_RPM × C_SPEED_LN	0.01586	0.00793	0.00255	3.11	0.00	2.80
C_RPM × CARGO_CAT						
H	0.02161	0.01080	0.00175	6.18	0.00	6.37
L	0.00056	0.00028	0.00303	0.09	0.93	5.76
C_RPM × DRAFT_BALLAST						
AFT_BALLAST	0.04403	0.02201	0.00382	5.77	0.00	9.41
AFT_LADEN	−0.00331	−0.00165	0.00176	−0.94	0.35	5.14
C_SPEED_LN × DRAFT_BALLAST						
AFT_BALLAST	0.03834	0.01917	0.00322	5.96	0.00	4.11
AFT_LADEN	0.02644	0.01322	0.00142	9.3	0.00	2.39
C_TOTFUEL × DRAFT_BALLAST						
AFT_BALLAST	−0.00463	−0.00232	0.00220	−1.05	0.29	2.37
AFT_LADEN	−0.01174	−0.00587	0.00164	−3.58	0.00	7.10

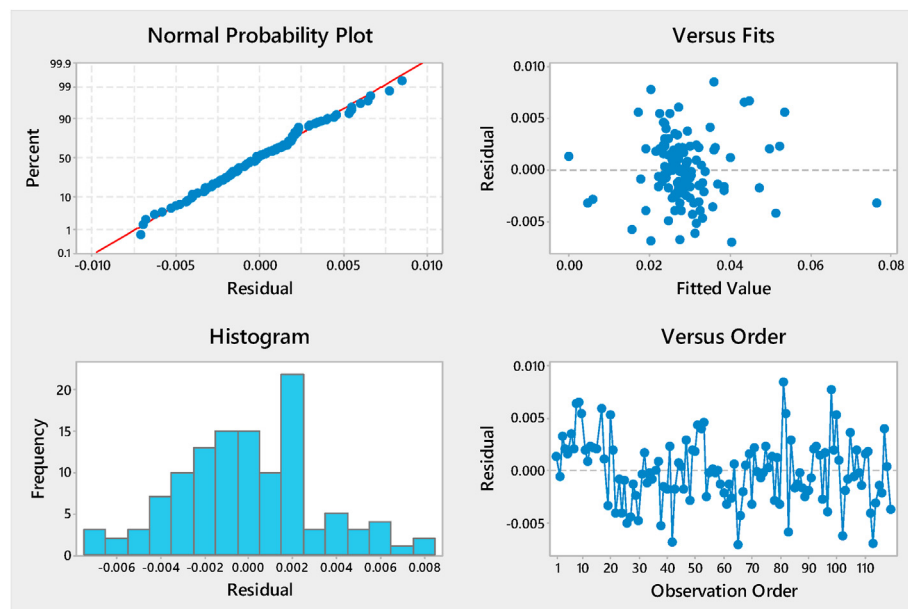


Fig. 6. Residual plots for the final training model.

meet the emission limits regulated by some institutions and to create efficient energy usage, finding ways to save fuel has become increasingly popular. For the reduction of fuel consumption and GHGs, ship owners and operators, should first think through their energy use and create energy efficient solutions for the industry.

Ship fuel consumption changes instantaneously depending on dynamic variable conditions (environment and machinery). Therefore, predicting fuel consumption of a ship before operation is a difficult and complex problem to tackle. On the other hand, overcoming this problem and performing fuel consumption prediction in advance can enable economically realistic fuel cost estimations for ship owners, while calculating the pollutant emissions directly related to the fuel consumed and determining the compliance with the IMO criteria. Precise estimation of fuel

consumption can enable ship owners to purchase fuel on an as-needed basis, preventing overproduction and creating a more environment-friendly and cleaner fuel production process.

In this study, several factors that affect fuel consumption and energy demand of ships were considered based on a thorough review of the related literature. Using the RSM, alternative models for fuel consumption prediction were built. In terms of significance, the results of our study are in parallel with those reported in the literature; however, including quadratic and interaction effects of the key factors along with estimating an exponent for the response make the functional form more specific. As the main data source, we utilized noon reports, which are data sheets that contain information on the environmental conditions, fuel consumption, machinery, etc. Since they contain actual ship data, noon reports

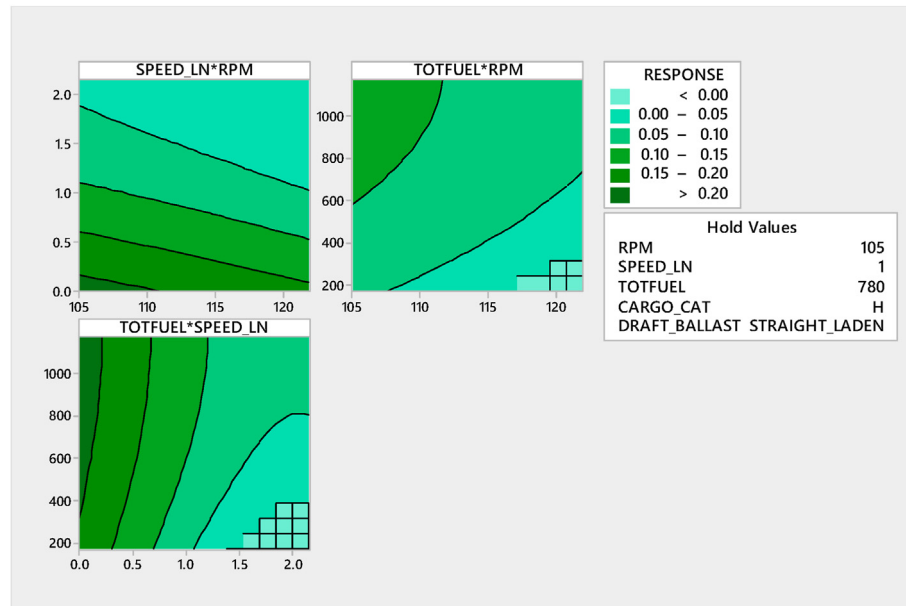


Fig. 7. Contour plots of the response.

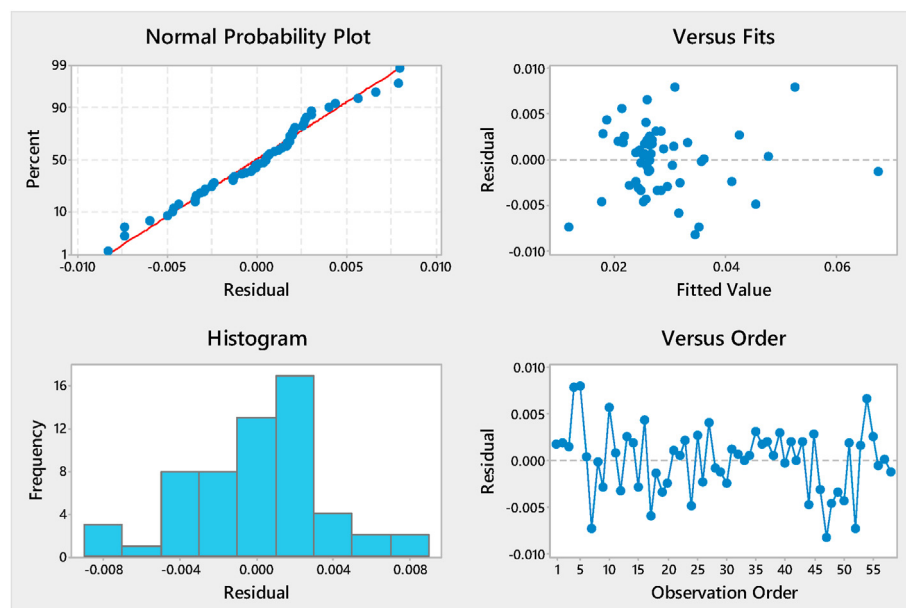


Fig. 8. Residual plots for the final training model in the validation set.

have been of great benefit in examining the direct and actual impact of environmental and machinery conditions on fuel consumption. One of the major points that provide novelty to this study is the prediction with actual recorded data. Although it is almost impossible to reach the results that can be described as absolutely correct due to dynamic variable conditions, the outputs are considered as close to realistic values because the data set used as input is real.

To increase the reliability of fuel consumption equation, we first screened data for missing values and possible outliers/influential points. Various transformations were undertaken to make data suitable for the RSM. The results indicate that the speed of ship along with the frequency of rotation of the ship's engines are the most notable input factors when estimating the HSIFO

consumption per mile. The fuel consumption equation also suggests the need for considering the interaction between the input factors in hand.

The present study aims to help interested parties to find an efficient fuel economy with the control and alteration of some related factors. Such a predictive model that performs well can greatly aid ship operators and shipping companies in making decisions that are both economic and environment-friendly. In other words, parameters such as ship speed and RPM can be changed effectively or one can respond to the situations accordingly considering various factors such as wind effect to reduce fuel consumption and GHGs. This study contributes to the related literature by urging the use of statistical experimentation when predicting the fuel consumptions of cargo ships so that the

resulting CO₂ emissions can be assessed. Since the IMO's policy tends to change to estimate the emissions during the pre-design stage, developing innovative methods by utilizing noon reports is extremely important for accurate estimations. The approach adopted here can be applied to any type of ship that has accurate data.

The present study has only examined the fuel consumption equations for HSIFO; however, ships can consume many other fuels like MDO, MGO, LSIFO, etc. As further suggestions, consumption equations for other fuels can be estimated. To construct fuel consumption equations for all fuels at the same time, one can use the "Multiple Responses" technique within an RSM framework. In addition, if we know the design characteristics of ships, instead of constructing fuel consumption equations for each ship, we can generally construct an equation, which compromise all the ships. To do this, we can insert the design factors (e.g., width, depth, core weight) of these ships into the equations so we can find the fuel consumption of all ships in a simple equation. The adoption of Gaussian Process Modeling in energy consumption has also been increasing. Future research should thus find ways in which such non-parametric models assist in the prediction of fuel consumption in maritime transport.

Further work is also required to establish the influence of climate change. Due to the regulation enacted by IMO as of January 1, 2020, which obliges ships to use low sulfur fuel, future studies should investigate the effects of energy capacities and calorific values of different fuel types on ship efficiency and global climate change. Increasing emissions generated by fossil oils is a critical issue in today's world. Therefore, as a further suggestion, emission values or equations from the ships can be calculated using fuel consumption equations. As a result, we can make some further decisions for the reduction of emissions from ships or vessels.

One of the limitations of such predictive models lies within the fact that any type of fuel consumption does not stay constant over time since it depends on the main engine load. Future research should also consider overcoming this problem using real-time data or high-frequency data.

CRediT authorship contribution statement

Erkan Işıklı: Conceptualization, Methodology, Software, Validation, Formal analysis, Writing - original draft. **Nezir Aydın:** Conceptualization, Writing - review & editing, Supervision. **Levent Bilgili:** Investigation, Resources, Writing - original draft. **Ali Toprak:** Conceptualization, Methodology, Software.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jclepro.2020.124142>.

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