

The Relationship between Trim and Fuel Consumption for a Vessel

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Abstract. The objective of this study is to find the influence of the trim of a ship on the hydrodynamic resistance and the associated fuel consumption of a container ship. The KRISO Container Ship (KCS) design is used in this study as the reference vessel. It is a container ship that has been used in many research studies and towing tank experiments. The main dimensions of the ship are 232.5 m in length, 32.2 m in breadth, and 10.8 m in draft. In this study, we develop a data-driven model that can predict the total resistance coefficient under different trim angles, weather, and operational conditions. A dataset was generated using experimental results from towing tank tests conducted in NIMALA (a LAB developed by Sharif University of Technology, Tehran, Iran). The dataset includes the vessel's speed, trim, wave characteristics, and list angle. Various regression algorithms were used and evaluated to find the most accurate predictive model. The results indicate that trim has a measurable influence on the total resistance coefficient and therefore indirectly affects the fuel consumption. The findings of this research could contribute to a better understanding of trim optimization and assist in improving fuel efficiency in merchant ship operations.

1. Introduction

1.1 Reduction of fuel consumption

Fuel consumption is a key point in the maritime industry due to its economic and environmental effects. Sometimes, half of all operational expenses is related to fuel cost, which shows its share of the total operating expenses. Environmental factors also make fuel consumption crucial. Sulphur oxides (SO_x), nitrogen oxides (NO_x), and carbon dioxide (CO₂) are some of the greenhouse gases released by the shipping sector.

International agreements such as MARPOL Annex VI set restrictions on sulphur oxide (SO_x) emissions and require vessels to implement measures to lower their environmental impact. [1]. IMO has established regulations that additionally assist in reducing the CO₂ emissions. EEDI (Energy Efficiency Design Index), IMO is setting mandatory efficiency standards for new ships, anticipating a 30% reduction in CO₂ emissions per tonne-mile by 2025 [2]. Also, by providing best practices and performance monitoring techniques in SEEMP (the Ship Energy Efficiency Management Plan), it guides ship operators to optimize their fuel consumption. Large merchant ships may consume thousands of litres of fuel per hour; thus, even small changes would be

valuable. It shows why energy efficiency programs are getting more and more important in modern marine operations, as they can result in significant economic savings and environmental benefits. [3].

1.2. Vessel trim

The trim of a ship means the horizontal inclination of the vessel caused by the distribution of weight on board. It is defined as the difference in the draft (vertical distance between the waterline and the keel of the ship) at the bow and stern. Usually, redistributing cargo, fuel, and ballast water helps to control the trim. Minimal resistance guaranteed by optimal trim helps the ship to pass through water, lowering the energy consumption and fuel economy. On the other hand, incorrect trim might cause more resistance, more fuel consumption, and even structural strain. Trimming optimization is important in modern ship design and operations to improve environmental sustainability and energy economy. [4].

1.3 Effects of ballast and freshwater tanks on trim and fuel consumption.

Real-time changes of trim can make it possible, by technologies including dynamic trim optimization and weather routing, to minimize the negative consequences of wind and waves. Ballast tanks are integral components of ships that help adjust trim, stability, and buoyancy. By filling or emptying these tanks with water, the weight distribution on the vessel can change and lead to the required draft and trim conditions. Excessive ballast water could, however, increase resistance and fuel consumption, since it raises the displacement of the ship. Also, ballast tanks should be kept full to avoid free surface effects, which can negatively affect the stability if not managed properly. Because of this, several ballast water tanks are available on modern ships. Advanced ballast water management systems and trim optimization software are being used more and more in recent years.

In many cases, a ship adjusts trim by emptying the ballast tanks. But today, for environmental reasons, draining the ballast tanks requires very special care to avoid pollution and the spreading of biomaterial. The water inside these tanks can contain small marine organisms, sediments, and sometimes pollutants picked up from other regions. If this water is released without proper control, it can introduce non-native species into new ecosystems, where they may harm local marine life. There is also a risk of spreading harmful bacteria or contaminating coastal waters. Because of this, strict regulations [5] require ships to manage and treat ballast water before discharge to reduce these environmental risks. Accordingly, the desired trim cannot be achieved by just draining the water. Another basic way to adjust trim is to transfer the ballast water longitudinally. This is only possible if the water level in the tanks is not too high. Therefore, if the water level in the ballast tanks is high, it is practically impossible to move large amounts of water. Thus, there will be little change in the amount of trim of the vessel. Therefore, it is necessary to be aware of the conditions and rules of ballast dumping.

1.4 Study objectives

The main research question of this study is:

- How does ship trim influence the total resistance coefficient of a container ship under different operational conditions, and can data-driven models accurately predict this relationship?

To address the research question, the following objectives are defined:

- Analyzing the influence of ship trim on the hydrodynamic resistance of a container ship.
- Developing a data-driven predictive model for the total resistance coefficient.

- Comparing different machine learning regression models for predicting ship resistance.
- Identifying trim configurations that minimize resistance under different operational conditions.

The use of trim to reduce fuel consumption should also incorporate practical considerations. Trim is very important for safe and smooth operation in ports and canals. These areas are often narrow and shallow, so ships need to be handled carefully to avoid accidents. Trim could reduce the under-keel distance so the vessel could hit the seabed and get stuck or damaged. In tight channels, wrong trim can also make the ship sink deeper in water because of speed and shallow depth, which increases the probability of grounding. For example, in the Ever-Given case in the Suez Canal, incorrect trim was one of the reasons the ship got stuck, showing why trim must be managed properly in such places.

1.5 Study assumptions

The vessel was tested at different speeds; however, only the tests using a constant vessel speed are considered in this paper. Under this assumption, any change in hydrodynamic resistance can be seen as a change in the propulsion power needed to keep the same speed, which is closely related to fuel consumption.

The draft of the vessel is assumed to remain equal to the design draft (10.8m) throughout the analysis. This assumption helps the study to focus on the effect of trim on the resistance coefficient, regardless of the effect of different drafts.

The hydrodynamic behaviour of the ship is evaluated based on experimental data obtained from towing tank tests performed in NIMALA (a LAB operated by Sharif University of Technology, Tehran, Iran) on a model of the KRISO Container Ship (KCS). In these tests, the hull is considered as a bare hull; the interaction between the propeller and the hull, propulsion efficiency, and engine performance are not directly included in the analysis. Also, the model's hull was smooth in the tests, while in real operating conditions, the hull may have corrosion, coating degradation, or marine growth that could increase the actual resistance of the vessel.

The environmental conditions, such as wave direction, length, and height, are also simplified in this study due to controlled experimental conditions, whereas in real sea operations, these parameters of waves and sea states may continuously change.

2. Literature study

This chapter provides an overview of existing research on trim optimization. Topics such as recent developments in data analysis, machine learning, modeling, and simulation tools are the main concerns in this literature review. The results of this review show why data-driven methods are going to be used for this research. It will also clarify which types of assumptions in this study could provide a closer situation with reality, and the reliability of the findings of this study.

2.1 Data Analytics and Machine Learning

Many recent studies have used data-driven approaches and machine learning techniques for optimizing trim and, as a direct consequence, reducing fuel consumption. These methods not only offer acceptable accuracy but also are much simpler and faster. In this section, important studies that are related to this research are reviewed.

Coraddu et al. [6] introduced a framework for predicting ship fuel consumption and optimizing trim by using data analysis methods. Their study shows that historical operational data can predict future performance.

Wang et al. [7], by adding engine data as extra inputs to other data, expanded this research by proposing new modeling approaches for optimizing speed and trim. Their findings emphasize that to improve prediction accuracy, integrating real-time engine parameters could be helpful.

Xie et al. [8] explored the use of machine learning to find the best combination of ship speed and trim, while also considering the effect of loading conditions. Optimizing these factors separately may not lead to the best outcome, and they should be evaluated together to achieve better fuel efficiency.

Also, Tu et al. [9] show that machine learning models can make predictions a lot more accurately, which can lead to better trim choices that lower the resistance.

Panagiotakopoulos et al. [4] show that by collecting data in real time, operations can make better decisions that could improve the energy economy in the long run.

2.2 Modeling and Simulation

Previous studies in this field have utilized various software tools to simulate hydrodynamic behavior for optimizing trim and reducing fuel consumption. Computational Fluid Dynamics (CFD) is a highly powerful, relatively simple tool. However, it has significant weaknesses in hydrodynamic simulations. The main reason for this limitation is the scale of the problem. Typically, a commercial vessel model requires large-scale computations. An additional challenge is that the simulation must be conducted in two phases (water and air), making it difficult to accurately model surface disturbances. Moreover, the complex geometry of the vessel's hull makes it challenging to generate a structured grid around it. Overcoming these issues requires an extremely powerful system, which leads to high computational costs.

The effect of optimizing trim on lowering fuel use was investigated by [10], who provided evidence that even small changes can result in notable fuel usage savings.

To anticipate the best trim configurations for vessels in terms of fuel consumption, see also [9] and [11- 18].

2.3 Experimental Studies

Experimental studies are one of the most important research methods for validating results. Typically, optimal trim for different vessels is obtained through model tests in basins under various sea conditions. Although the quantitative data from such studies may not be extensive due to the high costs and time-consuming nature of the experiments, their reliability makes them essential for comparison with the findings of existing numerical studies. In this section, several experimental studies are reviewed individually.

Musulini et al. [19] investigated how trim affects how much fuel container ships use and how safe they are to navigate. Their data showed that by choosing proper trim angles, fuel usage could be reduced by up to 15% in some situations.

A study by [20] found that using air lubrication and optimizing the trim could save more than 20% on fuel over time. For additional references, see [21 -23]

2.4 Theoretical Studies

While experimental studies are used to verify and determine accurate results, theoretical studies are very useful in understanding the principles governing a phenomenon. Extracting results from such methods requires the use of appropriate assumptions and tools, and this requires mastery of the equations governing the problem. Some theoretical studies related to trim optimization and reducing fuel consumption of various vessels are given in [24 – 26]

2.5 Case Studies

Case studies are highly focused on a specific objective and will usually lead to improved results related to a specific phenomenon. See [27]. In [28], the authors emphasized the necessity of training crews and making them aware of how trim affects energy efficiency.

3. Research gap and research methodology

There is limited work that combines towing tank experimental data with machine learning methods to analyse how trim and operating parameters influence the total resistance coefficient. This investigation will explore this relationship using a benchmark vessel dataset. To address this gap, this study uses experimental data from model testing the KRISO Container Ship (KCS), see Table 1 and Figure 1, together with data-driven modelling approaches to analyse the influence of trim and operational parameters on ship resistance [29]. Note that all parameters related to the vessel's geometry, sea conditions, and cruise conditions will directly affect the resistance of the vessel and, consequently, the fuel consumption of the vessel.

Table 1. Information on the Prototype and Experimental Models [30]

Parameter	Unit	Prototype	Lab. Model
Length (LBP)*	[m]	232.5	1.185
Breadth (B)	[m]	32.2	0.161
Draft (d)	[m]	10.8	0.055
Wetted Area (S)	[m ²]	9530	0.25
Block Coefficient (C _B)*	[-]	0.651	0.651
Water Density (ρ)	[kg/m ³]	1025	1025

*LBP = Length between perpendiculars

** The block coefficient C_B is the ratio between the displacement volume, ∇, of the vessel and the equivalent cubic volume, LBPd.



Figure 1. The model of the KCS ship that was tested in the towing tank [30].

4. Parameters of the real KCS ship and the model

The block coefficient of the KCS vessel is 0.651, which is not considered a slender merchant vessel. At the same time, the vessel does not have a high enough block coefficient to be considered a «fat» vessel.

The Froude number (Fn) is a dimensionless quantity that is used in fluid dynamics to show the ratio between inertial forces and gravity forces, $Fn = v / \sqrt{gL}$, where v is the characteristic flow velocity. In this study, the Froude number is used as one of the main parameters affecting the behavior of the vessel.

The total resistance coefficient is obtained through the following equation: $C_t = R_t / (0.5\rho Sv^2)$, where R_t is the total resistance of the vessel's hull, S is the wetted surface of the vessel.

The wavelength ratio, D , determines the ratio of the wavelength (λ) to the length of the ship (L). To create a complete similarity between the experiment and reality, dynamic, kinematic, and geometric similarities must be created simultaneously. The similarity ratio is defined as follows: $\lambda_s = D_p/D_m$. Here, D is the characteristic geometric parameter, such as length or diameter. The subscripts p and m stand for prototype or model, respectively. In this experiment, the ship length is considered the main geometric parameter. The similarity factors (based on Froude similarity, $Fr_p = Fr_m$) used in this study are summarized in Table 2.

Table 2. Similarity coefficients used in analyzing the results of the KCS vessel towing tank tests

Parameter	Symbol	Unit	Prototype/ Model
Length	L	[m]	λs
Velocity	V	[m/s]	$\sqrt{\lambda s}$
Time	T	[s]	$\sqrt{\lambda s}$
Frequency	f	[Hz]	$\frac{1}{\sqrt{\lambda s}}$
Acceleration	a	[m/s ²]	$\frac{1}{\lambda s}$
Force	F	[N]	λs^3
Mass	m	[kg]	λs^3
Power	P	[W]	$\lambda s^{3.5}$

5. Extending the database with machine learning algorithms.

A very large volume of data was removed from the dataset due to incomplete effective parameter values, as different scientists had carried out the tests. Finally, 891 data rows were considered as the main data. Many models in Python can be used to train datasets and predict results for various problems [31]. (Garreta & Moncecchi, 2013). The process of training datasets has some similarities in all models, but there are also some differences that will lead to differences in the answers to the problem. Therefore, in this study, several models were evaluated, and the results were compared for prediction and regression accuracy. 5 different regression models were used to find which method has the highest accuracy, and, in the end, the best method was chosen to predict the results. Different Standard Metrics were considered, and the results were compared with each other. Finally, the Extra Tree (ET) regression model was selected [32, 33]. By using this trained model, the influence of different operational parameters on the total resistance coefficient has been evaluated.

6. Results

The results from using the extended database show that a small trim can reduce the total resistance coefficient C_t , see Figures 2 to 4. For all sea states and the three representative Froude numbers ($Fn = 0.20, 0.26, 0.32$), the curves show a U-shaped behavior. This also shows that a slight bow trim could be the optimal trim, and moving away from this value towards larger positive trim leads to an intensive increase in C_t . Regarding the sensitivity of the parameters, the results did show that in the dataset used, dimensionless trim has the largest contribution to explaining the C_t variations. After that, List angle, Wavesteeptness, and then wavelength ratio were ranked [32].

An important point to note is that in real ship operation, maintaining optimal trim for the whole voyage is impossible due to ballast constraints, loading conditions, or operational limitations. Thus, it is essential to quantify the effect of deviation from optimal trim on the increase in C_t and fuel consumption. The increase in C_t caused by deviation from optimal trim is nonlinear [32]. Small deviations of ± 0.5 m response to relatively minor increases in C_t (1–4%), whereas moderate deviations of ± 1.5 m result in bigger increases ranging from approximately 7% up to 20%. Severe

deviations of ± 3 m produce the biggest resistance penalties approaching 45%, confirming that trim misalignment can significantly destroy the hydrodynamic performance. Therefore, understanding how trim evolves during a voyage and how it can be corrected in an operationally realistic way becomes an important step toward maintaining energy-efficient operation. For a vessel that is assumed to operate at a constant service speed, the change in the resistance coefficient can be interpreted as a similar change in fuel consumption. Therefore, neglecting trim correction during the voyage may lead to an increase in fuel consumption of roughly 1–1.5% [32] over two days. Maintaining the vessel close to the optimal trim condition through periodic ballast transfer can help avoid this additional fuel demand. It is, however, necessary to note that the conclusions are based on analysis of a certain ship; similar analysis must be conducted case by case to identify the effects for new ship geometries.

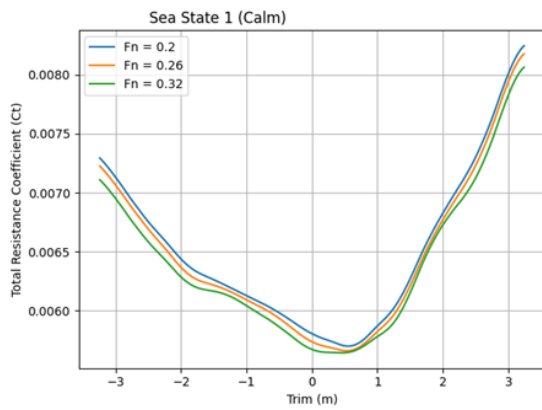


Figure 2. C_t -Trim at Calm water

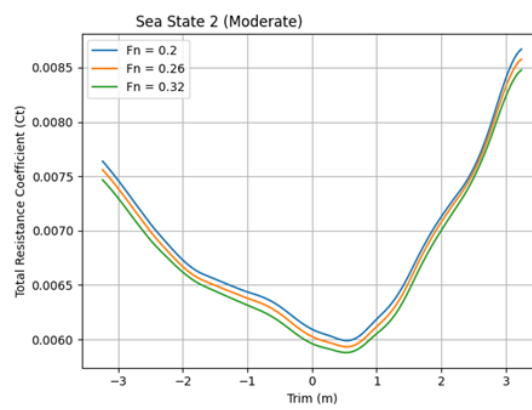


Figure 3. C_t -Trim at Moderate Sea state

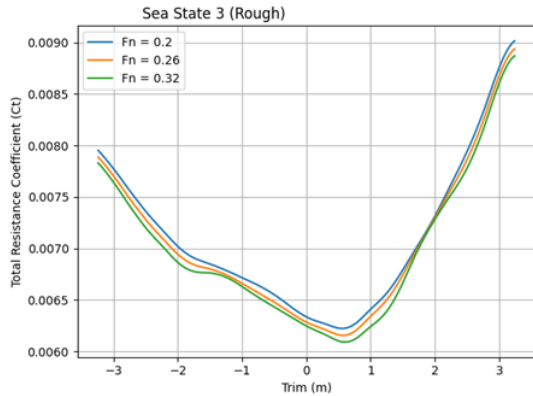


Figure 4. C_t -Trim at Rough Sea state

7. Limitations of the study and future work.

7.1 Limitations

Several limitations should be considered when interpreting the results of this study. First, the dataset used for training the machine learning model was obtained from towing tank experiments performed on a bare hull. Therefore, the effects of propeller–hull interaction, propulsion efficiency, and engine performance were not directly included in the analysis. Second, the hull condition in model tests is assumed to be smooth, while in real ship operations, hull roughness, fouling, and coating degradation may increase the actual resistance.

Another limitation of this study is the limited variation of ship speed. In the investigated speed range, the effect of trim on the total resistance coefficient was not always strongly seen.

Finally, the environmental conditions used in this study were simpler than real sea conditions. In the towing tank experiments, waves were generated in controlled conditions with fixed characteristics, while in real voyages, the sea state changes continuously and irregularly, and the wave direction may vary. In addition, operational factors such as cargo distribution, wind forces, and steering corrections were simplified in this study. As a result, the numerical values obtained in this work should be interpreted mainly as trends rather than exact operational predictions.

7.2 Future work

The proposed framework demonstrates that data-driven models can provide useful insights into the relationship between trim and ship resistance. Machine learning methods offer a relatively fast way to evaluate many operational scenarios and can support decision-making processes for ship operators.

Future work could extend the present study in several directions. One possible improvement would be the integration of propulsion system data, including engine power, propeller characteristics, and specific fuel consumption. Including these parameters would allow a more direct prediction of fuel consumption instead of relying on resistance as an indirect indicator.

Another important extension would be the use of real operational data collected from ships during voyages. Such datasets may include navigation data, weather information, and engine monitoring parameters. Combining this data with machine learning methods could lead to more accurate models that better represent real operational conditions.

Finally, the concept of dynamic trim correction could be further developed. In practical applications, trim optimization could be integrated with onboard monitoring systems that continuously evaluate the vessel condition and recommend ballast transfers when the trim deviates from the optimal range. Such systems could operate in combination with weather routing and voyage optimization tools, allowing ships to maintain energy-efficient conditions throughout the voyage.

Overall, this study shows that trim management remains an important operational parameter for improving the energy efficiency of merchant vessels. Even small improvements in resistance performance can contribute to noticeable fuel savings when applied over long voyages or across large fleets.

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