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ORIGINAL ARTICLE

Optimizing ship speed depending on cargo and wind-sea conditions for sustainable blue growth and climate change mitigation

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Abstract
The impact of fuel consumption on merchant ships is categorized in both economic and environmental ways in terms of sustainable blue growth. Apart from the economic benefits of reducing fuel consumption, attention should be paid to related environmental concerns with ship fuels. As a result of global regulations and agreements concerning mitigating greenhouse gases on board, such as the International Maritime Organization and Paris Agreement, ships have to take a step to reduce fuel consumption to adopt these regulations. The present study aims to determine optimal speed diversity depending on ships' cargo amounts and wind-sea states to reduce fuel consumption. Within this context, one-year voyage data from two model sister Ro–Ro cargo ships were used, including daily ship speed, daily fuel consumption, ballast water consumption, total ship cargo consumption, sea state, and wind state. The genetic algorithm method was used to determine the optimal diversity rate. In conclusion, after speed optimization, optimum speed result values are calculated between 16.59 and 17.29 knots; thus, approximately 18% of exhaust gas emissions were also reduced.

Keywords Shipping emissions · Impact category · Genetic algorithm · Speed optimization · Fuel consumption · Blue growth

1 Introduction

Blue growth, which is a long-term strategy to support the sustainable development of the blue economy, focuses on the growth of marine renewable energies, blue biotechnologies, coastal tourism, seabed mining and aquaculture alongside shipbuilding, bunker, fisheries, maritime transportation etc. [1–6]. The blue economy also aims to optimize the benefits of sustainable marine environment development [1, 4]. The impact of maritime transportation, regarded as one of the industries with high potential in terms of the blue growth strategy, is categorized as both economic and environmental on the blue growth [7, 8].

Although the maritime trade volume decreased by 3.8% in 2020 to a total of 10.6 billion metric tons due to the COVID-19 pandemic, worldwide seaborne trade volume represents 80% of the total world merchandise trade [9]. Therefore, maritime transportation is getting more profitable as a result of globalization. However, the economic activities under the blue growth agenda bring out environmental impacts. Greenhouse gases (GHG) increasing in the atmosphere with the effect of emissions from ships trigger global warming [10]. An average of 50 million tons of gas is emitted into the atmosphere annually, 16.2% of which is due to transportation. Maritime transport also constitutes 1.7% of the total emissions [11]. According to a study by International Maritime Organization (IMO) in 2020, total shipping emitted 1,056 million tonnes of CO_2 in 2018, accounting for about 2.89% of the total global anthropogenic CO_2 emissions for that year [12]. In addition, it has been revealed that inland water transport is one of the 5 sectors that cause the most pollution and that emissions from ships contain the most serious 64 air pollutants. Thus, emissions from ships pose devastating risks to the blue growth strategy [13]. In this context, one of the main issues to be focused on in order to prevent climate change is emissions offsetting from ships. In this way, it will contribute to the blue growth strategy [14]. The focus has been on fuel efficiency, which is important in reducing the environmental footprint of ship-borne air pollution, besides alternative fuels to reduce emissions from ships, and international regulations on the subject have been

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implemented, such as Paris Agreement, IMO 2020 Sulphur Regulation and NO_x Technical Code 2008.

In 2021 Paris Agreement entered into force with its 196 signatory countries in United Nations. The main purpose of this agreement is to reduce global emissions, especially in the logistics and power sectors, which maintain nearly 70% of total global emissions [15]. In addition, the IMO 2020 sulphur emission regulation has already entered into force. Before the IMO 2020 Sulphur regulation, in the main engines of the ships, except for Emission Control Areas (ECA) regions, the maximum sulphur content was 3.5% fuel, while this value was reduced to 0.5% after regulation. In ECA regions, the maximum sulphur content of the fuel has been reduced to 0.1%. With the legislation of IMO 2020 Sulphur regulation, there has been no change in the NO_x limit values originating from ship fuels. The maximum NO_x values specified in the NO_x Technical Code 2008, which entered into force in 2008, continue to be used. Table 1 shows the NO_x categories (Tier) according to the shipbuilding years and the maximum NO_x emission values that the ships in these categories will give to the atmosphere according to their turnover.

As it can be seen in Table 1, the allowed NO_x values for ships built on or after January 1, 2000 vary between 9.8–17.0 (g/kWh), while the allowed NO_x values for ships built on or after January 1, 2016 are vary between 2.0 and 3.4 (g/kWh).

In light of the aforementioned regulations and agreements, reducing ship-sourced greenhouse gas emissions is important for the environmental objectives of blue growth. As a matter of fact, an average of 1.5 °C increase in seasonal temperatures is expected in 2030 in global warming caused by greenhouse gases. To get ahead of that increase, maritime transport activities should be reduced by 8.6%. To prevent a temperature increase of 2 °C, it needs to reduce its maritime transport activities by 24.2% [18]. However, maritime transportation, which accounts for 90% of the international trade and supply of cargo, has no alternative compared to other modes of transport [9]. For this reason, it is not possible to expect a contraction in the aforementioned sector in order to reduce gas emissions. Therefore, reducing emissions with

Table 1 NO_x limit values of ships according to IMO NO_x Technical Code [17]

Tier	Ship construction date on or after	Total weighted cycle emission limit (g/kWh) n = engine's rated speed (rpm)		
		n < 130	n = 130–1999	n ≥ 2000
I	1 January 2000	17.0	$45 \cdot n^{(-0.2)}$	9.8
II	1 January 2011	14.4	$44 \cdot n^{(-0.23)}$	7.7
III	1 January 2016	3.4	$9 \cdot n^{(-0.2)}$	2.0

an alternative fuel or speed optimization would be a more appropriate strategy.

This paper aims to determine optimal speed values of model ships depending on ships' cargo amounts and wind-sea states in order to reduce fuel consumption and exhaust gas emissions. In this way, it is aimed to contribute to the efforts to reduce the carbon footprint of ships. Two sister Ro–Ro cargo ships in liner shipping service were used as model ships to determine optimum speed, depending on varied cargo amounts. Different parameters, including sea and wind state forces, ship daily average speed, daily total fuel consumption, daily ballast water amount and daily cargo amount, were used in the study. These data that affect ship speed were gathered from shipping company one-year documents named daily fuel oil statements and weekly ship stability reports. The model presented in this paper is defined as the genetic algorithms (GA) method, which is used to optimize different ship speeds depending on varied cargo amounts by using the one-year data of model sister ships. This study will contribute to the research on connected and automated ships, energy savings and environmental impacts of ships.

The main topic of this paper is organized as follows. After the introduction and literature review sections, the subject and data set are mentioned in the third section. Also, speed optimization factors are mentioned in Sect. 3. The method of the study, model components, and mathematical model are summarized in Sect. 4. In Sect. 5, the computational results of the optimization method are discussed. Finally, the conclusion and outlook of the study are mentioned in Sect. 6.

2 Summary of previous work

Studies in the field of ship optimum speed can be divided into optimum speed works of liner and tramp shipping. Many studies about ship optimum speed are also combined with route optimizations by using various optimization algorithms and mathematical models. Although existing many optimum speed studies related to tramp and liner shipping exist, speed optimizations related to cargo amount in liner shipping are restricted.

Norstad et al. [19] present a model for tramp shipping using Tramp Ship Routing and Scheduling Problem with Speed Optimization (TSRSPSO). They consider allocating cargo to fleet ships and optimizing ship routes and speed in order to reach the best results. Gelareh and Meng [20] and Qi and Song [21] work on route optimization in liner containership using the methods of Mixed Integer Programming (MIP) and Stochastic Optimization, respectively. Du et al. [22] solve the slow steaming and Berth Allocation Problem (BAP) with optimization on liner containership. They present that mitigating emissions and fuel consumption can be reached with correct berth allocation. Using regression analysis, Kontovas and Psaraftis [23] also work on slow steaming in liner containerships. They conclude that slow steaming is the most advantageous way at high fuel prices and low freight demand.

Several papers focus on speed and route optimization on container ships. Wang and Meng [24] make calibration work on container ships by using old fuel consumption and speed data from three container ships at five different routes. They solve that speed increasing depending on the ship's main engine power is an important factor of fuel consumption, considering that consumption is a cubic function of speed. They also find out that ship voyage routes are also remarkable for determining speed regression. Kim et al. [25] do similar studies about container ships' routes and speed optimization. They also consider port durations and gas emissions in their study and reveal that speed optimization reduces both fuel consumption and gas emissions. Wijayaningrum and Mahmudy [26] work on route optimization in liner shipping by using GA and conclude that optimization results by GA are more successful than randomly selected results. Zhen et al. [27] focus on speed and route optimization on container ships and find out that sailing speed in the ECA will be reduced while the speed outside the ECA will be increased to satisfy the time window requirements of the ports. Psaraftis [28] discusses speed optimization and speed reduction depending on GHG and bunker levy on a transpacific container ship and concludes that the speed limit option shows a number of disadvantages as an instrument to reduce GHG emissions, at least for the bunker levy option. Ma et al. [29] study ship route and speed optimization in order to mitigate sailing cost and time considering ECA regulations and weather conditions. Results show that optimizing both ship speed and route reduces sailing cost and time. Ships can avoid potential increases in low sulphur fuel oil (LSFO) prices using ship speed and route optimization. Tran [30] searched for an energy efficiency model on bulk carriers in order to reduce fuel consumption while increasing engine power. He used Simulink/MATLAB to maintain a model with parameters, including wind and sea conditions, cargo mass, vessel travel distance, and ship daily data. The results of that paper show that the model is acceptable, and a reduction of CO_2 emission occurred. Yang et al. [31] determine the optimum ship speed on a tanker between two fixed ports considering ocean currents. They find out that an oil product tanker can save 2,20% of bunker fuel during a 280-h voyage with speed optimization. Tzortsis and Sakalis [32] make speed optimization on container fleets, identifying the problem as a dynamic optimization problem. They use a full-time horizon to gain small-time regions for forecasting weather conditions. They conclude that nearly 2% of fuel consumption savings can be achieved. Zhou et al. [33] worked on fuel consumption estimation on a tanker ship using noon report data and weather-sea conditions. They compared the results by using four machine learning algorithms and found that the accuracy rate was acceptable.

Several papers also focus on speed and bunker optimization in liner shipping. Aydın et al. [34] work on speed optimization by considering port durations, auxiliary engine fuel consumption, bunker prices, and late arrival penalty of the next port entrance. They use a dynamic programming model and find out that increasing ship speed is advantageous for not paying port penalties in some cases. Yao et al. [35] solve speed optimization related to bunkering on liner containerships. They use an empirical model and conclude that determining the bunkering port, bunkering price, bunker amount, and the speed of sailing to the bunkering port is remarkable for reducing bunker cost. Similarly, Kim et al. [36] solve the best bunkering port by algorithms. They also consider CO_2 emissions and penalty costs.

Mao et al. [37] investigate one-year container ship data. They use weather conditions and ship main engine speed to find out the effects of speed optimization. According to the results by regression analysis, without considering weather conditions determining ship speed with only main engine speed reveals weak results. They conclude that weather conditions have a remarkable impact on determining ship speed. Li et al. [38] study the model 4250 TEU container ship in their paper about speed optimization. They calculate speed optimizations with or without voluntary speed loss and the main engine fuel consumption, the ship operating costs, and greenhouse gas emissions under the two conditions. Optimization results show that voluntary speed loss is remarkably different from without voluntary speed loss. After optimizing speed with voluntary speed loss, main engine fuel consumption reduces, so ship operating costs do.

As seen, speed optimization studies mainly focus on a containership and are also related to route optimization. However, works about ship speed optimization depending on net cargo amounts and weather conditions (hull resistance) and determining speed values on Ro–Ro cargo ships are restricted. Therefore, this paper has contributed to the existing literature with speed optimization according to different cargo amounts and weather conditions to reduce fuel consumption and gas emissions.

3 Speed optimization depending on cargo amount

It is possible to reduce fuel consumption by speed optimization on Ro–Ro cargo ships under liner shipping service. Thus, both economic and environmental profits could be maintained. Two sister Ro–Ro cargo ships' one-year sailing data were used to provide speed optimization in this work. Sailing data, including cargo amounts (frequently carried by ships in both weight and percentage values) and three kinds of weather conditions that frequently occurred at sailing periods were used to determine speed optimization depending on cargo amount. Table 2 includes an overview of the model ships' technical data.

As seen in Table 2, Model ship 1 and Model ship 2 have similar engine and cargo characteristics. However, build dates are different. Figure 1 gives the sailing legs of model ships.

Figure 1 indicates that model ships frequently sail on Pendik-Trieste and Pendik-Toulon legs and sometimes on the Mersin-Trieste leg. According to Monthly Fuel Oil Statement Reports (FOS), given by company records, the Pendik-Toulon course is 1370 miles, while the Toulon-Pendik course is 1369 miles. Pendik-Trieste and Trieste-Pendik courses are 1181 miles and 1191 miles, respectively.

Besides, FOS monthly reports showed that model ships completed both the Pendik-Trieste-Pendik course (123,86 h) and the Pendik-Toulon-Pendik course (143.02 h) with 19.15 knots average speed and 2.37 ton/hour average fuel consumption for a whole year.

Factors affecting ship fuel consumption should be investigated to determine speed optimization and reach optimal sailing speed results depending on cargo amount and weather conditions. However, other independent variables such as safety concerns at severe weather conditions, cargo types, environmental effects (emissions), bunker price, port duration, and auxiliaries' fuel consumption and bunker price are neglected and will be thought of used in future studies.

Table 2 Model ships' technical data [39]

	Model ship 1	Model ship 2
Main engine	MAK 9M43C	MAK 9M43C
Main engine power	2 × 8400 KW	2 × 8400 KW
Main engine speed	500 rpm	500 rpm
Length overall	193 m	193 m
Lane meter	3735 LM	3735 LM
Trailer capacity	240 pcs	240 pcs
Ship maximum speed	21.5 knots	21.5 knots
Flag	Turkish	Turkish
Build date	2008	2009

3.1 Factors affecting ship fuel consumption and ship speed

There are several factors that affect ship fuel consumption. Foremost among them, ship displacement (total ship and ballast amount weight) and ship speed are the main factors [41]. Moreover, depending on previous studies, ship resistance (ship hull form and trim, hull resistance), main engine power, and propeller pitch are other factors considering ship fuel consumption [42, 43].

Among the mentioned factors, ship speed is the main factor in ship fuel consumption [44]. Even little changes in ship

Fig. 1 Model ships' sailing legs [40]

speed affect energy efficiency on board [45]. Beşikçi et al. [46] indicated that 10% of ship speed reduction makes 27% of less fuel consumption. For this reason, slow steaming is a remarkable fact for shipping companies to resist increasing petrol prices and comply with environmental regulations coming into force by IMO [45].

Longer sailing duration and, thereby, longer delivery time is the main negative side of slow steaming [47]. For this reason, in order to achieve less fuel consumption on board determining a ship's optimum speed is better choice for shipping companies. As a matter of fact, focusing on the factors affecting ship speed is needed for ship speed optimization.

Ship fuel consumption comprises a cubic function of ship speed, not a linear function [48, 49]. There are technical, physical, economic, and strategic factors affecting ship speed. The main factors among these will be investigated in subheadings.

3.1.1 Ship displacement and cargo amount

Ship displacement is a ship's total deadweight and lightweight, including weights of fuel oil and lubricating oil. Lightship weight is constant, and in liner shipping, fuel and lubricating oil amounts are nearly at the same levels at each timetable. Therefore, in the ship displacement category, cargo amount is the main factor affecting ship displacement, that is to say, affecting ship speed [41]. In the case of a ship being fully laden, half laden, or less laden, ship fuel consumption and ship speed can change. If the ship is fully laden, the ship's fuel consumption will increase to maintain the ship speed steady. If other factors affecting ship speed are constant, at the same engine load, ship speed changes inverse proportion depending on ship cargo amount. Consequently, the cargo amount of a ship should be considered highly whenever to determine the ship's optimum speed [48].

3.1.2 Ballast amount

Although sailing with more cargo and less ballast is appropriate in the economic aspect for shipping companies, ships have to sail with ballast at the service of less-laden, half-laden, and even full-laden situations for ship stability. The ballast amount on board directly affects ship speed and fuel consumption. Perakis and Papadakis [50, 51] found two ship speed values in their study about speed optimization. The first ship's speed was arrival speed at full laden between two ports. The second speed was the ship's departure speed with no ballast. Wang and Xu [52] conducted a similar study about ship speed optimization, and they also determined two different ship speeds. After setting the optimum ballast for ship stability, additional ballast water makes extra weight for a ship. So, the reduction will occur at ship speed value. The ballast water amount is a remarkable factor in determining ship speed optimization.

3.1.3 Hull resistance

Hull resistance is the combination of still water resistance and added resistance due to waves and wind resistance [53]. Still water resistance emerges from a ship's own weight and its character of buoyancy. Still water resistance is seen, especially during the sailing period and causes little speed changes. Long ships having aft and fore fuel tanks, especially tankers, are more likely to speed changes depending on still water resistance [54]. These resistances affect ship speed in a negative aspect. One year after the dry dock period, ship resistances could increase by nearly 12%, and at the end of 5 years, these resistances could reach up to 40% [55]. Keel fouling is another resistance for ship resistance. Beşikçi et al. [56] stated that on board anti-fouling systems could increase ship speed by up to 40%.

Besides mentioned resistances, added resistances (wind and sea resistance) have instant and highly changes in ship speed. Added resistance is a function of wave height, direction, and force of waves and wind. Waves coming from the fore side reduce ship speed, whereas waves coming from the aft side increase ship speed depending on direction of winds and currents. According to the Beaufort wind scale and sea state scale [57, 58], at 5 scale and higher scales, significant waves and wind forces occur. Perera and Mo [59] state that ship speed is affected positively or negatively depending on wind direction under high wind conditions. Bassam et al. [60] worked on the simulation study of wind and sea states' effect on ship speed and submitted that at 5 and 8 Beaufort scales, ship speed decreased by 6.1% and 34.4%, respectively. So, determining ship speed is fairly difficult under variable and heavy weather conditions [61]. On the other hand, a ship's propeller can move outside the water in heavy weather conditions, allowing air to move around the propeller. Because of this ventilation effect, ship resistance increases while ship speed reduces [62].

Therefore, captains on board and shipping companies should take necessary measures to reduce the performance loss of the ship. The sailing plan depending on weather conditions should be prepared, and the optimum speed should be found. In this way, both fuel consumption and ship crew risk factors can be decreased [63]. Speed optimization depending on weather (sea-wind states) conditions makes a 3% reduction in fuel consumption on board [64].

3.1.4 Other factors

Ship propeller and seawater depth are other factors affecting ship speed. The propeller is the main item facing sea resistance. Ship speed is affected more by ships having a controllable pitch propeller (CPP). In CPP, propeller blade angles should move synchronically with bridge and engine control room commands. A reduction in fuel consumption on board is obtained to ensure proper propeller/pitch optimization regarding bridge and engine control room commands [49, 65]. Based on the impact of water on ship speed, if the other factors affecting ship speed stay constant, ship speed decreases in shallow waters compared to deep waters [65]. In other words, this effect is called the squat effect. In shallow waters, draught increases because of hydrodynamic impacts between the hull and the sea bottom. So, the water amount that the propeller can absorb decreases, and back resistance increases. Ship speed also decreases depending on increasing resistance [66].

3.1.5 Assumptions and limitations

In this study, some factors, including still water resistance, vertical forces, keel fouling resistance, propeller/pitch optimization, and seawater depth, were neglected while determining optimal ship speed depending on different cargo amounts. As a result of determining and measuring still water resistance and vertical forces needing more specific work and data, these variables were neglected. In addition, because the dataset of this work involves a one-year period, the keel fouling effect on ship speed was also neglected. Furthermore, the model sister ships had similar dry dock dates in the past, and propeller/pitch optimization was carried out on these ships. So, pitch optimization is another neglected factor. Lastly, model ships sail under liner shipping service, so the sailing route is nearly the same at each timetable. That is why the seawater depth factor was also neglected in this work.

On the other hand, related to hull resistance, daily sailing data, including the direction of waves and wind angle that positively affects the ship, are subtracted from the dataset. Wind and sea states' daily data, which only affects resistance to ship, is considered.

Finally, some lack of daily sailing data, the days when the main engine had breakdowns, and the days' data of voluntary speed reduction (passage sail, fuel savings, etc.), which affect work's reliability, are subtracted from the data set.

4 Genetic algorithm (GA) model and speed optimization

The GA model and its adaptation to speed optimization are formally defined in this section. The GA is used to solve a problem by using evolutionary theory. Using GA, obtaining an optimal solution is not certain; however, acceptable results are certainly obtained [67, 68].

Optimization by GA is done by imitating biological evolution. In GA, a cloud is comprised of genes, and it is called a chromosome. Chromosomes can also be defined as individuals or solutions. The population is another cloud that is comprised of a large number of chromosomes. GA applications are unlimited and used everywhere. However, getting a solution process is usually long, and achievement depends on problem coding [69]. GA progress is shown in Fig. 2.

As seen in Fig. 2, firstly, all solutions necessary for solving the problem are coded in series. The initial population is created by random selection. Then, the fitness values of the initial population are calculated for each series. These fitness values determine the quality of the solution. If solution quality is good, in other words, the fitness value reaches the necessary iteration number, the optimum solution is reached. But if the necessary iteration value is not reached, crossover and mutation processes are performed, respectively. When the necessary population number is reached, the iteration process ends. Thereby, optimal series are selected and reach the solution [70].

The support vector machine (SVM) was used to determine the fitness function in this work. SVM applicate the reasoning principle to make a good generalization level and minimize risks. Obtaining meaningful information from the database and reaching correct information are important matters that depend on the achievement of algorithm generalization. In other words, the reality of results coming from data depends on the performance of algorithm generalization. At this point, SVM ensures the performance of algorithm generalization [71].

Some of the factors that affect ship speed and also some input data from the ship sailing records, including ship daily fuel consumption, ship daily average speed, wind and sea states, and ship cargo amounts, were used in the concerned GA method in order to find ship optimum speed values depending on cargo amounts.

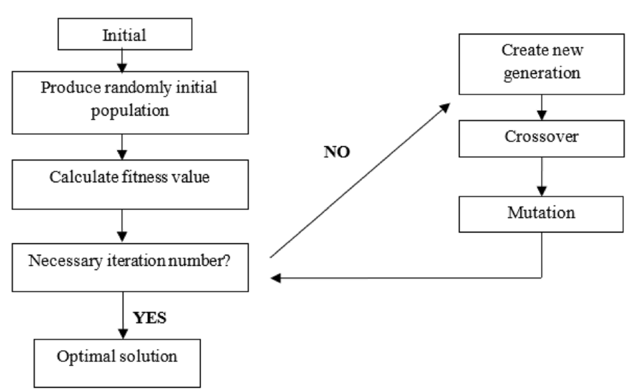


Fig. 2 Genetic algorithm process [70]

4.1 Support vector machine (SVM)

In this paper, SVM was used to model fuel consumption through previous sailing data of model ships. Support Vector machine, one of the promising algorithms for classification, regression and outlier determination, was firstly used in 1995 by Vladir Vapnik, Berhard Boser, and Isabelle Guyon. SVM, which is based on the working principle of supersize learning, uses optimization techniques in order to minimize the fault (epsilon) between real system output and real value. The optimization problem gives rise to finding the maximum margin splitting the hyperplane, as rightly sorting as many training points as possible [72]. SVM's geometric target is to produce support vectors that maximize between the borders in Fig. 3.

The f(x) function, enough distance to hyper planes can be written as follows in equilibrium (1):

$$y = f(x) = \langle w, x \rangle + b = \sum_{j=1}^{M} w_j x_j + b, y, b \in R, x, w \in R^M \tag{1}$$

$$f(x) = \begin{bmatrix} w \\ b \end{bmatrix}^T \begin{bmatrix} x \\ 1 \end{bmatrix} = w^T x + b \quad x, w \in R^{M+1} \tag{2}$$

For linear regression support vector regression (SVR) was used. The aim of SVR is to obtain a function $f(x)$ that has at most ε deviation from the actual target value yi for all the training data. Mentioned linear function f is presented in Eq. 1. A training data is a combination of input-target pairs, $\{(\times 1, y1), \ldots, (xi, yi)\} \subset X \times R$. In case of a function $f(x)$ is hyperplane, the size of ε is margin, the symbol <•, •> is the dot product in X, $b \in R$ and $w \in X$. The hyperplane has small margin in which the SVR has to find it [72]. In linear regression, features of linear function are shown below;$x = \left(x_1, \ldots, x_D\right) \in R^D$ to make predictions y of the target value $t \in R$, y is the prediction, w is the weights and b is the bias (or intercept).

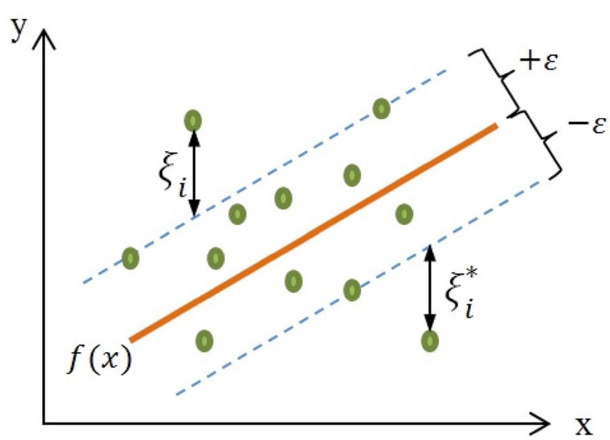


Fig. 3 Geometric demonstration of SVM [72]

For multi-dimensional data, this function can be expanded as seen in equilibrium (2). The next stage ||w|| (the magnitude of normal vector) system becomes the minimization of function as seen in equilibrium (3).

$$min_w \frac{1}{2} w^2 \tag{3}$$

The mentioned technique is the most basic support vector regression technique and was used in this paper as linear support vector regression.

4.2 Model components

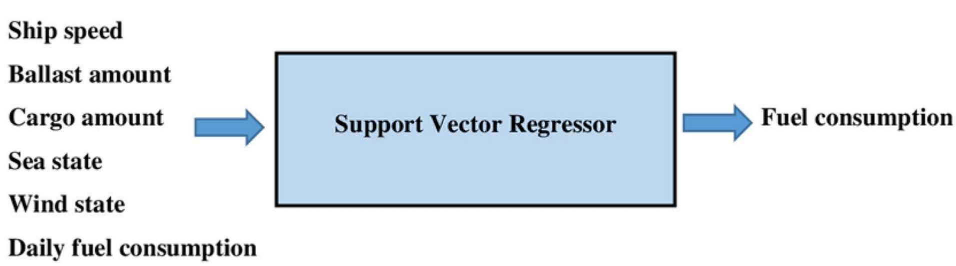
In this part of the study, factors that affect ship speed were specifically determined depending on the dataset. Considering the reliability of the study, the direction of waves and wind angle that affect ships in a positive way are subtracted from the dataset. Structure of fitness function is shown in Fig. 4.

Fitness function is a sample of Supper Vector Regressor which has 6 inputs and 1 output. Regressor uses L1 soft-margin minimization by quadratic programming, linear Kernel type. Model uses ship speed, ballast, cargo amount, sea state, wind state and daily fuel consumption as inputs and predicts fuel consumption.

Firstly, fixed values of three conditions of wind and sea states that model ships frequently sailed were determined as follows:

- Condition 1 (sea state: 2, wind state: 3): weather conditions affect hull resistance lightly.

Fig. 4 Structure of fitness function



- Condition 2 (sea state: 5, wind state: 5): weather conditions affect hull resistance reasonably.
- Condition 3 (sea state: 7, wind state: 8): weather conditions affect hull resistance remarkably.

Secondly, in order to find out the optimum ship speed depending on cargo amount, cargo amounts and percentages were determined according to the ship stability manual. The maximum cargo amount that ship can safely portage is 7114.5 tons. With reference to the frequency of model ships' sailing records, five different cargo amounts and percentages were determined as follows: below 33% cargo rate (1000 tons), 33% cargo rate (2372 tons), 66% cargo rate (4743 tons) and above 66% cargo rate (5900 tons) and fully cargo rate (7114.5 tons).

Finally, vessel speed range of the model in GA structure was determined between 16.5 and 21.5 knots because of model ships are in liner shipping service and preventing ships from out of service. Besides, some daily sailing data, the days when the main engine had breakdowns, and the days' data of voluntary speed reduction (passage sail, fuel savings, etc.) are subtracted from the dataset because of improper distribution. One of the other factors affecting ship speed, the ballast amount scale, was determined according to the ship stability manual from 1056.0 tons to 4053.4 tons.

A GA structure was made in this optimization, and this optimization is a minimization problem. Chromosomes were encoded as the binary mode, and the tournament selection was used among selection methods. In addition, the prediction value of this model was determined by SVM as the objective function. Finally, the quadratic calculation was used to solve the problem of the model. The results values of model components arising from MATLAB calculation are shown in Table 3.

The mu (M) value is defined as the mean of the normal distribution, specified as a scalar value or an array of scalar values.

M values of model = [2730.15254237289, 4673.15254237289, 19.1800847457628, 2.74576271186441, 3.74576271186441].

Sigma (σ) value plots the singular values of the frequency response of a dynamic system model sys. sigma automatically determines frequencies to plot based on system dynamics.

Σ values of model = [328.002182531791 1278.29217348987 1.03861223629041 1.6339686921122 1.81723204882631].

In Fig. 5, the speed optimization study depending on parameters is seen. Firstly, the dataset was divided into two equal parts randomly: training data and test data. If the test success rate value is not higher than the intended rate value, training data and test data are selected randomly from the start, and GA has applied again. If the test success rate value reaches the intended value, in other words, results are compromised with real data, SVM that provides fitness function is confirmed. After that, parameters from the dataset are optimized with GA to obtain the best fit results. GA model is run by using MATLAB for 5 different cargo amounts under three different weather conditions (sea and wind states). Finally, output results show optimum ship speeds at the lowest fuel consumption depending on weather conditions and cargo amounts.

Table 3 Result values of model components

Computational results	Values
Cn (chromosome number)	50
Gn (gene number in chromosome)	60
MR (mutation rate)	0.767
CR (crossover rate)	0.75
Max. In (max. iteration number)	20
No of OBs (number of observations)	118

5 Computational results

In this part, in order to determine the targeted optimum speed, the GA model was run by using MATLAB for three different weather conditions. The model was run 30 times for more efficient distribution. In regard of no remarkable changes on optimization results after 30 run times of model in MATLAB, model run was left off at 30th iteration.

5.1 Weather condition 1

Within this framework, Fig. 6 provides optimum speed values for each cargo amount in weather condition 1 (sea state: 2, wind state: 3).

As seen in Fig. 6 for weather condition 1, optimum speed values at different cargo amounts are close and approximately around 17 knots. During speed optimization, fuel consumption was reduced to the optimum level at MATLAB run. Figure 7a, b show the iteration of the GA model and drop graphs of fuel consumption at the lowest and highest cargo status for weather condition 1.

Figure 7a, b indicate that during speed optimization by GA model, after the third iteration, fuel consumption values drop from 2.1 to 1.48 tons/h and from 2.2 to 1.87 tons/h at cargo status < 33% and 100% respectively. For more detailed information, Table 5 summarizes average speed and fuel consumption values for each cargo status at weather condition 1.

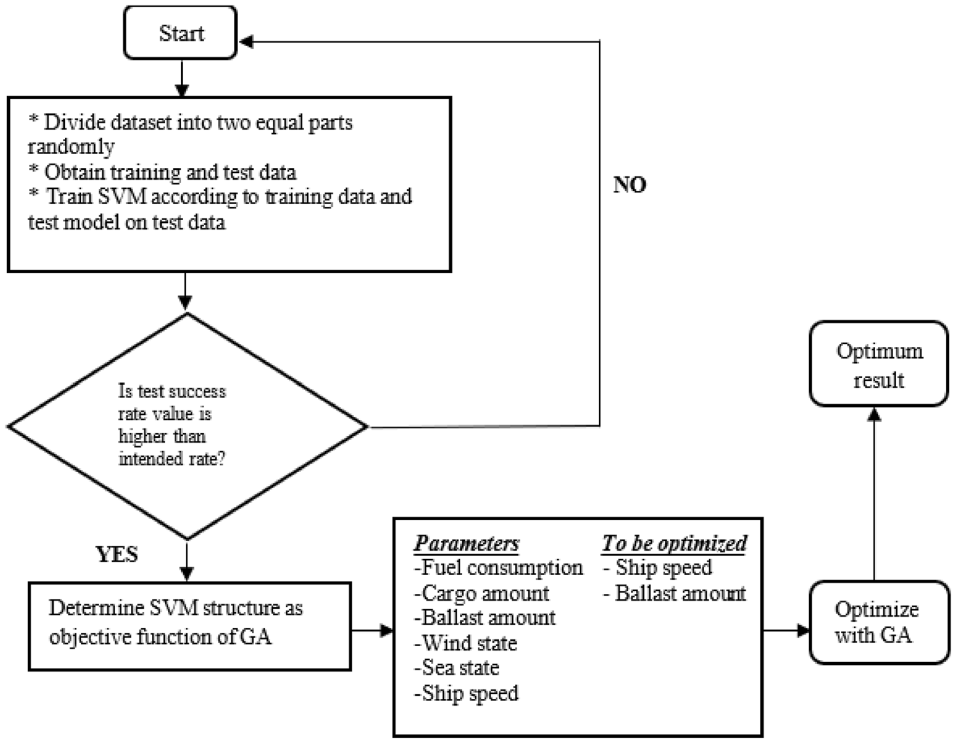


Fig. 5 Genetic algorithm process of the study

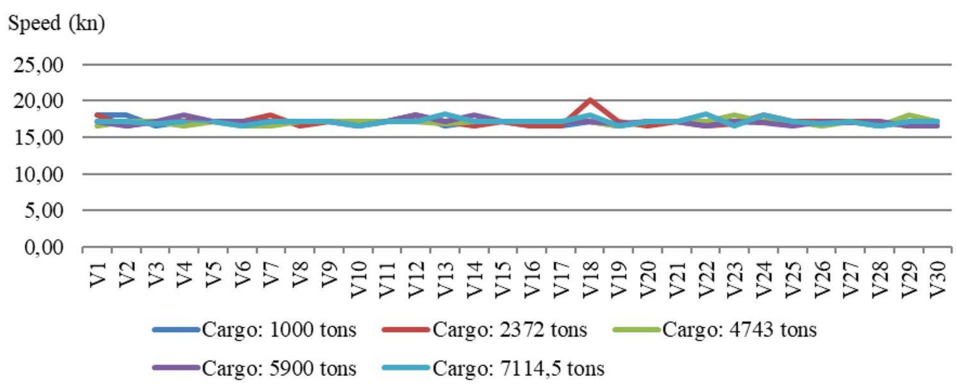


Fig. 6 Optimum speeds at different cargo status for weather condition 1

5.2 Weather condition 2

Figure 8 summarizes optimum speed values for each cargo amount in weather condition 2 (sea state: 5, wind state: 5).

Figure 8 indicates that the optimum speed values graph is almost the same with the weather condition 1 graph (Fig. 6). The speed values are around 17 knots. Iteration of the GA model and fuel consumption drop graphs at the lowest and highest cargo status for weather condition 2 are shown in Fig. 9a, b.

Figure 9a, b indicate an overview of the resulting GA model iterations at different cargo statuses. After the 10th iteration, fuel consumption reduces from 1.64 to 1.56 tons/h at cargo status < 33%. However, after the third iteration fuel consumption drops from 2.3 to 1.95 tons/h at 100% cargo status.

The difference in iteration sequence between the different cargo states indicates the occurrence of optimization in which repeat period. However, it does not have a meaning depending on optimization quality.

5.3 Weather condition 3

Ship speed values after 30 times GA model run on MATLAB are shown in Fig. 10. The values have similarities with the values in both weather condition 1 and weather condition 2. The average speed value is around 17 knots.

Iteration of the GA model and changes of fuel consumption graphs at the lowest and highest cargo statuses for weather condition 3 are shown in Fig. 11a, b.

When the cargo status is lower than 33% cargo capacity, after the 17th iteration fuel consumption reduces from 2.00

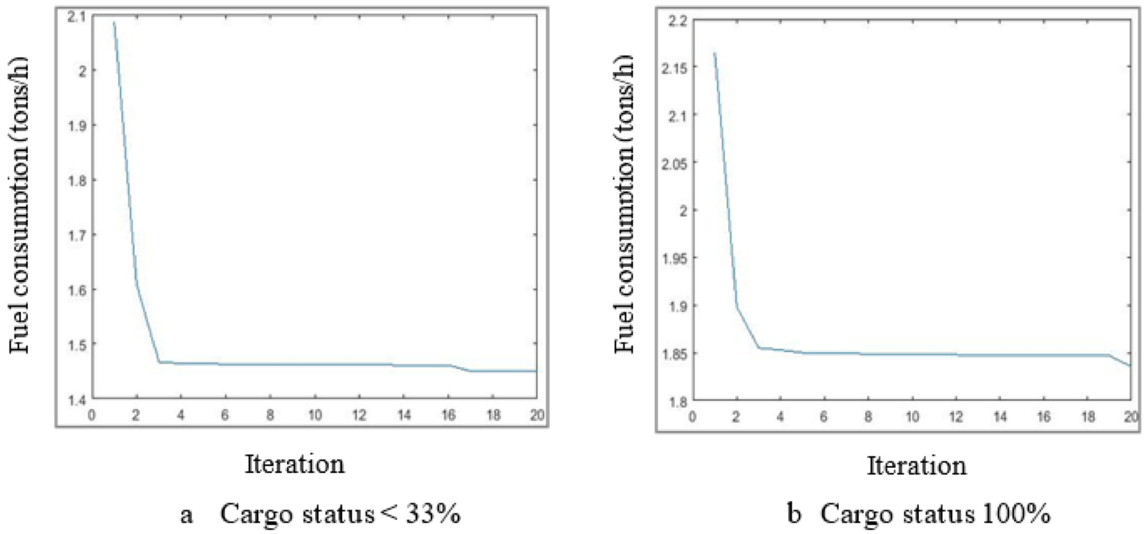
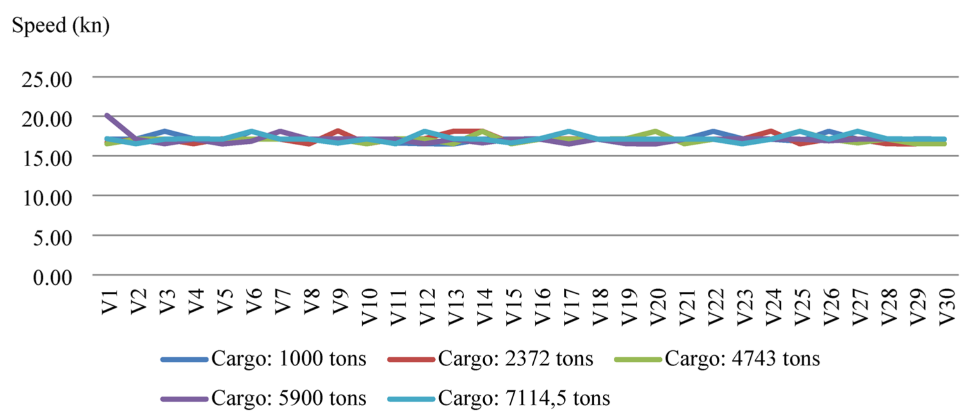


Fig. 7 GA iteration and fuel consumption graphs at weather condition 1

Fig. 8 Optimum speeds at different cargo status for weather condition 2



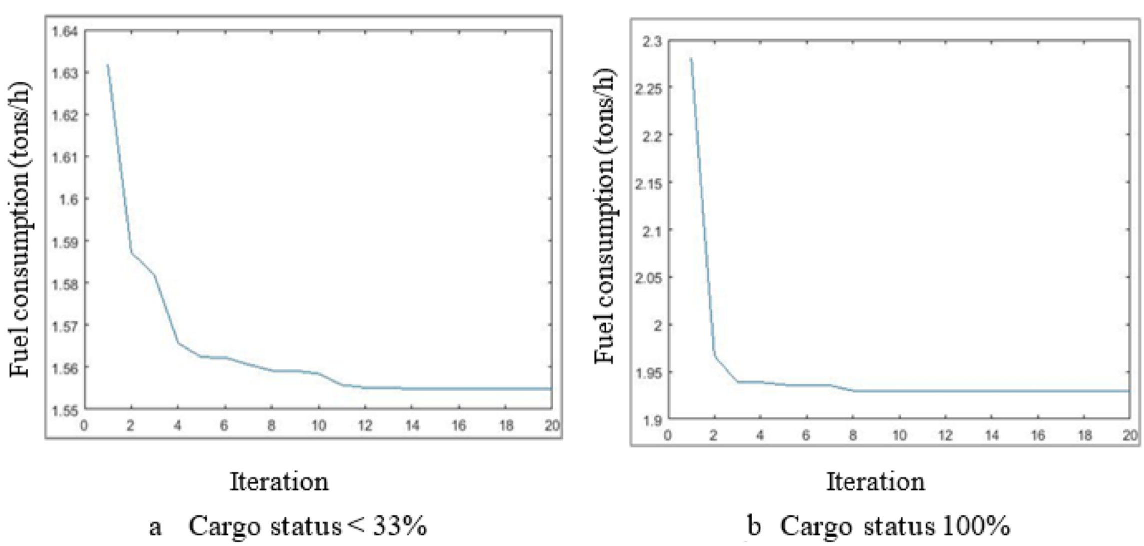
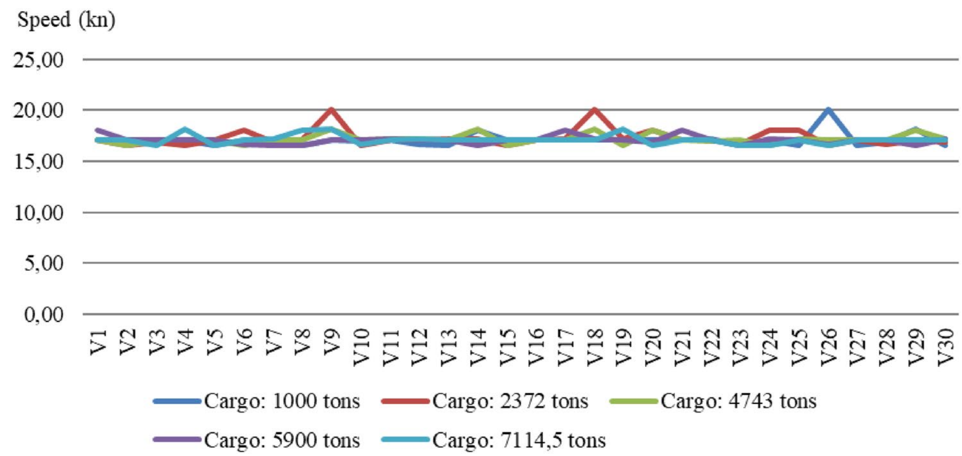


Fig. 9 GA iteration and fuel consumption graphs at weather condition 2

Fig. 10 Optimum speeds at different cargo statuses for weather condition 3



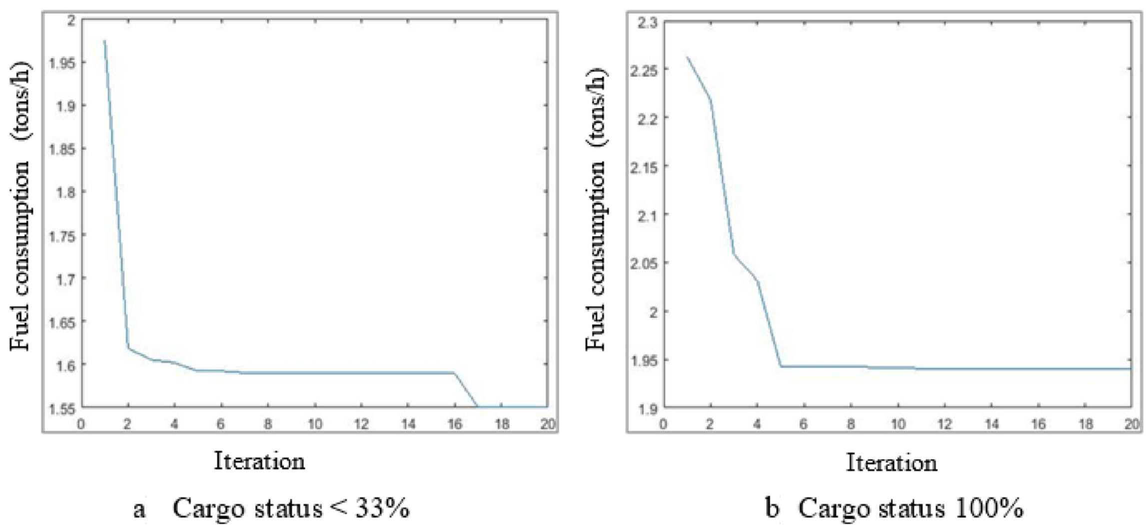


Fig. 11 GA iteration and fuel consumption graphs at weather condition 3

Table 4 Model ships' 236 days of data

Cargo status		Sailing period (days)	Average speed (kn)	Average fuel consumption (tons/h)
Rate (%)	Amount (tons)			
< 33	< 2372	16	19.14	2.24
33–66	2372–4743	78	19.28	2.33
66–100	4743–7114.5	142	19.09	2.40

to 1.55 tons/h (Fig. 11a). On the other hand, at 100% cargo status after 5th fuel consumption drops from 2.25 to 1.95 tons/h (Fig. 11b).

Model ships' 236 days of data is shown in Table 4 in order to compare with optimization results.

According to model ships' data, as shown in Table 4, on average, model ships sailed with three different cargo rates at 236 days' period of total sailing data. Ships sailed with the highest rate of cargo (66–100%) within 142 days, whereas the sailing period with the lowest rate of cargo (< 33%) is just 16 days. In addition to this, the average wind and sea states of a total of 236 days sailing period are 4 and 3, respectively.

For a more detailed explanation of speed optimization, the results for all weather conditions were summarized in Table 5.

As seen in Table 5, optimum speed values at all cargo statuses for each weather condition are in the same range, between 16.59 and 17.29 kn. On the other side, there is a correlation between fuel consumption and cargo status. Fuel consumption rises whenever freight increases. The lowest fuel consumption at all weather conditions occurs at the lowest cargo rate (< 33%, 1000 tons), while the highest fuel consumption occurs at the highest cargo rate (100%, 7114.5 tons). Besides, it is already known that cargo amount is directly proportional to fuel consumption [41, 48].

Table 5 Speed and fuel consumption values at all weather conditions

Cargo status		Weather condition 1 *Sea state: 2* *Wind state:3*		Weather condition 2 *Sea state: 5* *Wind state:5*		Weather condition 3 *Sea state: 7* *Wind state: 8*	
Rate (%)	Amount (tons)	Speed (kn)	Fuel consumption (tons/h)	Speed (kn)	Fuel consumption (tons/h)	Speed (kn)	Fuel consumption (tons/h)
< 33	1000	17.10	1.48	17.13	1.56	17.10	1.59
33	2372	17.18	1.55	16.59	1.66	17.29	1.65
66	4743	17.04	1.70	17.06	1.78	17.18	1.79
> 66	5900	17.00	1.77	17.09	1.85	17.00	1.87
100	7114.5	17.00	1.87	17.19	1.96	17.00	1.95

When viewed from the hull resistance respect, heavier weather conditions cause more fuel consumption. When the cargo status is constant, fuel consumption increases distinctly, especially in weather condition 2 in comparison with weather condition 1. In 1000 tons of cargo (< 33%) status, fuel consumption is 1.48 tons/h at weather condition 1, while fuel consumption is 1.56 tons/h at weather condition 2. But then exceptional cases exist. When the cargo amounts are 2372 tons and 7114.5 tons in weather condition 2, fuel consumptions are 0.01 tons/h lower than the values in weather condition 3. Computational results show that at the same cargo status, passing from weather condition 1 to 2 gives rise to more fuel consumption than from weather condition 2 to 3. Even in some cargo statuses, fuel consumption reduces too little while passing from weather condition 2 to 3. This situation does not support the idea that wind and sea states affect ship speed negatively and increase fuel consumption [61, 62, 64].

It is known that the ballast amount on board is one of the other factors affecting ship speed [73]. Within this framework, ballast amounts on board were used in the GA model in order find out the optimum ballast amount depending on weather conditions and cargo status. However, GA model findings show that the ballast amount for all cargo and weather conditions varies between 1118.0 and 1354.0 tons. These values are close and do not have an obvious effect on ship speed.

As a whole, speed optimization results indicate that there are no significant speed changes depending on cargo status in three different weather conditions. All values are close to each other. The root cause of this situation is that model ships are under the liner shipping service; further, independent cargo status ships have to maintain their speed in order to prevent any delay in the voyage table. Moreover, whenever cargo amount increases, ships' engine load increases. Engine load makes the frictional loads higher, so ship speed decreases. Furthermore, as the ship's cargo increases and the weather conditions worsen, fuel consumption rises in order to maintain ship service speed. This finding supports the related works in the literature [19, 20, 23, 24, 41].

5.4 The impact of speed optimization on exhaust gas emissions

As a result of speed optimization, the ships now have the lowest fuel usage. Thus, hazardous gas emissions from ships are decreased as well. The quantity of hazardous gas emissions caused by ship fuels is known to be calculated by multiplying the amount of fuel consumed and the emission factors of the corresponding gas [74–76].

It is relatively rare for the load amounts and weather conditions determined in the study to be identical in the data set. Therefore, rather than focusing on specific load and weather circumstances, the effect of reducing harmful gas emissions to the environment by determining the optimum speeds has been analyzed from a broad perspective. In this regard, the total fuel consumption of model ships at two different navigation points was first computed using their average fuel consumption and average speed for all cargo-weather conditions. Then, based on the average of the optimal speeds determined by the study and the associated average fuel consumptions, the total fuel usage for two distinct navigation points was estimated. Table 6 shows the overall fuel consumptions based on two different voyage points where the model ships operate.

Table 6 represents the comparison of the values obtained as a result of speed optimization and the values in the data set (before speed optimization) for two different voyage points on which model ships operate. The Pendik-Trieste-Pendik (PEN-TRI-PEN) line is 2372 miles long, while the Pendik-Toulon-Pendik (PEN-TOU-PEN) line is 2739 miles long. The optimal speeds determined by these two route lengths and the average speeds in the data set were compared, and the voyage durations and total fuel consumption were calculated. In both cases, strait crossings and manoeuvring periods are not calculated and are not added to fuel

Table 6 A comparison of the values obtained as a result of speed optimization and the data set values

Voyage legs	Average speed (kn)	Average consumption (t/h)	Average consumption (ton)	Duration (h)
Values obtained as a result of speed optimization				
Pendik-Trieste-Pendik (2372 miles)	17.06	1.73	240.52	139.03
Pendik-Toulon-Pendik (2739 miles)	17.06	1.73	277.75	160.55
Values obtained before speed optimization				
Pendik-Trieste-Pendik (2372 miles)	19.15	2.37	293.54	123.86
Pendik-Toulon- Pendik (2739 miles)	19.15	2.37	338.95	143.02

consumption and voyage duration. While the average optimal speed for two voyage points is 17.06 knots, the average speed from the dataset is 19.15 knots. The overall cost for the PEN-TRI-PEN line is 240.52 tonnes, with an hourly expenditure of 1.73 tonnes coming from the average optimum speeds reached. Compared to the former speed average, this result is 53.02 tonnes less than the fuel consumption (293.54 tonnes). On the other hand, the PEN-TOU-PEN line consumes a total of 277.75 tonnes of fuel during the voyage as a result of fuel consumption based on optimum speeds, compared to 338.95 tonnes prior to determining the optimum speed. As a result, because the optimum speed of the PEN-TOU-PEN line is calculated, fuel consumption is decreased by an average of 61.20 tonnes.

Using the difference in total fuel consumption between the two voyage points before and after optimum speeds are determined, it is possible to find optimum speeds that result in less hazardous gas emissions. The amount of harmful gas emissions resulting from the total amount of fuel consumed during the voyage is determined by the amount of fuel consumed and the corresponding gas emission factor [74–76].

$$Et = Fc \times Ef \tag{4}$$

Above is the equation for this calculation. The following are the symbols used in this equation:

Et: amount of emission produced, *Fc*: total fuel consumption, *Ef*: emission factor.

As a result of speed optimization, 53.02 tonnes less fuel was consumed during the PEN-TRI-PEN voyage, and 61.20 tonnes less fuel was consumed during the PEN-TOU-PEN voyage. The emission quantities resulting from these changes in fuel consumption are as follows:

5.4.1 *CO_2 emission*

Since model ships utilize HFO as fuel, the emission factor (Ef) for CO_2 is 3.11440 tonnes of CO_2/ton of fuel [77, 78]. The fuel consumption (Fc) for the PEN-TRI-PEN voyage is 53.02 tonnes, whereas the PEN-TOU-PEN voyage is 61.20 tonnes. When the relevant values are replaced in the formula:

The lower CO_2 amount emitted into the atmosphere with the determination of speed optimization for the PEN-TRI-PEN voyage is:

$$Et = 53.02 \times 3.11440 = 165.12\,\textit{tonnes of}\ \mathrm{CO_2},$$

The lower CO_2 amount emitted into the atmosphere with the determination of speed optimization for the PEN-TOU-PEN voyage is:

$$Et = 61.20 \times 3.11440 = 190.60\,\textit{tonnes of}\ \mathrm{CO_2}.$$

5.4.2 *NO_x emission*

In calculating the amount of NO_x emissions, the NO_x factor is determined based on the engine's speed. The main engines of the model ships operate at 500 rpm. Ships with a main engine speed between 200 and 1000 rpm emit around 70 kg of NO_x per ton [16, 79]. According to the calculation, the emission factor (*Ef*) for NO_x is thus 70 kg/ton of fuel. The lower NO_x amount emitted into the atmosphere with the determination of speed optimization for the PEN-TRI-PEN voyage is:

$$Et = 53.02 \times 70 = 3711.40\,\mathrm{kg\,NO_x},$$

The lower NO_x amount emitted into the atmosphere with the determination of speed optimization for the PEN-TOU-PEN voyage is:

$$Et = 61.20 \times 70 = 4284.00\ \mathrm{kg\ NO_x}.$$

5.4.3 *SO_x emission*

During the voyage, model ships used HFO fuel with a sulphur level of 3.5%. Multiplying the sulphur ratio with the coefficient value "20" gives the sulphur emission factor [16, 80]. When the relevant values are replaced in the formula, the SO_x emission factor is calculated as follows:

$$Ef = 3.5(\%) \times 20\ \mathrm{kg/ton} = 70\ \mathrm{kg/ton}.$$

Table 7 Changes in fuel consumption and harmful gas emissions resulting from speed optimization

Pendik-Trieste-Pendik line			Pendik-Toulon-Pendik line		
Fuel consumption change (ton)	Emission amount change (ton)		Fuel consumption change (ton)	Emission amount change (ton)	
– 53.02	CO_2	– 165.12	– 61.20	CO_2	– 190.60
	NO_x	– 3.7114		NO_x	– 4.284
	SO_x	– 3.7114		SO_x	– 4.284

The lower SO_x amount emitted into the atmosphere with the determination of speed optimization for the PEN-TRI-PEN voyage is:

$Et = 53.02 \times 70 = 3711.40$ kg SO_x.

The lower SO_x amount emitted into the atmosphere with the determination of speed optimization for the PEN-TOU-PEN voyage is:

$Et = 61.20 \times 70 = 4284.00$ kg SO_x.

Table 7 displays the harmful gas emission levels computed based on fuel consumption as a consequence of determining speed optimization.

As shown in Table 7, speed optimization results in a 53.02-ton reduction in voyage-based fuel consumption on the Pendik-Trieste-Pendik line and a 61.20-ton reduction on the Pendik-Toulon-Pendik line. On the Pendik-Trieste-Pendik line, the speed optimization reduced CO_2 emissions by 165.12 tonnes and NO_x and SO_x emissions by 3.71 tonnes and 3.7114 tonnes, respectively. Depending on the speed optimization, CO_2 emissions on the Pendik-Toulon-Pendik line are lowered by 190.60 tonnes, and NO_x and SO_x emissions are reduced by 4.28 tonnes per hour. According to the data obtained, based on one-time fuel consumption, speed optimization reduces fuel consumption and, consequently, the amount of harmful gas emissions emitted to the atmosphere. Studies on speed optimization and the reduction of harmful gas emissions are currently being published in the literature [22, 36]. In this context, the study's findings are consistent with the literature.

6 Conclusions

The present study aims to determine speed optimization depending on ships' cargo amounts and wind-sea states to reduce fuel consumption and of course GHG emissions. We presented an analysis of two models of Ro–Ro cargo sister ships' previous data related to fuel consumption, including daily fuel consumption, daily average ship speed, sea and wind states, ballast water amount, and cargo amount. Some factors including still water resistance, vertical forces, keel fouling resistance, propeller/pitch optimization, and seawater depth, were neglected and speed limitation was determined since the model ships are under liner shipping service. Based on the model ships' stability manual and previous voyage timetables, five different cargo levels and three different weather conditions that model ships frequently sailed were determined. Optimum speed values resulting in low fuel consumption were determined for different cargo levels and weather conditions. Almost the same speed values were found for each cargo level, even in different weather conditions. Fuel consumption rises depending on severe weather conditions and higher cargo levels in which ship speed stays constant. This situation can be explained by the fact that model ships are under liner shipping service, and in liner shipping, ships have to maintain the service speed in order to avoid any delay on voyage timetables.

Apart from well-known conclusions, this study found optimum speed values (16.59–17.29 kn) for each cargo level depending on weather conditions for Ro–Ro cargo ships working in round-trip service. However, independent of voluntary speed reduction and positive wind and sea states, this study shed light on determining optimum speed values of Ro–Ro cargo fleets that are in round trip service. In addition, depending on speed optimization and reduction of total voyage fuel consumption, a nearly 18% of reduction in exhaust gas emission in mass sourcing from the ship's main engine occurred.

Future research can be carried out to analyse more complex speed optimization on the whole fleet, adding other factors, including pitch/rpm settings, hull fouling and fuel consumption values at the port period. On the other hand, exhaust gas emissions beyond sourcing from ships' main engines, such as auxiliary engines and boilers and different fuel types, can be considered in future studies for improving and expanding the other studies.

Data availability Data are available on request due to privacy or other restrictions.

References

1. Lillebøa AI, Pitab C, Garcia Rodrigues J, Ramose S, Villasante S (2017) How can marine ecosystem services support the blue growth agenda? Mar Policy 81:132–142
2. European Commission (2012) Blue growth opportunities for marine and maritime sustainable growth. http://eur-lex.europa.eu. Accessed 19 Oct 2022
3. IOC/UNESC (2011) A blueprint for ocean and coastal sustainability. http://www.unesco.org. Accessed 17 Oct 2022
4. UNEP (2015) Blue economy: sharing success stories to inspire change. http://unep.org/greeneconomy. Accessed 11 Oct 2022
5. Eikeseta AM, Mazzarellaa AB, Davíðsdóttire B, Klingerb DH, Levinb SA, Rovenskayac E, Stenseth NC (2018) What is blue growth? The semantics of "Sustainable Development" of marine environments. Mar Policy 87:177–179
6. Burgess MG, Clemence M, McDermott GR, Costello C, Gaines SD (2018) Five rules for pragmatic blue growth. Mar Policy 87:331–339
7. Fernández-Macho J, Murillas A, Ansuategi A, Escapa M, Gallastegui C, González P, Prellezo R, Virto J (2015) Measuring the maritime economy: Spain in the European Atlantic Arc. Mar Policy 60:49–61
8. Tijan E, Jović M, Hadžić AP (2021) Achieving blue economy goals by implementing digital technologies in the maritime transport sector. Sci J Marit Res 35:241–247
9. UNCTAD (2022) Review of maritime transport 2021. https://unctad.org/system/files/official-document/rmt2021_en_0.pdf. Accessed 10 Oct 2022
10. Bialystocki N, Konovessis D (2016) On the estimation of ship's fuel consumption and speed curve: a statistical approach. J Ocean Eng Sci 1:157–166
11. Ritchie H, Roser M (2020) Emissions by sector. https://ourworldindata.org/emissions-by-sector. Accessed 05 Oct 2022
12. IMO (2020) Fourth IMO GHG Study 2020. https://wwwcdn.imo.org/localresources/en/OurWork/Environment/Documents/Fourth%20IMO%20GHG%20Study%202020%20-%20Full%20report%20and%20annexes.pdf. Accessed 10 May 2022
13. Bagoulla C, Guillotreau P (2020) Maritime transport in the French economy and its impact on air pollution: an input-output analysis. Mar Policy 116:1–9
14. Froehlich HE, Afflerbach JC, Frazier M, Halpern BS (2019) Blue growth potential to mitigate climate change through seaweed offsetting. Curr Biol 29:3087–3093
15. UNFCCC (2022) United Nations climate change, The Paris Agreement. https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement. Accessed 03 Mar 2022
16. IMO (2020) Cutting sulphur oxide emissions. https://www.imo.org/en/MediaCentre/HotTopics/Pages/Sulphur-2020.aspx. Accessed 12 Apr 2022
17. IMO (2008) Nitrogen oxides (NOx)—Regulation 13. https://www.imo.org/en/OurWork/Environment/Pages/Nitrogen-oxides-(NOx)-%E2%80%93-Regulation-13.aspx. Accessed 14 Apr 2022
18. Traut M, Larkin A, Anderson K, McGlade C, Sharmina M, Smith T (2018) CO_2 abatement goals for international shipping. Clim Policy 18:1066–1075
19. Norstad I, Fagerholt K, Laporte G (2011) Tramp ship routing and scheduling with speed optimization. Transp Res Part C 19:853–865
20. Gelareh S, Meng Q (2010) A novel modelling approach for the fleet deployment problem within a short-term planning horizon. Transp Res Part E 46:76–89
21. Qi X, Song DP (2012) Minimizing fuel emissions by optimizing vessel schedules in liner shipping with uncertain port times. Transp Res Part E 48:863–880
22. Du Y, Chen Q, Quan X, Long L, Fung RYK (2011) Berth allocation considering fuel consumption and vessel emissions. Transp Res Part E 47:1021–1037
23. Kontovas C, Psaraftis H (2011) Reduction of emissions along the maritime intermodal container chain: operational models and policies. Marit Pol Manag 38:451–469
24. Wang S, Meng Q (2012) Sailing speed optimization for container ships in a liner shipping network. Transp Res Part E 48:701–714
25. Kim JG, Kim HJ, Lee TW (2014) Optimizing ship speed to minimize fuel consumption. Transp Lett 6:109–117
26. Wijayaningrum VN, Mahmudy WF (2016) Optimization of ship's route scheduling using genetic algorithm. Indones J Electr Eng Comput Sci 2:180–186
27. Zhen L, Hu Z, Yan R, Zhuge D, Wang S (2020) Route and speed optimization for liner ships under emission control policies. Transp Res Part C Emerg Technol 110:330–345
28. Psaraftis HN (2019) Speed optimization vs speed reduction: the choice between speed limits and a bunker levy. Sustainability 11:1–18
29. Ma W, Lu T, Ma D, Wang D, Qu F (2020) Ship route and speed multi-objective optimization considering weather conditions and emission control area regulations. Marit Policy Manag 48:1053–1068
30. Tran AT (2019) Investigate the energy efficiency operation model for bulk carriers based on Simulink/Matlab. J Ocean Eng Sci 4:211–226
31. Yang L, Chen G, Zhao J, Rytter NGM (2020) Ship speed optimization considering ocean currents to enhance environmental sustainability in maritime shipping. Sustainability 12:3649
32. Tzortzis G, Sakalis G (2021) A dynamic ship speed optimization method with time horizon segmentation. Ocean Eng 226:108840
33. Zhou T, Hu Q, Zhen R (2022) An adaptive hyper parameter tuning model for ship fuel consumption prediction under complex maritime environments. J Ocean Eng Sci 7:255–263
34. Aydın N, Lee H, Mansouri SA (2017) Speed optimization and bunkering in liner shipping in the presence of uncertain service times and time windows at ports. Eur J Oper Res 259:143–154
35. Yao Z, Ng HS, Lee LH (2012) A study on bunker fuel management for the shipping liner services. Comput Oper Res 39:1160–1172
36. Kim HJ, Chang YT, Kim TK, Kim KT (2012) An epsilon-optimal algorithm considering greenhouse gas emissions for the management of a ship's bunker fuel. Transp Res Part D 17:97–103
37. Mao W, Rychlik I, Wallin J, Storhaug G (2016) Statistical models for the speed prediction of a container ship. Ocean Eng 126:152–162
38. Li X, Sun B, Guo C, Du W, Li Y (2020) Speed optimization of a container ship on a given route considering voluntary speed loss and emissions. Appl Ocean Res 94:1–10
39. DFDS (2022) Fleet. http://www.dfds.com.tr/company-profile/en/665/fleet/48. Accessed 10 Mar 2022
40. DFDS (2022) Route information. http://www.dfds.com.tr/intermodal/en/5/trieste-munich/1545. Accessed 10 Mar 2022
41. Meng Q, Du Y, Wang Y (2016) Shipping log data based container-ship fuel efficiency modelling. Transp Res Part B 83:207–229
42. Ballou P, Chen H, Horner JD (2008). Advanced methods of optimizing ship operations to reduce emissions detrimental to climate change. In: Oceans 08 conference, MTS/IEEE Proceedings
43. Thomas D, Surendran S, Vasa NJ (2021) A simplified approach for voyage analysis of fouled hull in a tropical marine environment. Ships Offshore Struct 16:762–772
44. Corbett JJ, Wang H, Winebrake JJ (2009) The effectiveness and costs of speed reductions on emissions from international shipping. Transp Res Part D 14:593–598
45. Smith TWP, Parker S, Rehmatulla N (2011) On the speed of ships. https://www.researchgate.net/profile/Nishatabbas_Rehma

tulla/publication/312041778_On_the_speed_of_ships/links/586c162808ae6eb871bb714a/On-the-speed-of-ships.pdf. Accessed 5 Apr 2022
46. Beşikçi EB, Kececi T, Arslan O, Turan O (2016) An application of fuzzy-AHP to ship operational energy efficiency measures. Ocean Eng 121:392–402
47. Wang S (2016) Fundamental properties and pseudo-polynomial time algorithm for network containership sailing speed optimization. Eur J Oper Res 250:46–55
48. Psaraftis HN, Kontovas CA (2014) Ship speed optimization: concepts, models and combined speed-routing scenarios. Transp Res Part C 44:52–69
49. Kowalski A (2013) Cost optimization of marine fuels consumption as important factor of control ship's sulphur and nitrogen oxides emissions. Sci J Marit Univ Szczecin 36:94–99
50. Perakis AN, Papadakis NA (2006) Fleet deployment optimization models. Part 1. Marit Pol Mangt 127–144
51. Perakis A N, Papadakis N A (2006) Fleet deployment optimization models. Part 2. Marit Pol Mangt 145–155
52. Wang S, Meng Q, Liu Z (2013) Bunker consumption optimization methods in shipping: a critical review and extensions. Transport Res Part E Logist Transport Rev 53:49–62
53. Shaoze L, Ning M, Hirakawa Y (2016) Evaluation of resistance increase and speed loss of a ship in wind and waves. J Ocean Eng Sci 1:212–218
54. Soares CG, Moan T (1988) Statistical analysis of stillwater load effects in ship structures. SNAME Trans 96:129–156
55. The Naval Architect (2022) Statistical analysis software & speed loss evaluation. https://www.academia.edu/29791325/Statistical_analysis_software_and_speed_loss_evaluation. Accessed 08 Mar 2022
56. Beşikçi EB, Arslan O, Turan O, Ölçer AI (2016) An artificial neural network based decision support system for energy efficient ship operations. Comput Oper Res 66:393–401
57. SPC (2022) Beaufort wind scale. https://www.spc.noaa.gov/faq/tornado/beaufort.html. Accessed 07 Mar 2022
58. WDCS (2022) Beaufort sea states. http://www.wdcs.org/submissions_bin/WDCS_Shorewatch_Seastate.pdf. Accessed 07 Mar 2022
59. Perera PL, Mo B (2018) Ship speed power performance under relative wind profiles in relation to sensor fault detection. J Ocean Eng Sci 3:355–366
60. Bassam AM, Philips AB, Turnock SR, Wilson PA (2015) Ship voyage energy efficiency assessment using ship simulators. In: VI international conference on computational methods in marine engineering MARINE 2015, Rome
61. Kosmas OT, Vlachos DS (2012) Simulated annealing for optimal ship routing. Comput Oper Res 39:576–581
62. Orsic JP, Faltinsen OM (2012) Estimation of ship speed loss and associated CO_2 emissions in a seaway. Ocean Eng 44:1–10
63. Wang HB, Li XG, Li PF, Veremey EI, Sotnikova MV (2018) Application of real-coded genetic algorithm in ship weather routing. J Navig 71:989–1010
64. Armstrong VN (2013) Vessel optimization for low carbon shipping. Ocean Eng 73:195–207
65. Hellstrom T (2004) Optimal pitch, speed and fuel control at sea. J Mar Sci Technol 12:71–77
66. Svetak J (2001) Ship squat. Promet-Traffic-Traffico 13:247–251
67. Dündar S, Şahin İ (2013) Train re-scheduling with genetic algorithms and artificial neural networks for single-track railways. Transport Res Part C Emerg Technol 27:1–15
68. Al-Hamad K, Al-İbrahim M, Al-Enezy E (2012) A genetic algorithm for ship routing and scheduling problem with time window. Am J Oper Res 2:417–429
69. Kruse R, Borgelt C, Klawonn C, Moewes C, Steinbrecher M, Held P (2013) Computational intelligence. Springer, London
70. Kunjur A, Krishnamurty S (1997) Genetic algorithms in mechanism synthesis. J Appl Mech Robot 4:18–24
71. Evgeniou T, Pontil M (2001) Support vector machines: theory and applications. Springer, Berlin
72. Awad M, Khanna R (2015) Support vector regression. In: Efficient learning machines. Apress, Berkeley
73. Wang C, Xu C (2015) Sailing speed optimization in voyage chartering ship considering different carbon emissions taxation. Comput Ind Eng 89:108–115
74. Gusti PA, Semin S (2016) The effect of vessel speed on fuel consumption and exhaust gas emissions. Am J Eng Appl Sci 9:1046–1053
75. Saputra H, Muvariz MF, Satoto SW, Koto J (2015) Estimation of exhaust ship emission from marine traffic in the straits of Singapore and Batom waterways using automatic identification system (AIS) data. Jurnal Teknologi 77:47–53
76. Pitana T, Kobayashi E, Wakabyashi N (2010) Estimation of exhaust emissions of marine traffic using automatic identification system data (case study: Madura strait area, Indonesia). In: Oceans 2010 IEEE conference publication, pp 1–6
77. IMO (2014) Third IMO GHG study. Executive summary and final report. https://greenvoyage2050.imo.org/wp-content/uploads/2021/01/third-imo-ghg-study-2014-executive-summary-and-final-report.pdf. Accessed 10 Apr 2022
78. Shipping KPI (2022) Key performance indicator. https://www.shipping-kpi.org/book/definition/KPI005. Accessed 12 Apr 2022
79. Shipping KPI (2022) Key performance indicator. https://www.shipping-kpi.org/book/definition/KPI021. Accessed 12 Apr 2022
80. Shipping KPI (2022) Key performance indicator. https://www.shipping-kpi.org/book/definition/KPI030. Accessed 12 Apr 2022