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Two-phase optimal solutions for ship speed and trim optimization over a voyage using voyage report data

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Abstract. In the daily operations of a shipping line, minimization of a ship's bunker fuel consumption over a voyage comprising a series of waypoints by adjusting its sailing speeds and trim settings plays a critical role in ship voyage management. To quantify the synergetic influence of sailing speed, displacement, trim, and weather and sea conditions on ship fuel efficiency, we first develop a tailored method to construct two artificial neural network models using ship voyage report data. We proceed to address this sailing speed and trim optimization problem by putting forward three viable countermeasures within a two-phase optimal solution framework: sailing speeds of the ship are optimized in an on-shore planning phase, whereas trim optimization is conducted dynamically by the captain in real time when she/he observes the actual weather and sea conditions at sea. In the on-shore speed optimization problem, simultaneous optimization of

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sailing speeds and trim settings is beneficial in suggesting more informed sailing speeds because both factors influence a ship's fuel efficiency. In Countermeasure 3, we address speed and trim optimization simultaneously by proposing a two-step global optimization algorithm that combines dynamic programming and a state-of-the-art simulation-based optimization approach. Numerical experiments with two 9000-TEU (twenty-foot equivalent unit) containerships show that (a) Countermeasure 1 saves 4.96% and 5.83% of bunker fuel for the two ships, respectively, compared to the real situation; (b) Countermeasure 2 increases the bunker fuel savings to 7.63% and 7.57%, respectively; and (c) the bunker fuel savings with Countermeasure 3 attain 8.25% on average. These remarkable bunker fuel savings can also translate into significant mitigation of CO_2 emissions.

Keywords: ship fuel efficiency; speed optimization; trim optimization; neural network; data-driven optimization

1. Introduction

Seaborne transportation is the backbone of international trade and the world economy: the volume of seaborne shipments totaled 10.7 billion tons in 2017 (UNCTAD, 2018). This large volume of seaborne cargoes is carried by ocean-going fleets consisting of 94,171 ships with a total tonnage of 1.92 billion (UNCTAD, 2018). In recent years, ship fuel efficiency has become a public concern in the shipping industry for environmental and commercial reasons. The International Maritime Organization (IMO) reported that the shipping industry was responsible for 949 million metric tons (MT) of global CO_2 emissions, or 2.7% of the total, in 2012 (Smith et al., 2014). In the commercial aspect, shipping companies are making unprecedented efforts to reduce ships' bunker consumption because the bunker fuel cost generally dominates the variable operating cost of a ship. After suffering from high fuel prices of USD 600 per MT and above for five years from 2009 to 2014, shipping companies still pay close attention to the fleet's bunker fuel consumption, mainly because of the current slump in the maritime transport market. To reduce fuel consumption, shipping lines have taken various measures, including slow steaming, virtual (just-in-time) arrival at ports, weather routing, hull and propeller cleaning, engine maintenance, and optimization of the operating plan for each ship or fleet (IMO, 2012).

A *voyage* represents the journey from the departure from one port to the arrival at the next port (IMO, 2009; all the consecutive voyages of a liner ship over a round service form a *trip*). Therefore, curbing the bunker fuel consumption of a ship over each voyage is one of the main concerns of a shipping line's ship operation department. Once a ship's sailing route over a voyage is determined, the main duty of voyage management that confronts the ship operation department is planning its daily sailing speeds and trim settings (aft draft minus forward draft; see Fig. 1). This voyage planning duty for speed and trim optimization can be explained as follows with the aid of

Fig. 2. The voyage under consideration, e.g. from Singapore to Jebel Ali, consists of n sailing *segments* connected by consecutive main *waypoints* at sea. The waypoints at the predefined geographic locations are used to verify the ship's on-time performance to avoid possible schedule delays over the voyage. Given the expected time of arrival (ETA) at the voyage's destination port and the weather and sea conditions over each sailing segment, the on-shore officers and/or the ship's captain at sea attempt to determine the ship's sailing speeds and trim settings over these n segments, denoted by $\{v_k\}_{k=1}^{n}$ and $\{t_k\}_{k=1}^{n}$, respectively, such that the bunker fuel consumption of the ship over the whole voyage is minimized while the ETA is maintained.

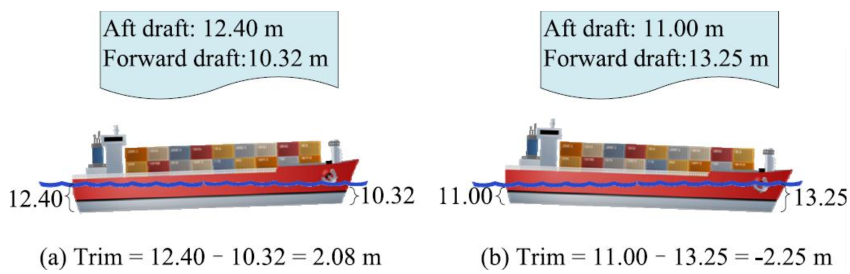


Fig. 1. Trim of a ship

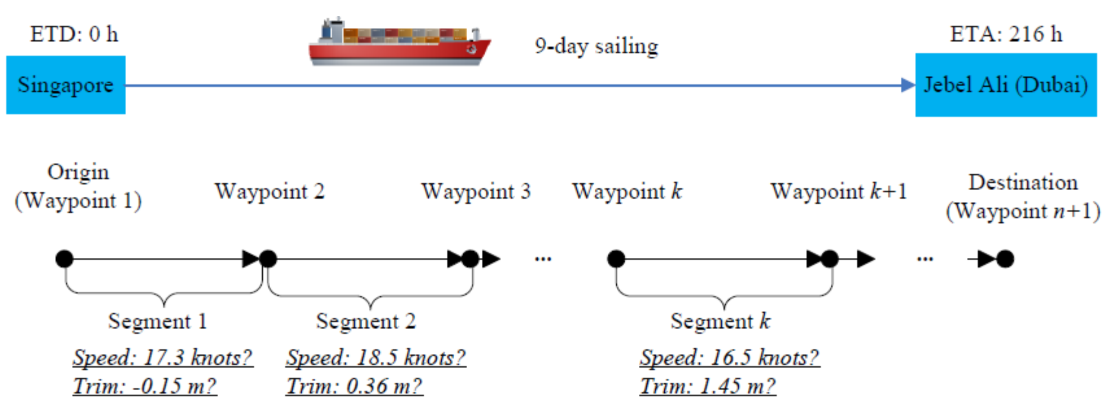


Fig. 2. Ship speed and trim optimization over a voyage

Let us first examine the current practice of ship speed and trim optimization over a voyage that has been adopted by the shipping industry, based on our long-term research collaboration with a global shipping line under a non-disclosure agreement.

Regarding speed management, the current practice is for the on-shore officers in charge of ship voyage management to simply issue the ETA at the destination and allow the captain at sea to determine the sailing speeds over the segments of the voyage. This practice is used because of the straightforward nature of the average speed calculation implied by the stringent ETA and because of the culture that has formed throughout the long history of commercial shipping in which the ETA is essentially the only speed-related instruction given by the shipping company to the captain, assuming that some special speed requirements (e.g., speed agreement items in a charter contract) are not considered. Therefore, planning of sailing speeds over consecutive segments of a voyage has basically been absent from ship voyage management. However, the high bunker fuel prices from 2009 to 2014 and the sluggish maritime transport market conditions in recent years have been motivating shipping companies to explore the possibility of further savings of bunker fuel by making fine adjustments in the daily sailing speeds of their ships by considering the actual weather, sea, and load conditions. One technical challenge that precludes finer planning of the ship's sailing speed is the lack of ship fuel efficiency models that enable on-shore officers to precisely estimate a ship's fuel efficiency at different speeds under different weather, sea, and load conditions.

Regarding trim optimization, captains use trim tables or charts (curves) in the process of trim adjustment. These trim tables or charts indicate which trim value leads to the highest energy efficiency given a combination of sailing speed and *displacement* (i.e., the total weight of the ship itself, the cargo, ballast water, and bunker, expressed in MT). The trim tables and charts for a particular ship are generally estimated from model-ship tests or computational fluid dynamics (CFD) simulations conducted by ship yards or classification societies, which usually adopt or assume a calm water environment (Reichel et al., 2014). Therefore, the current practice for ship speed and trim optimization over a voyage is very elementary without any advanced scientific support, and could be significantly improved by means of operations research techniques. The purpose of this study is to improve the current practice of speed and trim optimization over a voyage by developing some viable solution countermeasures based on optimization techniques and industry (voyage report) data collected by the operation department of a shipping company.

1.1. Literature Review

Many determinants influence the daily bunker fuel consumption of a ship at sea (referred to as *fuel efficiency* or *fuel consumption rate*, expressed in MT per day), including the sailing speed, displacement, trim, and weather and sea conditions (i.e., wind, waves, sea currents and sea water temperature). Among these factors, the influence of sailing speed is the most significant. It is well known that a ship's fuel consumption rate is proportional to its sailing speed to the power of α. The famous *cubic law* adopts $\alpha = 3$ (Carlton, 2012; MAN Diesel & Turbo, 2004). In reality, α can be much higher than 3 for containerships (e.g., 4, 5, or higher), especially at high speeds (Psaraftis and Kontovas, 2013). This inspired fruitful research into sailing speed optimization, together with optimization of shipping service network design (Agarwal and Ergun, 2008; Brouer et al., 2014; Angeloudis et al., 2016), service frequency determination (Notteboom and Vernimmen, 2009; Ronen, 2011), service capacity planning (Dong et al., 2015), service reliability (Lee et al., 2015), ship fleet deployment (Álvarez, 2009; Ng, 2015; Wang and Meng, 2017), schedule design or recovery (Fagerholt et al., 2010; Li et al., 2016), cargo routing (Bell et al., 2013; Song and Dong, 2012), and bunkering planning (Meng et al., 2015; Aydin et al., 2017). For the recent review on ship sailing speed optimization, readers are referred to Psaraftis and Kontovas (2013) and Wang et al. (2013).

According to the *Admiralty coefficient* (Carlton, 2012), a ship's actual displacement (thereby, the cargo load) also influences its fuel efficiency, which indicates that the decisions made in cargo booking and routing will influence the bunker consumption of the ship fleet. Therefore, some recent studies on fleet deployment, schedule design and cargo routing simultaneously considered the influence of both sailing speed and cargo load on the bunker fuel cost. Vilhelmsen et al. (2014) captured the influence of cargo load on tramp ships' bunker fuel consumption in ship routing decisions by considering two load states: laden (fully loaded) and ballast (without cargo). Xia et al. (2015) and Wang et al. (2015) addressed the joint planning of fleet deployment, speed optimization and cargo routing for liner container shipping.

When the fuel efficiency of a specific in-service ship is investigated at the operational level, the influence of the weather and sea conditions is generally more significant than that of the ship's displacement (Carlton, 2012; MAN Diesel & Turbo, 2004; Zhang et al, 2016; Meng et al., 2017). The influence of sea currents can be strong along coastal areas (i.e., the boundaries of the ocean basin), but when the ship enters the open sea for trans-ocean sailing, the influence of sea currents becomes weak and that of weather conditions (wind and waves) can be significant (Carlton, 2012; MAN Diesel & Turbo, 2004). Few empirical studies have been performed to quantify the influence of weather conditions on ship fuel efficiency (in terms of power or speed loss). Kwon (1982) and Townsin et al. (1993) proposed a nonlinear regression model to quantify the influence of wind and waves on a ship's fuel efficiency based on data taken from naval architectural experiments. Molinero and Mitsis (1984) included more determinants in their bunker fuel efficiency model for a cruise ship. Meng et al. (2016) adopted the models created by Kwon (1982) and Townsin et al. (1993), and updated the regression results for modern mega-containerships based on shipping log data from their industry partner. The operations research studies that examine the influence of weather and sea conditions focus mainly on the ship's environmental routing problem, especially the weather routing problem (Chen, 1978; Kosmas and Vlachos, 2012; Lo and McCord, 1995; Papadakis and Perakis, 1990). A few of the most recent studies also considered the speed loss or gain caused by the weather and sea conditions when optimizing the average sailing speed over each leg of a service. Lee et al. (2018) took the initiative to employ publicly accessible weather archive big data to mine the influence of weather and sea conditions on ship fuel efficiency (speed loss/gain) via machine learning techniques. They further incorporated it into a biobjective speed optimization model for a round liner service that considers both bunker fuel consumption minimization and service level maximization. This is also a pioneering data-driven optimization research in maritime studies.

The trim can also have a significant influence on a ship's fuel efficiency, and it is believed that trim optimization could save 4% to 6% of bunker fuel (even up to 15% in some conditions) (DNV GL, 2017; IMO, 2017; Reichel et al., 2014). However, the influence of trim is quite complicated; it depends on sailing speed, displacement, and weather and sea conditions, and cannot be captured by the white-box (regression) models in Kwon (1982), Molinero and Mitsis (1984), Townsin et al. (1993) and Meng et al. (2016). As mentioned above, CFD simulation may provide a means to address the influence of trim on a ship's fuel efficiency (Reichel et al., 2014). However, its incapability to incorporate the influence of weather and sea conditions frustrates marine operation practitioners. Analytical methods for trim optimization based on the calculation of ship resistance, propeller characteristics, and engine performance can account for the governing physical laws and their mutual interactions, but they generally have low estimation accuracy (Coraddu et al., 2017).

Some recent pioneering studies of ship fuel efficiency have attempted to develop black-box data analysis models to address the synergetic influence of several determinants (speed, displacement, trim, and weather and sea conditions) on a ship's fuel efficiency. Pedersen and Larsen (2009) and Beşikçi et al. (2016) developed some artificial neural network (ANN) models to examine the bunker fuel efficiency of tankers. Pedersen and Larsen (2009) studied ship fuel efficiency from the viewpoint of naval architectural experiments and thus introduced time as an input variable, which is necessary from the perspective of voyage management. Thus, in this sense, the ANN model used by Beşikçi et al. (2016) is more appropriate for ship voyage management. However, the knowledge of Beşikçi et al. (2016) regarding ship fuel efficiency is biased. They regarded engine revolutions per minute (RPM), together with speed, draft (equivalent to displacement), trim, and weather and sea conditions, as an input (exogenous) variable of the ANN, which actually confuses the effects of the factors outside the engine with the effects of engine performance. In fact, from the perspective of ship fuel efficiency estimation, engine RPM is an endogenous variable that depends on the factors outside the engine, including sailing speed, draft, trim, and weather and sea conditions. It is also worth noting that no operations research studies have been based on these ANN models.

A considerable gap exists between industry requirements and existing studies, as reflected in the current practices of ship voyage management and the literature review above: the existing studies mainly addressed ship speed optimization at the strategic or tactical level (i.e., the average speed over a service or leg) and did not provide a solution to the daily speed planning of the ship addressed in this study, which intrinsically requires consideration of the added influence of displacement, weather and sea conditions, and trim on ship fuel efficiency; the existing trim optimization studies produced trim charts and tables, but their failure to incorporate the influence of weather and sea conditions frustrated marine operation practitioners. This is not surprising because the empirical studies conducted to clearly quantify the synergetic influence of sailing speed, displacement, trim, and weather and sea conditions remain in their infancy.

1.2. Objectives and Methodological Approach

This study tackles the proposed ship speed and trim optimization problem over a voyage with the following objectives:

- Taking advantage of historical voyage report data, propose a tailored method to build ANN models that can precisely quantify the influence of sailing speed, displacement, trim, and weather and sea conditions on a ship's fuel consumption rate.
- With the ANN models, develop solution countermeasures to optimize the speed and trim for each segment with the objective of minimizing the total fuel consumption over the voyage while respecting the ETA.

Our industry collaborators shared with us the voyage report data from February 2014 to March 2015 for two 9000-TEU containerships (referred to as ships S1 and S2 hereinafter). These ships both operate on the Far East – Middle East services that connect main Asian ports (Busan, Kwangyang, Qingdao, Ningbo, Kaohsiung, Shenzhen, Singapore) and those in the Persian Gulf (Jebel Ali, Sohar). Based on the data, we constructed two ANN models. The first model [ANN1] quantifies the synergetic influence of sailing speed, displacement, trim, and weather and sea conditions on a ship's fuel consumption rate. It can be used by a captain at sea to determine the optimal trim for each segment. However, when the onshore officers determine the speed for each segment, they do not know the directions of the wind, waves and sea currents, because this information is not provided by their weather information service providers (WISPs). We, therefore, developed a second model [ANN2] that quantifies the influence of several factors but excludes the influence of the directions of the wind, waves, and sea currents.

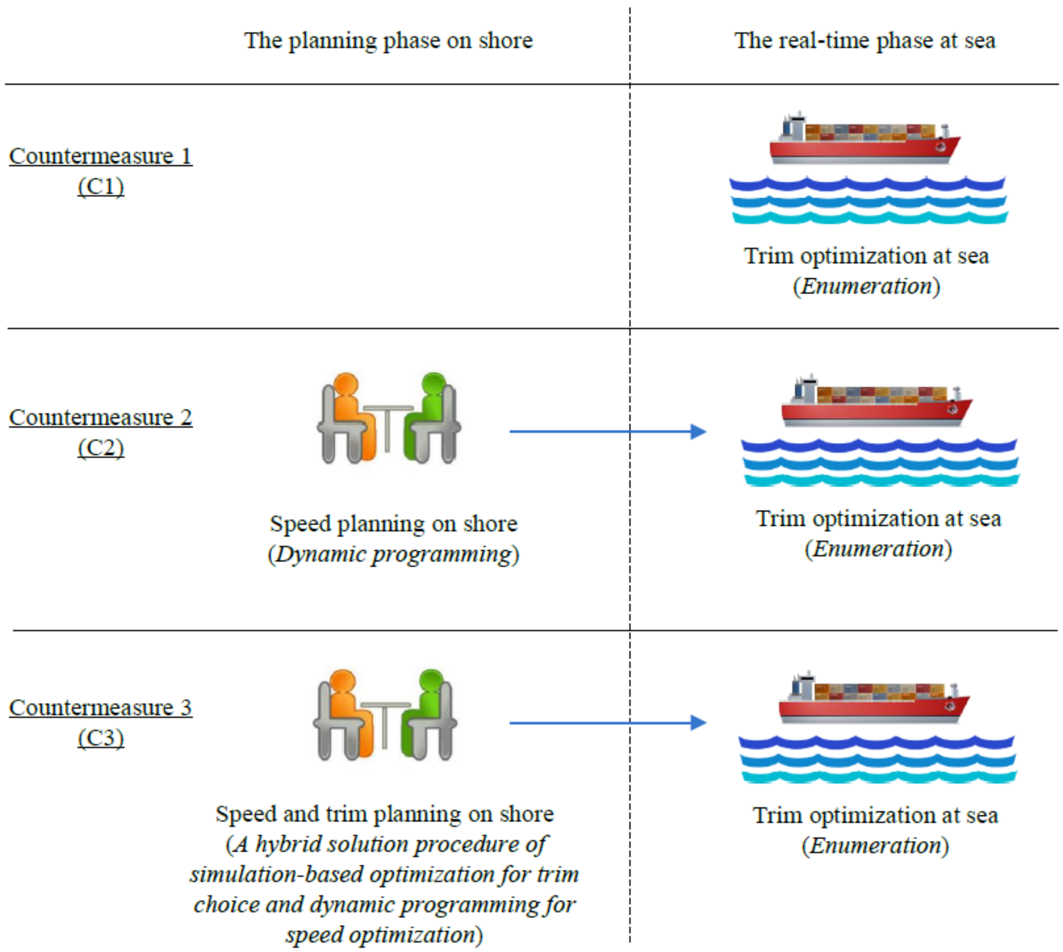


Fig. 3. Optimal solution countermeasures in a two-phase planning framework

With the developed ANN models on ship fuel efficiency, we then examine the speed and trim optimization problem and propose three optimal solution countermeasures in a two-phase planning framework, as shown in Fig. 3. In the first phase, the onshore officers plan the ship's sailing speeds $\{v_k\}_{k=1}^{n}$ over all segments of the voyage, whereas the captain at sea conducts trim optimization based on the observed weather and sea conditions. This two-phase planning framework is developed to improve the current practice of ship speed and trim optimization over a voyage. We introduce the onshore speed planning phase to address the recent attempts by shipping lines to explore the possibility of further saving bunker fuel by making fine adjustments to the daily sailing speeds. Speed optimization is conducted on shore because its purpose is to correct the arbitrary nature of the captain's rapid decision making at sea; in the meantime, the onshore officers have a global view of the weather and sea conditions over the whole voyage and of the consequences to shippers and to onward connections to other services if the ETA is violated. Trim optimization is conducted by the captain at sea during the second planning phase because the actual weather and sea conditions observed at sea are essential in trim decisions.

The three solution countermeasures can be explained in an incremental manner.

- Countermeasure 1 (C1) optimizes the ship's trim for each segment based on [ANN1], which considers the influence of weather and sea conditions (called *dynamic trim optimization*), instead of using static trim tables and charts; C1 adopts enumeration as the optimization method.
- Countermeasure 2 (C2) employs C1 as the real-time trim optimization procedure at sea, but it also allows the onshore officers to conduct speed optimization based on [ANN2]. In C2, the trim settings are assumed to be zero (i.e., an even keel) for all the segments. A dynamic programming model, rather than a mathematical programming model, is developed because ANN is regarded as a black-box function.
- Countermeasures 3 (C3) is similar to C2, but sailing speeds and trim settings are optimized simultaneously during the onshore speed planning phase to allow more informed speed decisions, because speed and trim both influence a ship's fuel efficiency and their influences are closely interwoven. In contrast, in C2, optimality is compromised because the trim is assumed to be zero in speed optimization. We propose a two-step global

optimization algorithmic procedure that combines dynamic programming and a state-of-the-art simulation-based optimization approach to address this simultaneous speed and trim optimization problem.

1.3. Potential Industrial Impact and Methodological Contributions

(i) Potential Industrial Impact

The improvements achieved by these three countermeasures over the current practice of speed and trim optimization can be revealed by comparison with the real situation. Numerical experiments with two 9000-TEU containerships show that (a) C1 saves 4.96% and 5.83% of bunker fuel for the two ships, respectively, compared to the real situation; (b) C2 increases the bunker fuel savings to 7.63% and 7.57%, respectively; and (c) C3 attains average bunker fuel savings of 8.25%. These remarkable bunker fuel savings could also translate into significant mitigation of CO_2 emissions. These promising results would encourage the shipping industry to improve their current practice of speed and trim planning. In the meantime, this study also provides tangible solutions to fulfil these bunker fuel savings from a technical perspective.

(ii) Methodological contributions

First, this study's methodological contributions to the literature on ship speed optimization can be summarized in the following two aspects.

- **Contribution 1**. This study introduces a highly accurate ANN model for ship fuel efficiency analysis to ship speed optimization. Our numerical experiments reveal the advantages of adopting ANN for ship fuel efficiency analysis in speed optimization: (a) compared to existing ship fuel efficiency models (e.g. the *cubic law* and the *Admiralty coefficient*), adopting ANN in speed optimization (C2) results in estimation of fuel consumption (i.e. the objective of the optimization model) that more closely matches the actual achievable fuel consumption. In contrast, the estimated fuel consumption calculated by speed optimization with the existing ship fuel efficiency model is not reliable because it differs greatly from the achievable situation. (b) Meanwhile, adopting a highly accurate ship fuel efficiency model like ANN may create the possibility of remarkable bunker fuel savings through speed optimization. Compared to speed optimization with the cubic law, C2 saves 0.57% and 3.69% of bunker fuel for ships S1 and S2, respectively.

- **Contribution 2**. This study takes the initiative to factor the influence of trim on ship fuel efficiency into speed optimization, which is desirable in theory because speed and trim both influence a ship's fuel efficiency and their influences are closely interwoven. Numerical experiments also reveal its advantages from an economic perspective: compared to speed optimization with the cubic law (plus C1 as the real-time dynamic trim optimization at sea), C3 additionally saves 1.10% and 4.34% of bunker fuel for ships S1 and S2, respectively; compared to C2 ignoring the influence of trim in on-shore speed optimization, C3 incrementally increases the bunker fuel savings over the real situation for the two ships by 0.58% and 0.72%, respectively. The mathematical complexity caused by simultaneous optimization of speed and trim brings considerable economic and environmental benefits.

Contribution 3. Our contribution to the existing studies on ship trim optimization is also significant. This study overcomes the drawbacks of trim tables and charts, which are the focus of the existing trim optimization literature, in the sense that trim tables and charts are unable to reflect the consideration of weather and sea conditions. C1 saves 4.96% and 5.83% of bunker fuel for the two ships, respectively, compared to the real situation. Numerical experiments also reveal that no matter what data model is adopted for ship fuel efficiency analysis in onshore speed optimization, the additional application of dynamic trim optimization at sea (C1) is always beneficial and can result in considerable bunker fuel savings.

2. ANN Models for Ship Fuel Efficiency

2.1. Voyage Report Data

When a commercial ship sails at sea, the captain is required to report the sailing profile to onshore officers on a regular basis, usually daily. The sailing profile includes many aspects of the ship's sailing behavior, such as the geographic location, local time and Greenwich Mean Time, the distance covered since last report, speed, cargo and ballast water loaded, displacement, trim, weather and sea conditions (wind, waves, sea currents, and sea water temperature), and fuel consumption by the main engine, auxiliary engines and boilers. At noon each day, the captain makes a data entry describing the recent sailing profile to the onshore officers, which is why captains refer to the voyage report data as *noon report* data. The voyage report data are also called *shipping log* data because these data are recorded in the logbook.

The voyage report data for ship S1 contained 1094 entries in total. After a data preprocessing procedure that removes the entries for ship operation in port areas or with absent values in some fields, 242 entries were obtained for fuel efficiency modeling. Similarly, 181 entries were used for ship S2's fuel efficiency modeling. Most data entries reflect a ship's daily sailing; however, data entries for the first or last segment of a voyage usually reflect durations shorter than 1 day because the departure from or arrival at a port rarely occurs at noon.

2.2. ANN Model Building for a Single Ship

Motivated by the studies by Beşikçi et al. (2016) and Pedersen and Larsen (2009), we constructed a feedforward ANN ship fuel efficiency model using voyage report data, as illustrated in Fig. 4. The input layer involves ten explanatory variables: sailing speed (knots), displacement

(MT), trim (m), wave height (m), wave direction, wind force (Beaufort scale number), wind direction, sea current speed (knots), sea current direction, and sea water temperature (˚C). The directions of the wind, waves, and sea currents, relative to the ship's movement, are recorded by the deck officers in a fuzzy manner, as defined in Fig. 5. For waves, "A" denotes the following wave, and "E" is the head wave. Waves from directions "B" and "H" (or "C" and "G", or "D" and "F") generally have the same influence because of the ship's symmetric structure. Unlike the study by Beşikçi et al. (2016), our study does not designate engine RPM as an input variable because the engine RPM is determined by the ten variables in the model. The output of the network is the fuel consumption rate, given in MT per day. In the hidden layer, ten neurons are adopted for two reasons: (a) Pedersen and Larsen (2009) verified that ten neurons are adequate with respect to fit performance; and (b) given the data sizes of ships S1 and S2, the use of more neurons in the hidden layer will cause a severe overfitting issue (poor generalization). Fig. 6 illustrates the distributions of the 181 data entries for ship S2 against these explanatory variables and the output fuel efficiency.

To ensure the good generalization of ANN, a total of L neural networks are trained in our study based on the same data set: $ANN1^{(1)},...,ANN1^{(L)}$. The L neural networks differ in that different initial weights are adopted for multiple consecutive trainings. For a given input $\mathbf{x}$ that contains information on speed, displacement, trim, and weather and sea conditions, the average of the outputs of these L networks is used as the prediction:

[ANN1]
$$f^{ANN1}(\mathbf{x}) = \frac{1}{L}\sum_{l=1}^{L} ANN1^{(l)}(\mathbf{x}) \tag{1}$$

The rationale behind Eq. (1) is that the output of a specific trained neural network might suffer greatly from overfitting, but the average of the outputs of multiple networks is generally sufficiently robust (Mathworks, 2015).

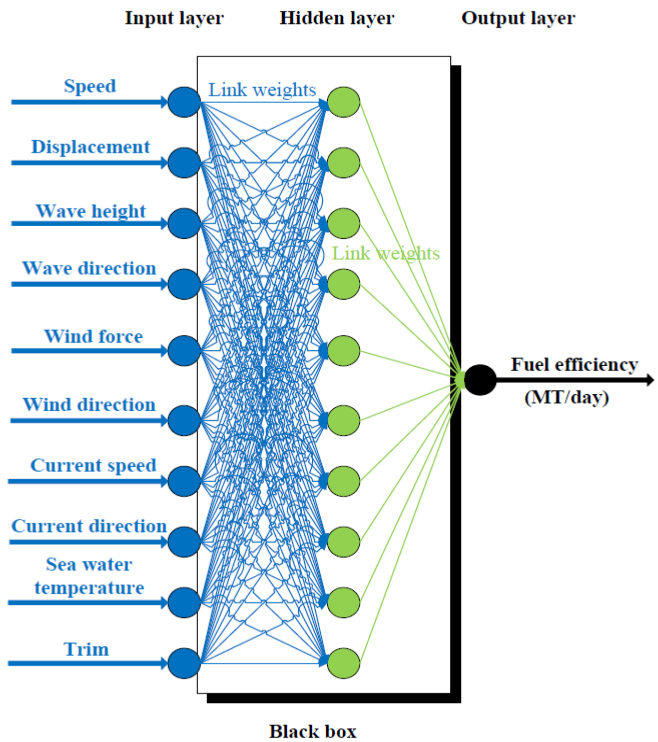


Fig. 4. An ANN model for ship fuel efficiency

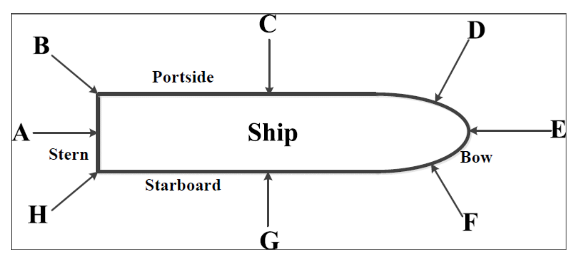
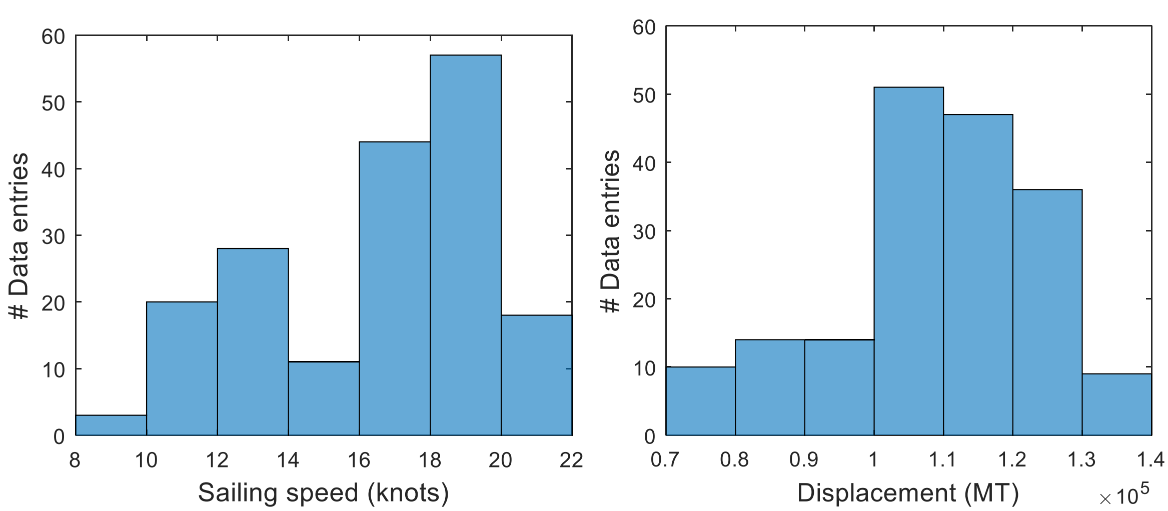


Fig. 5. Definition of wave (wind, sea currents) directions



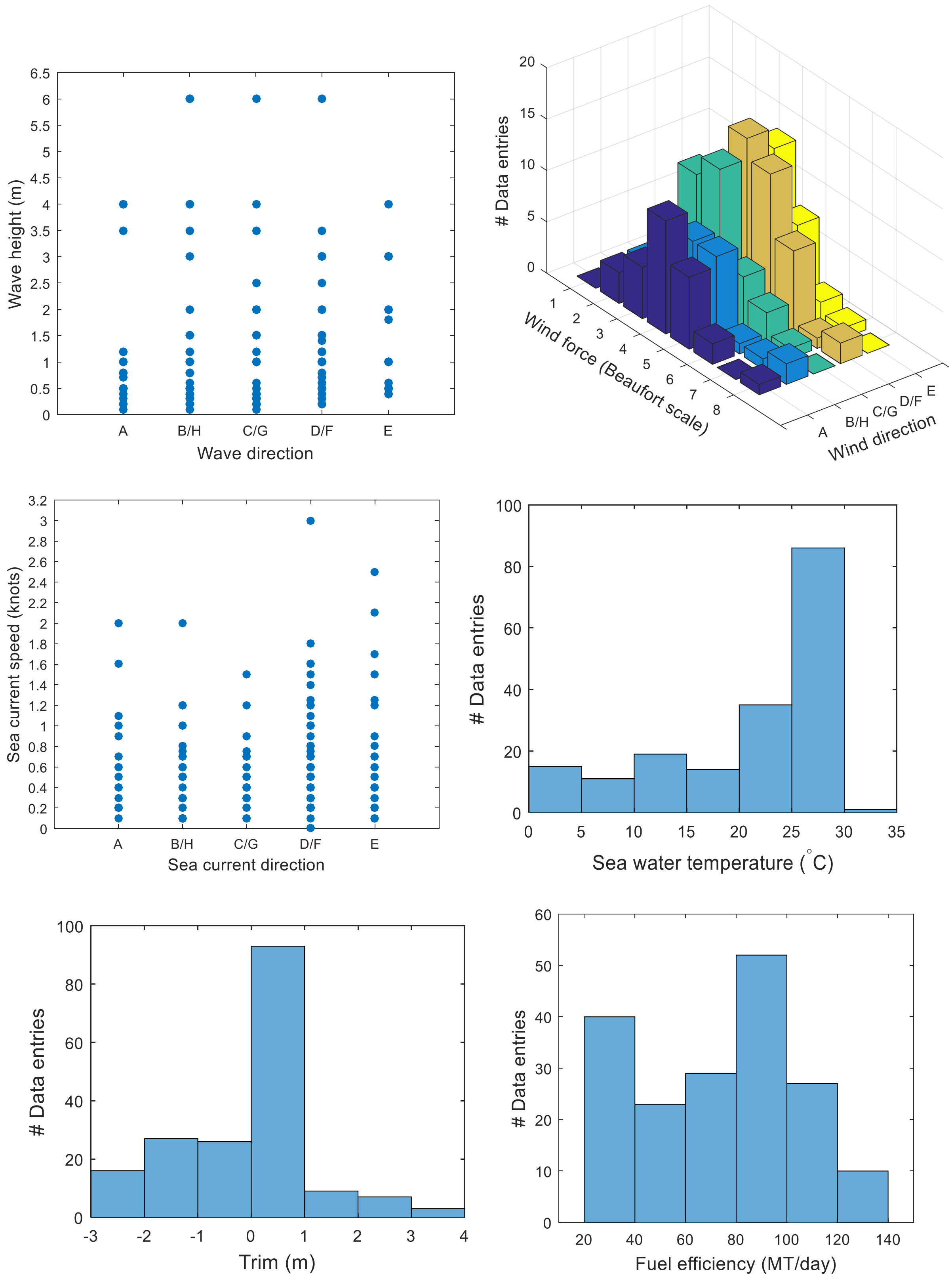


Fig. 6. Distribution of 181 voyage report data entries for ship S2

As mentioned above, when the onshore officers optimize the speed for each segment, they cannot determine the directions of the wind, waves and sea currents. We have therefore developed a second model [ANN2] that is the same as [ANN1] except that [ANN2] fixes the directions of wind, waves, and sea currents at a neutral value ("C" or "G" in Fig. 4):

[ANN2]
$$f^{ANN2}\left(\mathbf{x}\right)=\frac{1}{L}\sum_{l=1}^{L}ANN2^{(l)}\left(\mathbf{x}\right) \tag{2}$$

2.3. Performance of the ANN Models

The available voyage report data are randomly partitioned into two sets, with 80% of the data entries for the training set and 20% for the test set. To assess the fit performance of the ship fuel efficiency model [ANN1], we use the *root mean square error* (*RMSE*) defined by

$$RMSE=\sqrt{\frac{1}{N}\sum_{e=1}^{N}\left[f^{ANN1}\left(\mathbf{x}^{(e)}\right)-\mathbf{y}^{(e)}\right]^2}\,, \tag{3}$$

where $\mathbf{x}^{(e)}$ and $\mathbf{y}^{(e)}$ denote the network input information revealed by data entry $e=1,...,N$ and the corresponding actual fuel consumption rate, and the R^2 *value* for linear regression between the predicted fuel consumption rate $f^{ANN1}\left(\mathbf{x}\right)$ (output) and the actual rate $\mathbf{y}$ (target). Our preliminary experiments suggested that $L=10$ is sufficient for ships S1 and S2 in terms of RMSE and R^2 values over both the training and test tests.

An alternative method to show the performance of ANN models is comparison with that of ship fuel efficiency models of other forms in existing studies. *Multi-linear regression* is the simplest method of modeling the influence of many determinants on ship fuel efficiency (Molinero and Mitsis, 1984; Wang et al., 2017; referred to as the model [**MLR**]). However, a linear relationship between ship fuel efficiency and some determinants, such as the sailing speed and trim, is difficult to accept in the shipping industry. For instance, it is well known that the *cubic law*

(Carlton, 2012; MAN Diesel & Turbo, 2004) roughly quantifies the influence of a ship's sailing speed (V) on its ship fuel efficiency (r_F, MT/day):

[CBC] $$r_F = c_1 \cdot V^3, \tag{4}$$

where c_1 is a coefficient to be calibrated. To improve the fit performance, the power "3" can be replaced by another coefficient to be calibrated:

[CBC'] $$r_F = c_1 \cdot V^{c_2}. \tag{5}$$

If the effect of displacement (∇) is also considered, the cubic law becomes the *Admiralty coefficient* (Carlton, 2012) :

[ADM] $$r_F = c_1 \cdot V^3 \cdot \nabla^{2/3}, \tag{6}$$

or a more precise variant with more coefficients to be calibrated (Meng et al., 2016):

[ADM'] $$r_F = c_1 \cdot V^{c_2} \cdot \nabla^{c_3} \tag{7}$$

Existing studies (Jalkanen et al., 2009; Meng et al., 2016; Townsin et al., 1993) also modeled the influence of weather and sea conditions (e.g., wind and waves) on ship fuel efficiency as a penalty on the sailing speed by using a generalized nonlinear regression model:

[NLR] $$r_F = c_1 \cdot \left[\left(1 + p\left(WD, WH\right)\right)V\right]^{c_2} \cdot \nabla^{c_3}, \tag{8}$$

where the penalty is constructed based on the wave direction (WD) and wave height (WH),

$$p\left(WD, WH\right) = \mu\left(WD, WH\right)\left(c_1^E \cdot WH^{c_2^E} + c_3^E \cdot WH\right) \tag{9}$$

$$\mu\left(WD, WH\right) = \begin{cases} 1, & WD = E \\ c_1^D \cdot WH^2 + c_2^D \cdot WH + c_3^D, & WD = D \text{ or } F \\ c_1^C \cdot WH^2 + c_2^C \cdot WH + c_3^C, & WD = C \text{ or } G \\ c_1^B \cdot WH^2 + c_2^B \cdot WH + c_3^B, & WD = B \text{ or } H \\ c_1^A \cdot WH^2 + c_2^A \cdot WH + c_3^A, & WD = A \end{cases} \tag{10}$$

There are in total 18 coefficients to be calibrated in model [NLR]. In view of the strong correlation between the wave height and wind force, it is also possible to substitute wind force for wave height in model [NLR]. Table 1 shows the fit performance of models [ANN1] and [ANN2] over ships S1 and S2, against that of models [CBC], [CBC'], [ADM], [ADM'], [NLR], and [MLR].

Table 1 shows that the fit performance of [ANN1] is quite good for both training and test sets: the *RMSE* values are all less than 9.5 MT/day, and the R^2 values are also sufficiently high. The results on the test set verify the model's generalization ability. Moreover, the fit performance of model [ANN2], although worse than that of model [ANN1], is also acceptable from a practical viewpoint. The gap in the fit performance between the two models represents the value of directional information for weather and sea conditions in ship fuel efficiency estimation.

The fit performance of models [CBC], [CBC'], [ADM], [ADM'], and [NLR] is relatively worse. When the fit performance of these five models is compared, [CBC'] is better than [CBC], [ADM'] is better than [ADM], and [NLR] might further improve the fit performance over the training set. This offers the insight that the incorporation of more determinants and/or the introduction of more coefficients to be calibrated in ship fuel efficiency model will generally improve the fit performance. Model [MLR] has the same number of determinants of fuel efficiency as [ANN1], and its fit performance is also fair even though it simply adopts linear regression. The experiments in Section 4 reveal that model [MLR] is not reliable in speed optimization because of its incompetence in capturing the nonlinear influence of sailing speed on ship fuel efficiency. In contrast, models [CBC], [CBC'], [ADM], [ADM'], and [NLR] are quite reliable in speed optimization.

Table 1. Fitting performance of ANN against ship fuel efficiency models in existing literature (ship S1)

			CBC	CBC'	ADM	ADM'	NLR	MLR	ANN1	ANN2
Ship S1	Training set	# Data entries					193			
		RMSE (MT/day)	12.44	11.79	14.52	11.63	9.92	9.25	**6.56**	**9.70**
		R^2	0.7784	0.8009	0.6980	0.8628	0.8610 [a]	0.8770	**0.9706** [a]	**0.9311** [a]
		Adjusted R^2	0.7784	0.7998	0.6980	0.8613	-	0.8710	-	-
	Test set	# Data entries					49			
		RMSE (MT/day)	12.18	10.85	14.85	10.81	12.95	9.82	**8.23**	**10.25**
Ship S2	Training set	# Data entries					144			
		RMSE (MT/day)	13.63	11.84	13.77	11.61	9.00	8.55	**6.06**	**8.40**
		R^2	0.8011	0.8500	0.7969	0.8803	0.9210 [a]	0.9220	**0.9837** [a]	**0.9622** [a]
		Adjusted R^2	0.8011	0.8489	0.7969	0.8786	-	0.9160	-	-
	Test set	# Data entries					37			
		RMSE (MT/day)	15.25	12.74	15.57	12.49	17.42	10.20	**9.34**	**9.91**

Note: [a] R^2 value is obtained from linear regression between targets (actual fuel consumption rates) and outputs (estimated fuel consumption rates) of the model.

3. Countermeasures for Optimal Voyage Management of Ships

The ANN models of ship fuel efficiency in Section 2 enable us to predict how much bunker fuel a ship consumes on one segment when the ship's sailing speed, displacement, trim, and weather and sea conditions are known. Based on the models, this section proposes three countermeasures to improve the current practice of ship speed and trim optimization over a voyage.

3.1. Countermeasure 1 (C1): Dynamic Trim Optimization on the Sea

At the beginning of a specific sailing segment k of the voyage shown in Fig. 2, the captain at sea knows almost all the information about the ship's fuel efficiency on this segment: V_k — the sailing speed indicated by the sailing distance and the planned arrival time at the next waypoint; and I_k — the information on both displacement and weather and sea conditions. Trim optimization conducted by the captain is to determine an optimal trim setting t_k in a given interval $\left[\underline{T}_k, \overline{T}_k\right]$ such that the fuel consumption rate over this segment is minimized:

$$\min_{\underline{T}_k \le t_k \le \overline{T}_k} f_k^{ANN1}\left(V_k, t_k, I_k\right) = \frac{1}{L}\sum_{l=1}^{L} ANN1_k^{(l)}\left(V_k, t_k, I_k\right) \tag{11}$$

where $f_k^{ANN1}\left(V_k, t_k, I_k\right)$ is the predicted fuel consumption rate of model [ANN1] for the input $\mathbf{x} = \left\langle V_k, t_k, I_k \right\rangle$ on segment k. To solve the model in practice, we can discretize the trim interval $\left[\underline{T}_k, \overline{T}_k\right]$ with a fine granularity, e.g., 0.01 m, into a set

$$T_k := \left\{T_k^1, T_k^2, ..., T_k^{Q_k}\right\}, \quad \left|T_k\right| = Q_k \tag{12}$$

and perform an enumeration method to search for the optimal trim value:

$$t_k^* = \arg\min_{t_k \in T_k} f_k^{ANN1}\left(V_k, t_k, I_k\right) \tag{13}$$

Compared to the current practice of trim optimization relying on static trim tables/charts, C1 makes trim optimization at sea *dynamic*: in addition to sailing speed and displacement, the influence of weather and sea conditions on ship fuel efficiency is also considered when determining the optimal trim setting. Moreover, C1 is quite easy to deploy in practice.

3.2. Countermeasure 2 (C2): Speed Optimization on Shore + C1

As mentioned in Section 1, the onshore officers of a shipping company have strong motivation to finely plan the daily sailing speeds of a ship over a voyage to save bunker fuel by taking the influence of the actual weather, sea and load conditions into account. One difficulty that prevents them from fulfilling this delicate speed planning is their incapability of precisely predicting the ship's fuel consumption rates at different speeds under different weather, sea and load conditions. Fortunately, this shortcoming is now addressed by ship fuel efficiency models [ANN1] and [ANN2]. We, therefore, developed a decision-support tool for onshore officers to use in planning the sailing speeds of a ship over consecutive shipping segments before a voyage begins. This onshore speed optimization procedure, in conjunction with trim optimization of C1 at sea, constitutes our Countermeasure 2. Two points are noteworthy. First, we assume in C2 that onshore speed optimization does not account for trim optimization, that is, that the onshore officers assume a zero trim (*even keel*). This assumption will be relaxed in the next countermeasure. Second, due to the dynamic nature of air and sea movement, the weather and sea conditions experienced by the ship over a specific segment of the voyage, precisely speaking, depend on the speed decision over this segment and the preceding segments. However, our industry collaborators commented that the weather and sea conditions over each segment can be roughly treated as independent of speed because of the stringent ETA requirement and the additional restriction that the arrival time at each waypoint should not deviate excessively (e.g., maximum 12 hours) from the time implied by the average speed derived from ETA.

The sailing speed optimization problem over a voyage consisting of n segments for onshore officers is to design an optimal sailing speed v_k for each segment $k \in \{1,...,n\}$ to minimize the ship's fuel consumption over the whole voyage. Associated with each segment k, the information I'_k on ship displacement, wave height, wind force, sea current speed, and sea water temperature can be determined beforehand (note that I'_k differs from I_k in that I'_k does not contain information on the directions of wind, waves, and sea currents), and the ship's trim t_k is assumed to be zero. Here, the assumption of known weather and sea conditions on all the segments beforehand is justifiable for two reasons: (a) WISPs can usually provide 7-to-15-day weather and sea condition forecasts; and (b) the proposed models in Countermeasures C2 and C3 can be used in practice by following a rolling horizon principle.

If the ship adopts sailing speed v_k, its fuel consumption rate in MT/day over segment k can be predicted by model [ANN2] as $f_k^{ANN2}(v_k, t_k, I'_k)$, or say $f_k^{ANN2}(v_k, 0, I'_k)$. Thus, the bunker fuel consumption of the ship over this segment, with the sailing distance D_k, can be calculated by

$$F_k^{ANN2}(v_k, t_k, I'_k) = F_k^{ANN2}(v_k, 0, I'_k) = f_k^{ANN2}(v_k, 0, I'_k) \cdot \frac{D_k}{24 \cdot v_k} \tag{14}$$

in which $D_k / (24 \cdot v_k)$ is the sailing days on segment k. The onshore officers attempt to minimize the ship's total bunker fuel consumption over all the segments:

$$\min_{v_k, k\in\{1,...,n\}, a_k, k\in\{1,...,n,n+1\}} \quad F = \sum_{k=1}^{n} F_k^{ANN2}(v_k, 0, I'_k) = \sum_{k=1}^{n} \left\{ f_k^{ANN2}(v_k, 0, I'_k) \cdot \frac{D_k}{24 \cdot v_k} \right\} \tag{15}$$

subject to the ETA constraint at the end of the voyage:

$$a_{k+1} = a_k + \frac{D_k}{v_k}, \quad \forall k \in \{1,...,n\} \tag{16}$$

$$a_1 := 0\,,\ a_{n+1} \le ETA \tag{17}$$

where a_k denotes the arrival time at waypoint k. Meanwhile, the sailing speeds should be maintained in the technically feasible range:

$$\underline{V} \le v_k \le \overline{V}, \quad k \in \{1,...,n\} \tag{18}$$

The objective (15) and constraints (16)-(18), with v_k as the main decision variables and a_k as the auxiliary decision variables, mathematically model the speed optimization problem confronting onshore officers. A barrier in the solution of this model is the objective evaluation in Eq. (15): once a solution $\{v_k = V_k\}_{k=1}^{n}$ is constructed, it has to be input into model [ANN2] to query the ship fuel efficiency $\left\{ f_k^{ANN2}\left(V_k, 0, I'_k\right)\right\}_{k=1}^{n}$. Traditional solution methods for mathematical programming models thus do not work with this optimization problem. Fortunately, it can be seen from objective (15) that this model exhibits the properties of overlapping subproblems and an optimal substructure, which indicates that this complicated problem can be broken down into several simpler subproblems in a recursive manner. This encourages us to adopt a dynamic programming (DP) approach to solve this model.

In the DP approach, the problem has n stages, each of which representing a sailing segment connecting two main waypoints. At the beginning of stage k, the arrival time a_k of the ship at waypoint k is known as the system state, and the onshore officers devote their efforts to determine the arrival time a_{k+1} at the next waypoint to minimize bunker fuel consumption. The optimal value function at stage k, that is, the minimum total fuel consumption on segments $k, k+1, ..., n$, can be defined as

$$U_k\left(a_k\right) = \min_{\{v_k, v_{k+1}, ..., v_n\}} \quad \sum_{s=k}^{n} F_s^{ANN2}\left(v_s, 0, I'_s\right) \tag{19}$$

It can be rewritten in a recursive manner, yielding the *Bellman equation*:

$$\textbf{[DP}^{\textbf{SPEED}}\textbf{]} \quad \begin{aligned} U_k(a_k) &= \min_{\underline{V} \le v_k \le \overline{V}} \left\{ F_k^{ANN2}(v_k, 0, I_k') + U_{k+1}(a_{k+1}) \right\} \\ &= \min_{\underline{V} \le v_k \le \overline{V}} \left\{ f_k^{ANN2}(v_k, 0, I_k') \cdot \frac{D_k}{24 \cdot v_k} + U_{k+1}\left(a_k + \frac{D_k}{v_k} \right) \right\} \end{aligned}, \ k \in \{1, ..., n\} \tag{20}$$

where $U_{n+1}(a_{n+1}) = 0$ is the boundary condition, $a_{n+1} \le ETA$. In the first term of (20), the sailing time of the ship on segment k is calculated as $D_k / (24 \cdot v_k)$ instead of D_k / v_k because the unit of $f_k^{ANN2}(v_k, 0, I_k')$ is MT per day. The above DP formulation [DP$^{\text{SPEED}}$] can be solved via backward induction by using the Bellman equation (20) in a recursive manner.

In practice, the feasible range of state a_k can be discretized with a fine, say hourly, granularity:

$$a_k \in A_k \triangleq \left\{ A_k^1, A_k^2, ..., A_k^{M_k} \,\middle|\, A_k^{i+1} - A_k^i = 1, i = 1, ..., (M_k - 1) \right\}, \quad k \in \{2, 3, ..., n+1\} \tag{21}$$

where $M_k = |A_k|$ can be set to a value such as 24 for practical use. With the feasible ranges of state variables discretized, model [DP$^{\text{SPEED}}$] boils down to a shortest-path problem over a time-space network, as shown in Fig. 7. In this network, a node labeled as A_k^i in layer k represents a possible state at stage k, which indicates that the arrival time at waypoint k is A_k^i, i.e., $a_k = A_k^i$. The link that connects nodes A_k^i and A_{k+1}^j represents a possible state transition from stage k to stage $k+1$, over which the sailing speed is

$$V_k^{ij} = \frac{D_k}{A_{k+1}^j - A_k^i} \tag{22}$$

The cost associated with this link can be calculated as the corresponding bunker consumption:

$$c_k^{ij} = F_k^{ANN2}\left(V_k^{ij}, 0, I_k'\right) = f_k^{ANN2}\left(V_k^{ij}, 0, I_k'\right) \cdot \frac{D_k}{24 \cdot V_k^{ij}} = f_k^{ANN2}\left(\frac{D_k}{A_{k+1}^j - A_k^i}, 0, I_k' \right) \cdot \frac{A_{k+1}^j - A_k^i}{24} \tag{23}$$

Fig. 7 shows that determination of an optimal speed plan over the whole voyage to minimize bunker fuel consumption is equivalent to finding the shortest path in a time-space network. The idea of a shortest-path representation of ship speed optimization was originally proposed by Fagerholt et al. (2010). Therefore, both the DP approach and the traditional shortest-path algorithms (e.g., *Dijkstra's* algorithm) can be adopted to solve the optimization problem. Our preliminary experiments revealed that the DP approach and *Dijkstra's* algorithm can both solve realistic-sized instances to optimality within 1 second.

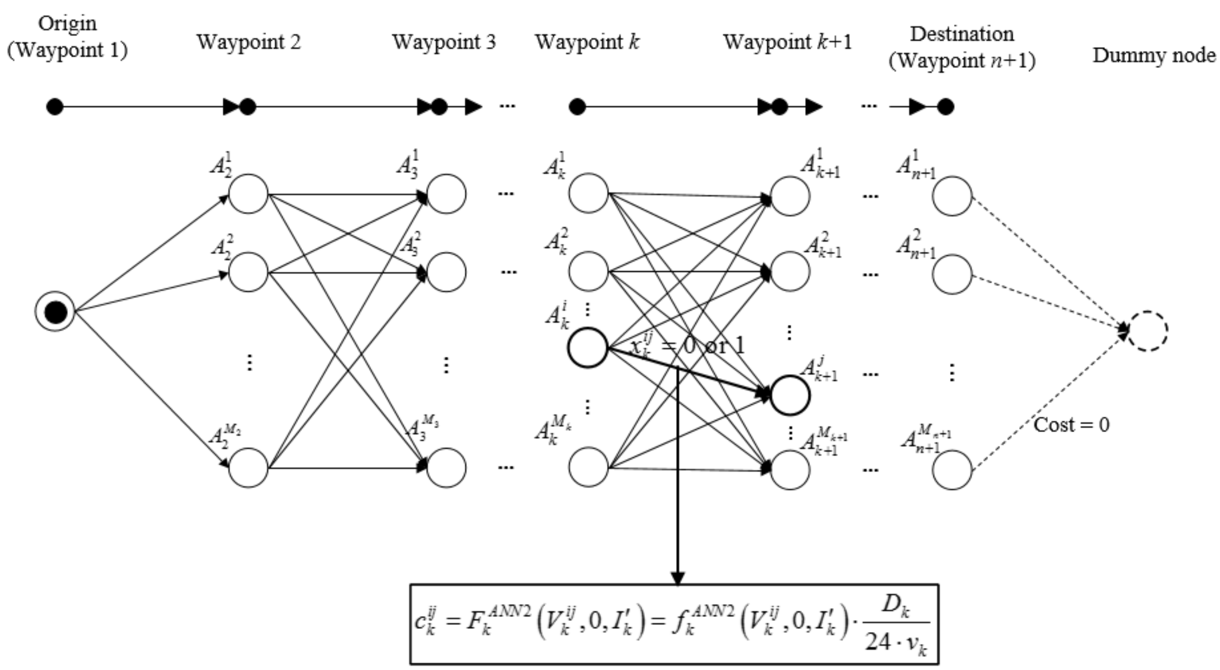


Fig. 7. Shortest-path representation of the dynamic programming model [DP^{SPEED}]

3.3. Countermeasure 3 (C3): Speed and Trim Optimization on Shore + C1

C2 optimizes the sailing speeds of the ship during the planning phase, without accounting for the influence of trim on the ship fuel efficiency by simply setting the trim values as zero. This policy can be further improved by simultaneously optimizing speed and trim by the onshore officers using [ANN2]. The purpose is to obtain better speed settings for the captain. The dynamic trim for each segment is still determined by the captain using C1 with [ANN1] after observation of the directions of the wind, waves, and sea currents.

3.3.1. Speed and Trim Optimization via Dynamic Programming

A straightforward approach for simultaneous optimization of speed and trim is to retrofit the models in Section 3.2 and address this problem via DP. If the available trim interval over segment (stage) k is expressed in a practical discretization form (12), the Bellman equation (20) can be revised accordingly to reflect trim optimization:

$$\begin{aligned} U_k\left(a_k\right) &= \min_{\underline{V} \le v_k \le \bar{V}, t_k \in T_k} \left\{ F_k^{ANN2}\left(v_k, t_k, I_k'\right) + U_{k+1}\left(a_{k+1}\right) \right\} \\ &= \min_{\underline{V} \le v_k \le \bar{V}, t_k \in T_k} \left\{ f_k^{ANN2}\left(v_k, t_k, I_k'\right) \cdot \frac{D_k}{24 \cdot v_k} + U_{k+1}\left(a_k + \frac{D_k}{v_k} \right) \right\}, \ k \in \{1, \ldots, n\} \end{aligned} \tag{24}$$

The boundary condition at the final stage is the same as in model [DP$^{\text{SPEED}}$]. In practice, we can discretize the speed range $\left[\underline{V}, \bar{V}\right]$ with a practical granularity of, for example, 0.1 knots,

$$V = \left\{V^1, V^2, \ldots, V^M\right\}, \quad |V| = M \tag{25}$$

and rewrite Eq. (24) as

[DP$^{\text{SPEED-TRIM}}$] $$U_k\left(a_k\right) = \min_{v_k \in V, t_k \in T_k} \left\{ f_k^{ANN2}\left(v_k, t_k, I_k'\right) \cdot \frac{D_k}{24 \cdot v_k} + U_{k+1}\left(a_k + \frac{D_k}{v_k} \right) \right\} \tag{26}$$

Additionally taking $\{t_k\}_{k=1}^{n}$ as decision variables further complicates the solution process because the dimension of model [DP$^{\text{SPEED-TRIM}}$] increases. To construct a shortest-path representation of model [DP$^{\text{SPEED-TRIM}}$], we must replace each link in Fig. 7 with several links to reflect the decisions on trim. Specifically, the link that represents the state transition from $a_k = A_k^i$ to $a_{k+1} = A_{k+1}^j$ should be replaced by exactly $Q_k = |T_k|$ links, with each link representing a possible choice on trim value over the set T_k, which is shown in Fig. 8(a). The costs over these links can respectively be calculated as

$$F_k^{ANN2}\left(V_k^{ij}, T_k^1, I_k'\right) = f_k^{ANN2}\left(V_k^{ij}, T_k^1, I_k'\right)\cdot\frac{D_k}{24\cdot V_k^{ij}} = f_k^{ANN2}\left(\frac{D_k}{A_{k+1}^j - A_k^i}, T_k^1, I_k'\right)\cdot\frac{A_{k+1}^j - A_k^i}{24},$$

$$F_k^{ANN2}\left(V_k^{ij}, T_k^2, I_k'\right) = f_k^{ANN2}\left(\frac{D_k}{A_{k+1}^j - A_k^i}, T_k^2, I_k'\right)\cdot\frac{A_{k+1}^j - A_k^i}{24},\ldots,$$

and

$$F_k^{ANN2}\left(V_k^{ij}, T_k^{Q_k}, I_k'\right) = f_k^{ANN2}\left(\frac{D_k}{A_{k+1}^j - A_k^i}, T_k^{Q_k}, I_k'\right)\cdot\frac{A_{k+1}^j - A_k^i}{24}.$$

This significantly complicates the structure of the time-space network.

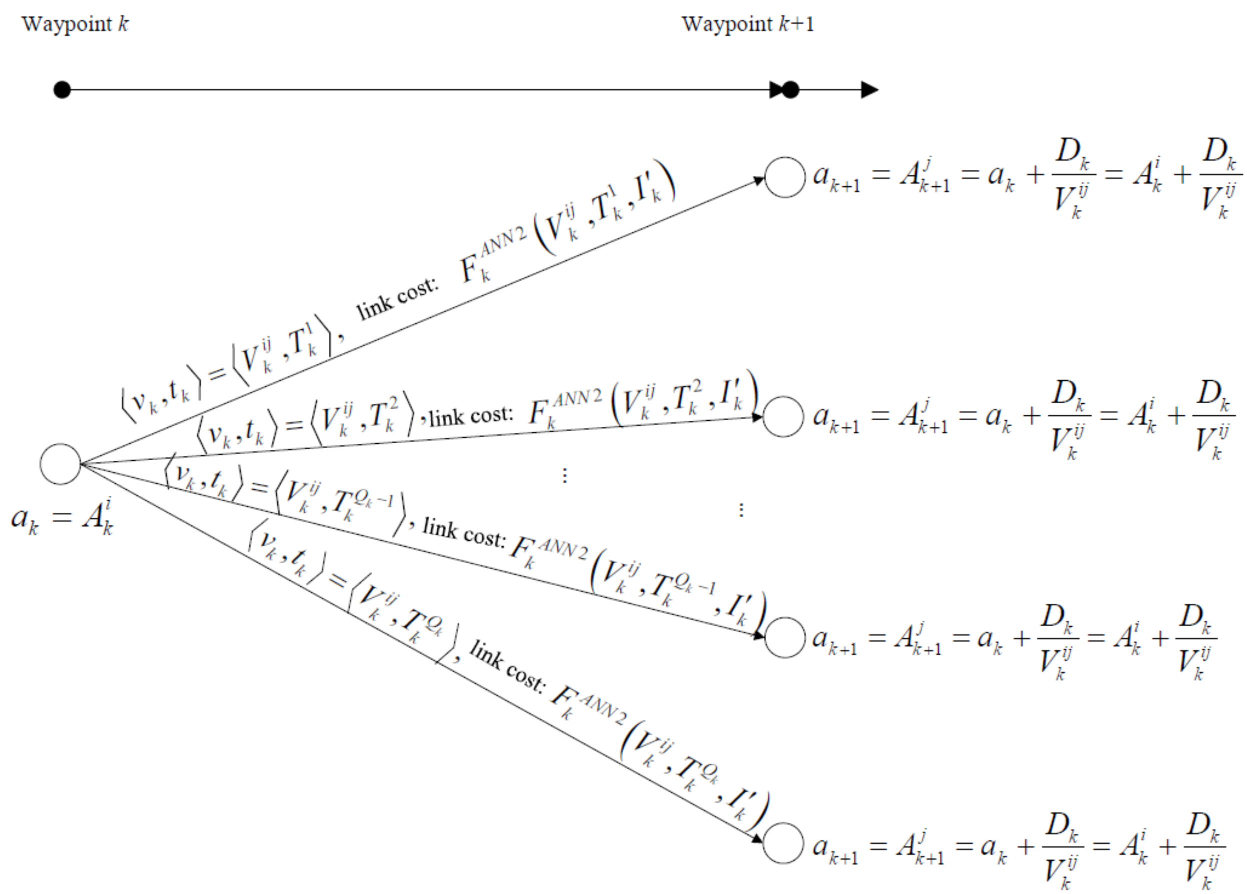
However, we notice that this problem has a nice structure: the trim t_k only affects the fuel consumption of stage k, and it has no effect on future states, and thereby no effect on the fuel consumption of future stages. This can be seen from Fig. 8(a): all the links start from the state $a_k = A_k^i$ and point to states $a_{k+1} = A_{k+1}^j$. We thus can merge the nodes to which these links point into one state $a_{k+1} = A_{k+1}^j$. Meanwhile, if we can determine the minimum bunker cost over these links via trim optimization

$$t_k^* = \arg\min_{t_k \in T_k} F_k^{ANN2}\left(V_k^{ij}, t_k, I_k'\right), \tag{27}$$

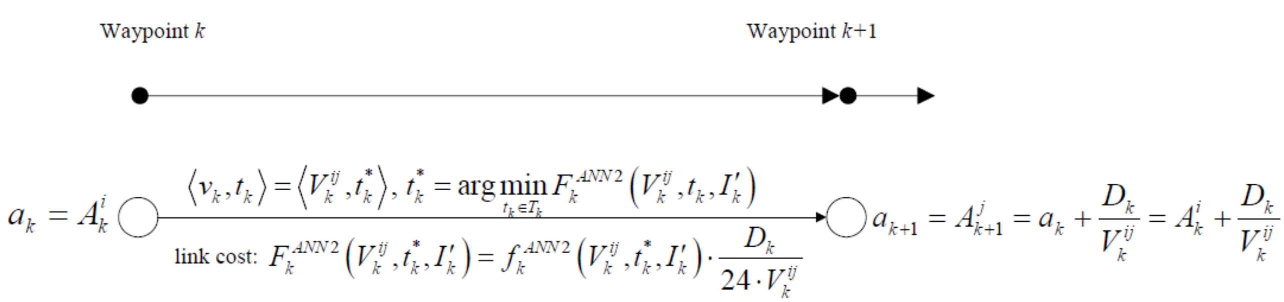
these links can also be merged into one with the cost

$$F_k^{ANN2}\left(V_k^{ij}, t_k^*, I_k'\right) = f_k^{ANN2}\left(V_k^{ij}, t_k^*, I_k'\right)\cdot\frac{D_k}{24\cdot V_k^{ij}} = f_k^{ANN2}\left(\frac{D_k}{A_{k+1}^j - A_k^i}, t_k^*, I_k'\right)\cdot\frac{A_{k+1}^j - A_k^i}{24} \tag{28}$$

The result of state merging is illustrated in Fig. 8(b).



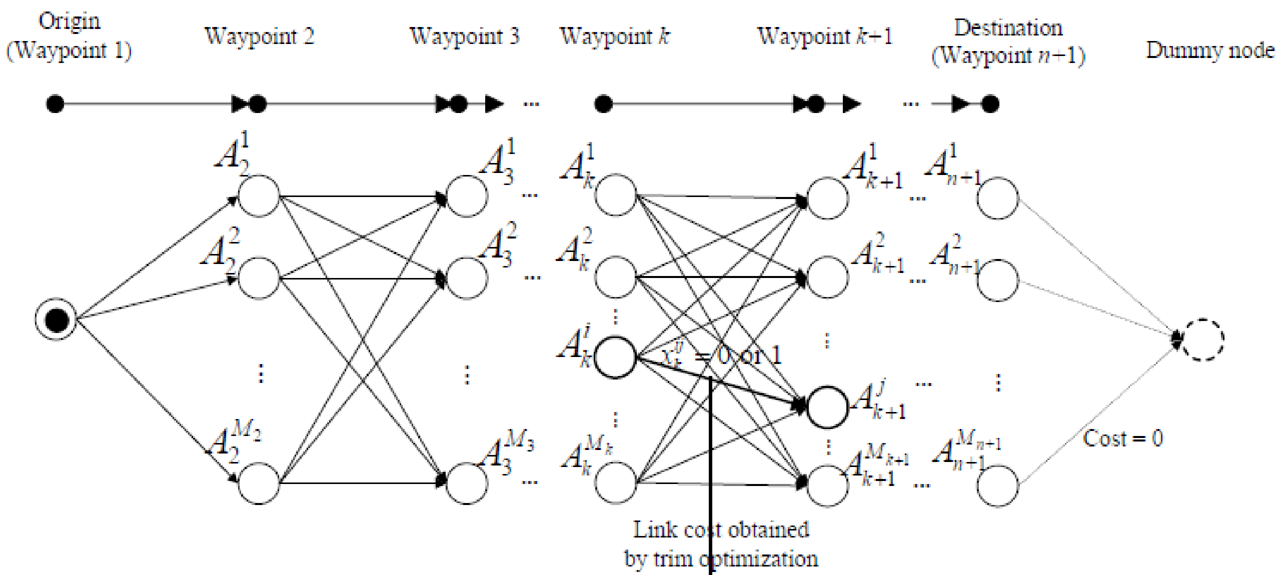
(a) Before state merging



(b) After state merging

Fig 8. State merging in dynamic programming model [DP$^{SPEED\text{-}TRIM}$] with trim optimization

With the state merging illustrated in Fig. 8, we finally have the shortest-path representation of model [DP$^{\text{SPEED-TRIM}}$] shown in Fig. 9. It can be seen that trim optimization and speed optimization are decoupled, though their effects on ship fuel efficiency are interwoven. Therefore, the following two-step procedure (*Procedure 1*) can be employed to globally solve model [DP$^{\text{SPEED-TRIM}}$], which implements trim optimization in the first step, and a shortest-path algorithm for speed optimization in the second step.



$$c_k^{ij} = F_k^{ANN2}\left(V_k^{ij}, t_k^*, I_k'\right) = \min_{t_k \in T_k} F_k^{ANN2}\left(V_k^{ij}, t_k, I_k'\right) = \min_{t_k \in T_k}\left\{ f_k^{ANN2}\left(V_k^{ij}, t_k, I_k'\right) \cdot \frac{D_k}{24 \cdot V_k^{ij}} \right\}$$

$$= \min_{t_k \in T_k}\left\{ f_k^{ANN2}\left(\frac{D_k}{A_{k+1}^j - A_k^i}, t_k, I_k'\right) \cdot \frac{A_{k+1}^j - A_k^i}{24} \right\}$$

$$= \min_{t_k \in T_k}\left\{ f_k^{ANN2}\left(\frac{D_k}{A_{k+1}^j - A_k^i}, t_k, I_k'\right) \right\} \cdot \frac{A_{k+1}^j - A_k^i}{24}$$

Fig. 9. Shortest-path representation of dynamic programming model [DP$^{\text{SPEED-TRIM}}$]

Procedure 1. Two-step global optimization algorithm for model [DP$^{\text{SPEED-TRIM}}$]

Step 1. (**Trim optimization**) Construct a DP network based on the main waypoints of the voyage and the discretization toward the arrival time at each waypoint (equivalent to speed range discretization). For each link over the DP network, determine the best trim value and update the link cost.

Step 2. (**Speed optimization**) Find a shortest path through the DP network constructed in Step 1, and output the speeds over the consecutive sailing segments indicated by the shortest path as the optimal speed plan.

3.3.2. Simulation-based Optimization Approach for Trim Optimization

A straightforward approach to solve the trim optimization problem in Eq. (27) is *enumeration*: we enumerate all the trim values in T_k, i.e., all the trim values in $\left[\underline{T},\overline{T}\right]$ with a granularity of e.g. 0.01 m, calculate the corresponding fuel consumption values and choose the best one. However, our preliminary experiments showed that this enumeration method cannot deliver the optimal solution within a practically acceptable time limit. For example, for a long-haul voyage from Singapore to the Persian Gulf, representing a 181-hour sailing of ship S2 over nine segments, the constructed network for DP consists of 218 nodes and 2931 links whose costs are to be determined. For each link, 657 trim values (min: −3.00 m, max: 3.56 m, granularity: 0.01 m is required in practice) must be tried (enumerated), and each trim value should be input into $L=10$ trained ANNs to query the ship fuel efficiency in terms of MT per day (see Eq. (2)). The total number of ANN queries reaches 2,931×657×10=19,256,670. We failed to construct this DP network within 10 h, though the CPU time for each ANN query is much less than 0.01 s (basically 0.001 to 0.005 s). We thus resorted to parallelizing the link cost calculation so that cost calculation (trim optimization in Eq. (27)) for several links can be conducted simultaneously over multiple processor cores. The construction of this DP network over a workstation with 12 cores consumed

7318 s (2.03 h) even when all the 12 cores were fully used. The onshore officers collaborating with us commented that this is still unacceptable from an industry viewpoint.

The above analysis indicates that the computational bottleneck lies in the great number of trim values enumerated and the consequent significant workload of ship fuel efficiency queries with ANNs. Hence, a smarter trim optimization method rather than enumeration may be required to reduce the computational burden. To this end, we propose a simulation-based optimization technique for trim optimization in Eq. (27). The state-of-the-art simulation-based optimization technique provides some efficient approaches for global optimization of a black-box function. A typical simulation-based optimization approach takes advantage of *surrogate models* (also known as *response surface models* or *metamodels*) to approximate the black-box function under examination. Compared to the black-box function, the corresponding surrogate models have explicit mathematical expressions and thus their function evaluations are much cheaper (although crude). Meanwhile, these well-defined surrogate models always possess fine mathematical properties, such as differentiability or twice differentiability. Once a new solution (point) is evaluated (sampled), the surrogate model is updated with a further reduction in approximation errors, thus yielding a better approximation to the black-box function. This study employs surrogate model-based optimization approaches because we wish to take advantage of their computational competence to find good solutions with a limited number of black-box function evaluations, which eliminates the necessity of enumerating and evaluating every trim value. Specifically, we adopt a *cubic radial basis function* (RBF) surrogate model (Müller and Shoemaker, 2014). In fact, we tested ten surrogate models including linear RBF (RBFlin), cubic RBF (RBFcub), thin-plate spline RBF (RBFtps), linear regression polynomial (POLYlin), reduced quadratic regression polynomial (POLYquadr), reduced cubic regression polynomial (POLYcubr), multivariate adaptive regression spline (MARS), a mixture of RBFcub and MARS (MIX_RcM), a mixture of RBFcub and POLYquadr (MIX_RcPqr), and a mixture of RBFcub and POLYcubr (MIX_RcPcr), and found that the choice of surrogate models has little influence on the computational time or solution quality of the simulation-based optimization algorithmic procedure. For instance, the experimental results for a long-haul voyage of ship S2 from Singapore to a port in the Persian Gulf are shown in Fig. 10.

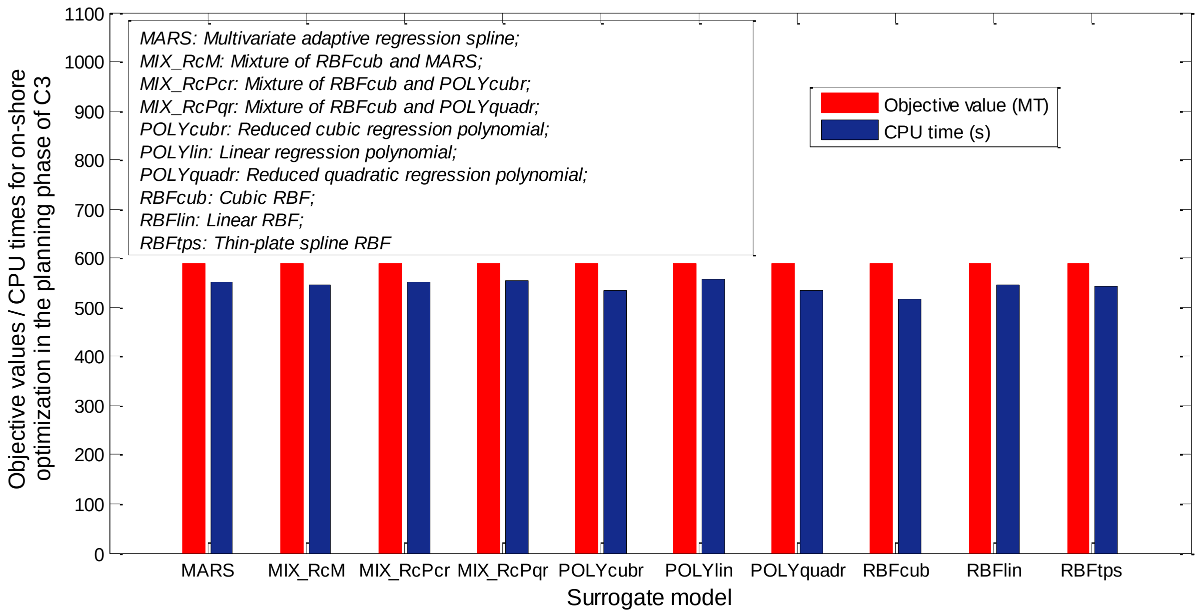


Fig. 10. Influence of surrogate model choice on optimal objectives and CPU times of on-shore optimization of C3

Specifically, for the trim optimization problem of segment k defined by Eq. (27), supposing that m trim values $t_k = T_{k(1)}, T_{k(2)}, \dots, T_{k(m)}$ and their corresponding function values $f_{k(1)}^{ANN2} := f_k^{ANN2}\left(V_k, T_{k(1)}, I'_k\right)$, $f_{k(2)}^{ANN2} := f_k^{ANN2}\left(V_k, T_{k(2)}, I'_k\right), \dots,$ $f_{k(m)}^{ANN2} := f_k^{ANN2}\left(V_k, T_{k(m)}, I'_k\right)$ are given, we attempt to find a surrogate function $g_k\left(t_k\right)$ of the form in the RBF surrogate model:

$$g_k\left(t_k\right)=\sum_{r=1}^{m}\lambda_{k,r}\left|t_k-T_{k(r)}\right|^3 \tag{29}$$

that interpolates the *data points* $\left(T_{k(1)}, f_{k(1)}^{ANN2}\right),\left(T_{k(2)}, f_{k(2)}^{ANN2}\right),...,\left(T_{k(m)}, f_{k(m)}^{ANN2}\right)$. In Eq. (29), $\lambda_{k,r}$, $r=1,...,m$, are real number coefficients to be calibrated. With the surrogate model (29), an algorithmic procedure repeating "surrogate model fitting - sampling" iterations can be designed for the trim optimization problem (27), which is illustrated by Fig. 11. For the details of the sampling strategy, we refer readers to Müller (2014).

To evaluate the performance of the surrogate model-based algorithmic procedure for trim optimization and to clarify how CPU times scale as the instance sizes increase, we constructed 16 voyages (instances) consisting of 2 to 32 sailing segments (representing a ship's sailing at sea in roughly 2 to 32 days) based on the voyage report data for ship S1. The maximum number of black-box function evaluations is set at 10. The experiments were tested on a 12-core workstation to allow us to parallelize the link cost calculation for the DP network over all the processor cores. The CPU time required for constructing the DP network is shown in Fig. 12. For a long voyage with a 32-day sail distance, the surrogate model-based trim optimization method requires about 40 min, which is only 15% of the time required by the enumeration method. The absolute gap between the objectives of the surrogate model-based algorithmic procedure and the enumeration method averages only 0.01 MT per voyage. As the average fuel consumption of a voyage exceeds 100 MT, the relative gap is less than 0.01%. We can thus conclude from a practical perspective that the surrogate model-based algorithmic procedure for trim optimization solves all instances (voyages) to global optimality.

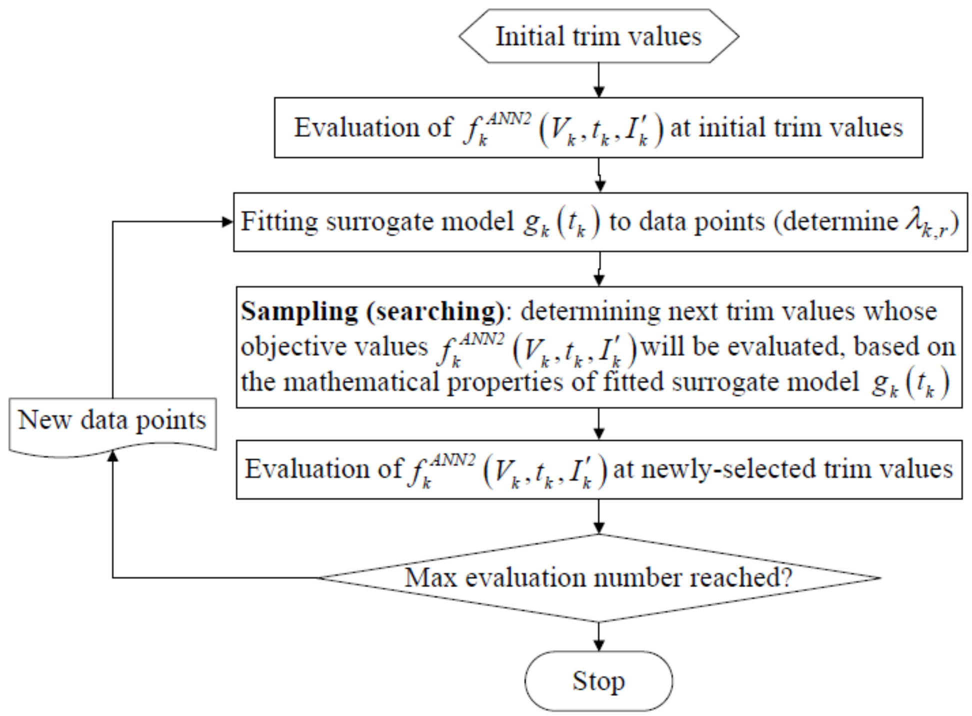


Fig. 11. The algorithmic procedure for trim optimization (20) based on the surrogate model

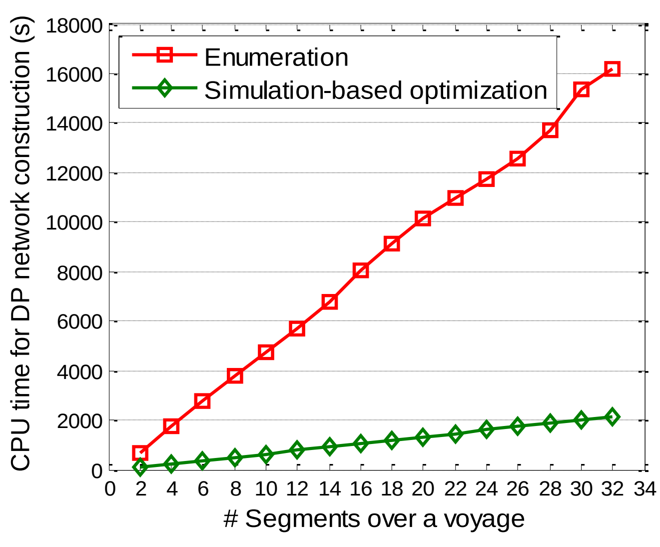


Fig. 12. CPU time for constructing the DP network against instance size

4. Numerical experiments

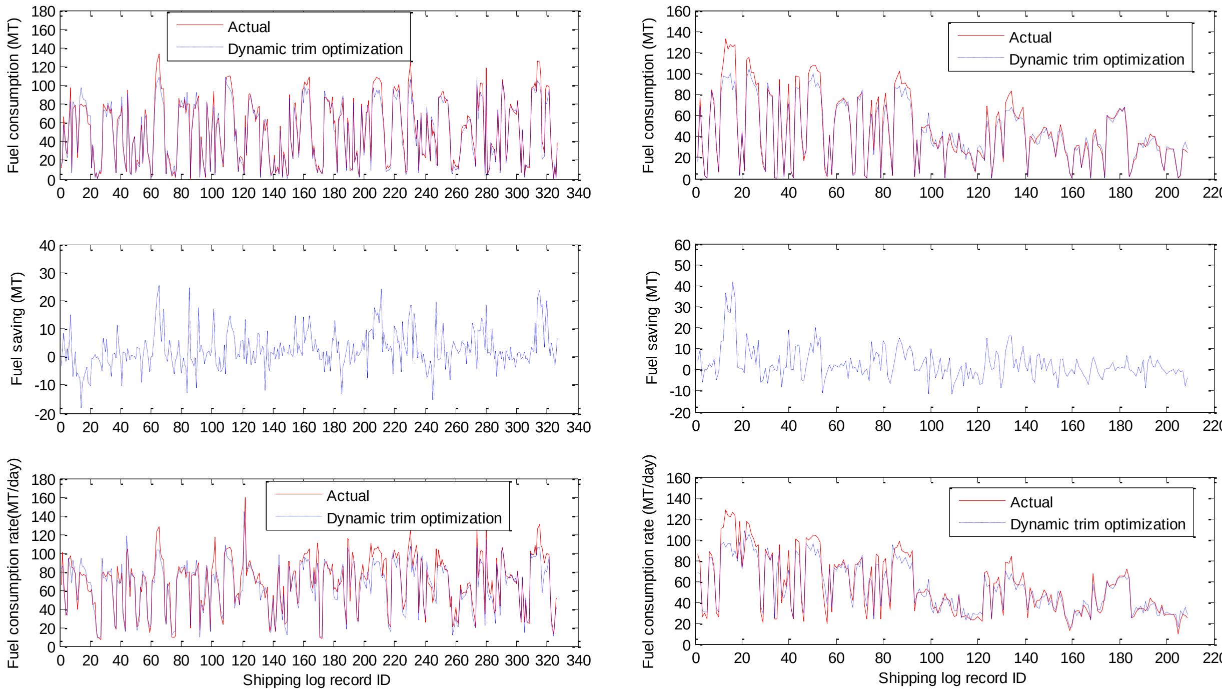
This section evaluates the performance of Countermeasures C1, C2, and C3 in ship speed and trim optimization. The voyage report data for ships S1 and S2 are used in these experiments. For S1, 327 report entries were extracted, representing its sailing over seven round trips (March 2014 to Feburary 2015) of which each contains 12 voyages (legs). For S2, only five round trips (June 2014 to March 2015), each of which contains 10 to 11 voyages, have complete data, and we have a total of 209 voyage report data entries. Note that for a small number of report data entries, if the values of some fields (basically the directions of wind and/or sea currents) were null, the industry specialists who provided the voyage report data filled in the values via interpolation from the entries for the previous segment and the next segment. As a result, the number of data entries used in this section is slightly larger than that used for calibrating the ANN models in Section 2.

We first evaluate the benefits of these three solution countermeasures in bunker fuel savings in comparison with the real situation, to reveal their practical implications for the shipping industry. We then further justify our methodology by comparing this study with the methodologies in existing studies with more numerical experiments. At last, we show the possibility of extending our speed optimization model in a multiobjective optimization framework.

4.1. Practical Implications of the Three Solution Countermeasures

4.1.1 C1 versus Real Situation: Bunker Fuel Savings via Dynamic Trim Optimization

For the 327 sailing segments of ship S1's 84 voyages, we collect the actual bunker fuel consumption, the bunker fuel consumption with C1, and the bunker fuel savings of C1 compared to the real situation, and present them in the top two diagrams of Fig. 13(a). The fuel consumption rates (MT/day) in the real situation and those fulfilled by C1 are also plotted in the bottom diagram of Fig. 13(a). Similarly, the results for the 209 sailing segments of ship S2's 51 voyages are presented in Fig. 13(b).



(a)Ship S1 (b) Ship S2

Fig. 13. Bunker fuel savings of C1

Fig. 13 shows that C1 brings significant fuel savings to ships S1 and S2. For the two ships, the bunker fuel savings with C1 over a daily sailing segment can reach 25 and 40 MT, respectively. The middle subplots of Fig. 13 show that the bunker fuel savings over some segments are negative, which indicates that in some scenarios, more bunker fuel would be consumed if C1 were adopted. In fact, these negative values originate from the prediction errors of ship fuel efficiency model [ANN1], which cannot be completely eliminated in theory.

To provide an overview of C1's bunker fuel savings for ships S1 and S2, we report the aggregated results in Table 2. We can see that compared to the real situation, C1 saves 849.80 MT

(4.96%) of bunker fuel for ship S1 over its seven round trips. For ship S2, C1 saves 554.87 MT (5.83%) of bunker fuel over its five round trips. This provides the insight that additional integration of the influence of weather and sea conditions into trim optimization could bring further considerable bunker fuel savings over the static trim optimization relying on trim charts or tables. This insight is highly consistent with industry specialists' observations. However, this study moves far beyond their observations by developing a systematic method of integrating the influence of weather and sea conditions into trim optimization and evaluating the corresponding benefits in a quantitative manner.

Table 2. Fuel savings of Ships S1 and S2 by C1 (dynamic trim optimization)

Ship	$Fuel^{Real}$	$Fuel^{C1}$	$Save^{C1\text{-}Real}$
S1 (7 round trips)	17129.71	16279.91	**849.80**(**4.96%**)
S2 (5 round trips)	9513.26	8958.39	**554.87**(**5.83%**)

Note: Unit: MT

4.1.2. C2 and C3 versus C1: Additional Benefits Produced by Speed Planning on Shore

Table 3 lists the experimental results of C2 and C3 for the seven trips of ship S1 and five trips of ship S2. It can be seen that compared to the real situation, C1 saves 4.96% and 5.83% of bunker fuel for ships S1 and S2, respectively; C2 attains 7.63% and 7.57%, respectively; and C3 increases the savings to 8.21% and 8.29%, respectively. The incremental bunker fuel savings of C2 relative to C1 are also remarkable: overall, C2 brings bunker fuel savings of 2.67% and 1.74% over the real situation for ships S1 and S2, respectively, compared to C1. We thus conclude that onshore officers' speed planning helps to correct the arbitrary nature of captains' decisions in operating ships at sea and therefore produces considerable bunker fuel savings. The incremental savings of C3 over the real situation for the two ships relative to C2 are 0.58% and 0.72% in percentage, and 98.51 and 67.67 MT in weight.

The results thus far are encouraging. If we take the average savings of the two ships with C3 over the reality, i.e., (8.21%+8.29%)/2 = 8.25%, considering that 50 million MT of bunker fuel was burned by the main engines of containerships in 2012 (Smith et al., 2014), the annual fuel savings with C3 would be remarkable. The monetary savings for shipping lines would be more considerable in the future because bunker fuel prices are expected to follow an increasing trend due to limited supply (Chen and Solak, 2015). Moreover, these remarkable bunker fuel savings could also translate into significant mitigation of CO_2 emissions.

Table 3. Fuel savings of Ships S1 and S2 by C1, C2, and C3

Ship	Trip	$Fuel^{Real}$	$Fuel^{C1}$	$Save^{C1\text{-}Real}$	$Fuel^{C2}$	$Save^{C2\text{-}Real}$	$Fuel^{C3}$	$Save^{C3\text{-}Real}$
S1	1	2183.30	2246.38	−63.08 (−2.89%)	2149.54	33.76 (1.55%)	2142.61	40.69 (1.86%)
	2	2391.90	2275.44	116.46 (4.87%)	2207.83	184.07 (7.70%)	2187.59	204.31 (8.54%)
	3	2383.40	2274.51	108.89 (4.57%)	2208.28	175.12 (7.35%)	2204.80	178.60 (7.49%)
	4	2485.41	2338.96	146.45 (5.89%)	2278.06	207.35 (8.34%)	2260.01	225.40 (9.07%)
	5	2758.20	2485.20	273.00 (9.90%)	2426.30	331.90 (12.03%)	2406.93	351.27 (12.74%)
	6	2384.00	2270.33	113.67 (4.77%)	2223.86	160.14 (6.72%)	2207.55	176.45 (7.40%)
	7	2543.50	2389.09	154.41 (6.07%)	2328.35	215.15 (8.46%)	2314.22	229.28 (9.01%)
	Overall	17129.71	**16279.91**	**849.8 (4.96%)**	**15822.22**	**1307.49 (7.63%)**	**15723.71**	**1406.00 (8.21%)**
S2	1	2361.60	2108.78	252.82 (10.71%)	2009.87	351.73 (14.89%)	1989.20	372.40 (15.77%)
	2	2087.00	1961.26	125.74 (6.02%)	1941.93	145.07 (6.95%)	1903.70	183.30 (8.78%)
	3	1959.80	1885.20	74.60 (3.81%)	1852.37	107.43 (5.48%)	1848.27	111.53 (5.69%)
	4	1679.90	1571.67	108.23 (6.44%)	1566.22	113.68 (6.77%)	1564.84	115.06 (6.85%)
	5	1424.96	1431.49	−6.53 (−0.46%)	1422.33	2.63 (0.18%)	1419.04	5.92 (0.42%)
	Overall	9513.26	**8958.40**	**554.86 (5.83%)**	**8792.72**	**720.54 (7.57%)**	**8725.05**	**788.21 (8.29%)**

Note: Unit: MT.

4.2. Implications from the Comparison with Existing Methodologies

As mentioned in Section 1.1, speed optimization for containerships has been well addressed by existing studies. This section attempts to compare this study with existing studies to reveal the benefits of adopting the methodology of our study. Most existing studies dealt with speed optimization of containerships in the context of a round service or service network and sought to determine the optimal average sailing speed over each leg. Few studies have addressed optimization of a ship's daily sailing speed over a voyage. On the other hand, it can be seen from

Section 3.2 that onshore daily speed optimization over a voyage can be well solved by DP via a shortest-path network: the global optimal solution can be easily found by an efficient algorithm. Thus, it will be difficult to justify the necessity of comparing this study with other studies in terms of the approaches of modeling and solving the onshore daily speed optimization over a voyage (i.e., an alternative method other than DP).

For onshore speed optimization over a voyage, the major difference between this study and existing studies lies in the choice of a ship fuel efficiency model, i.e., the method to quantify a ship's bunker fuel consumption in a time unit (e.g., day). Section 2.3 provides several representative ship fuel efficiency models used in existing studies, including [CBC], [CBC'], [ADM], [ADM'], [NLR], and [MLR]. Hence, we replaced model [ANN2] by an alternative ship fuel efficiency model ([CBC], [CBC'], [ADM], [ADM'], [NLR], or [MLR]) in onshore speed optimization of C2, and repeated all of the experiments for C2, to assess the influence of this replacement on the performance of sailing speed optimization. Specifically, we attempted to answer the following two questions:

- These fuel efficiency models ([CBC], [CBC'], [ADM], [ADM'], [NLR], and [MLR]) have different levels of accuracy in fuel efficiency estimation. Will this difference in accuracy have a great influence on the results of speed optimization?
- With this replacement of the ship fuel efficiency model used in onshore speed optimization of C2, will the trim optimization performed at sea (C1; based on [ANN1]) still bring considerable fuel consumption savings in addition to on-shore speed optimization?

4.2.1 Influence of Ship Fuel Efficiency Model Choice on Speed Optimization

Table 4 shows the optimal objective (referred to as *estimated fuel consumption*) of the speed optimization with each ship fuel efficiency model. The estimated fuel consumption of onshore planning with C3 (simultaneous speed and trim optimization to determine better sailing speeds) is also listed in the last column of Table 4. However, with a specific ship fuel efficiency model (such as [CBC]), it is still questionable whether the obtained solution (speeds) of speed optimization can fulfil the estimated fuel consumption listed in Table 4 in reality, because the accuracy issue of e.g. model [CBC] (R^2=0.7784 over the training set) might erode the reliability of the obtained optimal objective. To overcome this, we re-calculate the bunker fuel consumption of ships S1 and S2 by inputting the obtained optimal speeds associated with e.g. [CBC] and some important information from voyage report data (displacement and weather and sea conditions) into [ANN1] (i.e., the most reliable ship fuel efficiency model; see Table 1), and obtain the corresponding *achievable fuel consumption* in reality. Table 5 shows the achievable fuel consumption in reality with the optimal sailing speeds associated with each ship fuel efficiency model. Fig. 14 compares the estimated fuel consumption and the achievable fuel consumption.

Our first observation with Fig. 14 is that the achievable fuel consumption values associated with [CBC], [CBC'], [ADM], [ADM'] and [NLR] are nearly the same, which is also quite close to the achievable fuel consumption of C2 with [ANN2]. This observation reveals that models [CBC], [CBC'], [ADM], [ADM'], and [NLR] are competent to reflect the influence of sailing speed on ship fuel efficiency in a relatively accurate way, and thus the results (solutions) of speed optimization are rather reliable, although the optimal objective (estimated fuel consumption) of speed optimization might differ greatly from the achievable situation. In this sense, the accuracy issue of the ship fuel efficiency model will not have a significant influence on the result of speed optimization.

Fig. 14(b) shows that the adoption of [ANN2] in speed optimization (C2) would save 3.69% of bunker fuel in reality compared to speed optimization with [CBC]. This finding indicates that a highly accurate ship fuel efficiency model, like ANN, may create the possibility of remarkable fuel savings via speed optimization, which is one of the benefits of adopting the ANN ship fuel efficiency model in speed optimization.

Table 1 shows that the fit performance of [MLR] is quite good and much better than that of [CBC], [CBC'], [ADM], [ADM'], and [NLR]. However, Fig. 14 shows that the result of speed optimization with [MLR] is not reliable at all: a large difference exists between the achievable fuel consumption and the estimated fuel consumption (optimal objective), and the achievable fuel consumption is even much higher than the real situation recorded by the voyage report data. This finding reveals that [MLR] is unable to reflect the influence of sailing speed on ship fuel efficiency in a sufficiently accurate way, although its fit performance is attractive. Good fit performance of a ship fuel efficiency model does not necessarily imply a high degree of reliability in speed optimization. Actually, the reliability of a ship fuel efficiency model depends on whether it quantifies the influence of sailing speed on bunker fuel efficiency in a sufficiently accurate way because we are conducting speed optimization here.

4.2.2 Additional benefit of trim optimization at sea

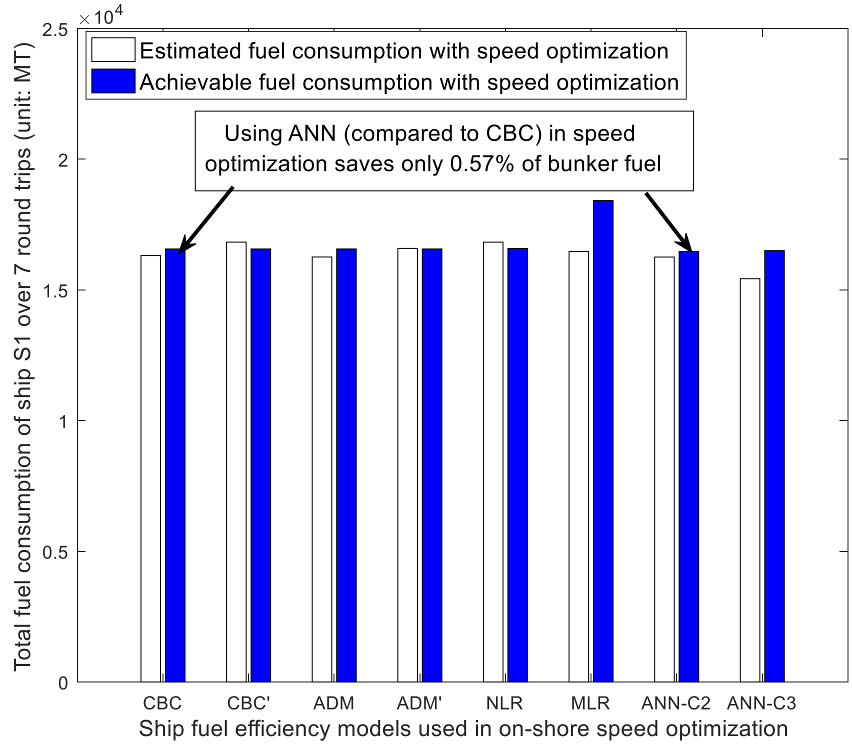
With the speed optimization results in Section 4.2.1 with each ship fuel efficiency model, such as C2, we also apply trim optimization at sea (C1) to evaluate the additional benefit of trim optimization at sea compared to the policy in which only speed optimization is conducted. Table 6 shows the achievable bunker fuel consumption with onshore speed optimization plus trim optimization at sea. Fig. 15 illustrates its comparison with the achievable bunker fuel consumption with speed optimization alone (i.e., the results shown in Table 5).

Table 4. Estimated bunker fuel consumption with on-shore speed optimization based on different ship fuel efficiency models (unit: MT)

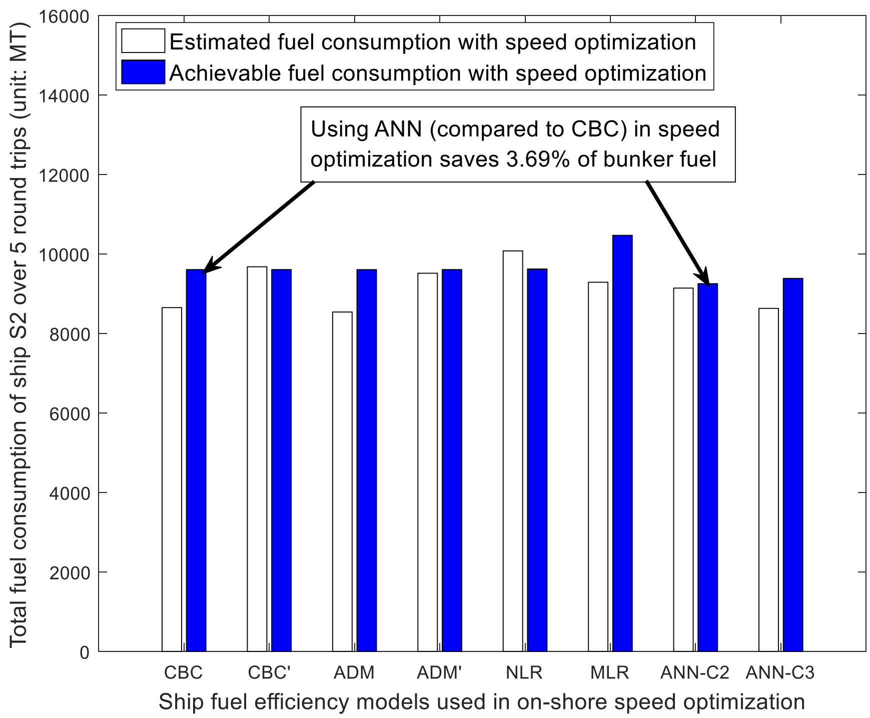
Ship	Trip	CBC	CBC’	ADM	ADM’	NLR	MLR	ANN (C2-Speed Opt)	ANN (C3-Speed Opt)
S1	1	2277.64	2362.77	2203.43	2308.73	2291.66	2246.97	2218.72	2109.12
	2	2291.09	2372.41	2316.26	2347.35	2400.52	2304.45	2319.10	2193.62
	3	2237.30	2337.33	2243.74	2304.36	2468.19	2370.38	2293.87	2176.71
	4	2353.39	2421.78	2339.89	2385.98	2405.34	2326.19	2332.85	2205.56
	5	2492.44	2530.14	2553.89	2517.22	2514.25	2496.63	2439.29	2323.83
	6	2214.39	2316.97	2193.69	2275.18	2317.84	2291.32	2228.38	2126.34
	7	2446.33	2486.68	2407.95	2448.92	2428.27	2434.61	2424.36	2292.54
	Overall	16312.59	16828.09	16258.85	16587.75	16826.07	16470.56	16256.57	**15427.72**
S2	1	2165.82	2219.07	2169.77	2185.45	2301.72	2260.41	2123.89	1975.88
	2	2054.63	2145.41	2030.80	2104.16	2147.71	2173.78	2037.79	1879.47
	3	1752.12	2034.28	1664.47	1975.82	2116.49	1847.87	1908.16	1810.81
	4	1388.16	1676.21	1386.18	1660.00	1801.76	1565.12	1572.98	1508.83
	5	1287.76	1600.42	1286.20	1587.43	1708.27	1439.28	1496.56	1453.84
	Overall	8648.48	9675.39	8537.42	9512.86	10075.94	9286.46	9139.37	**8628.83**

Table 5. Achievable bunker fuel consumption with on-shore speed optimization based on different ship fuel efficiency models in reality (unit: MT)

Ship	Trip	CBC	CBC’	ADM	ADM’	NLR	MLR	ANN (C2-Speed Opt)	ANN (C3-Speed Opt)
S1	1	2235.12	2235.12	2235.30	2235.12	2234.04	2604.72	2233.49	2234.92
	2	2320.32	2320.32	2320.32	2320.32	2326.98	2555.86	2300.56	2296.16
	3	2331.53	2331.53	2331.53	2331.53	2334.86	2595.47	2307.49	2322.26
	4	2370.80	2370.80	2370.80	2370.80	2372.39	2641.36	2364.14	2376.89
	5	2526.77	2526.77	2526.77	2526.77	2532.03	2737.01	2507.55	2495.05
	6	2321.01	2321.01	2321.01	2321.01	2325.13	2589.97	2301.17	2314.91
	7	2461.22	2461.22	2461.83	2461.22	2462.06	2692.74	2457.14	2463.24
	Overall	16566.78	16566.78	16567.58	16566.78	16587.49	18417.12	**16471.54**	**16503.43**
S2	1	2307.52	2307.52	2309.86	2307.52	2320.51	2264.87	2131.63	2174.37
	2	2158.36	2158.36	2155.31	2158.36	2159.50	2185.09	2062.58	2101.76
	3	1997.72	1997.72	1997.03	1997.72	1997.42	2231.84	1938.01	1962.92
	4	1660.69	1660.69	1660.69	1660.69	1660.89	1969.28	1646.73	1661.21
	5	1480.44	1480.44	1481.13	1481.13	1481.59	1815.46	1471.32	1482.86
	Overall	9604.72	9604.72	9604.01	9605.41	9619.90	10466.53	**9250.26**	**9383.11**



(a) Ship S1 over 7 round trips

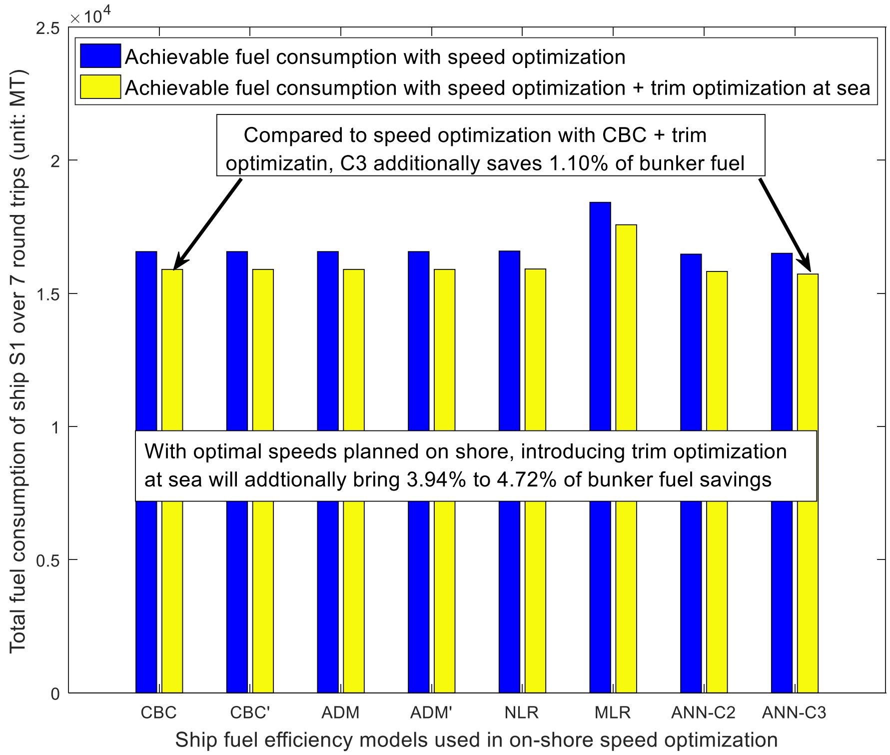


(b) Ship S2 over 5 round trips

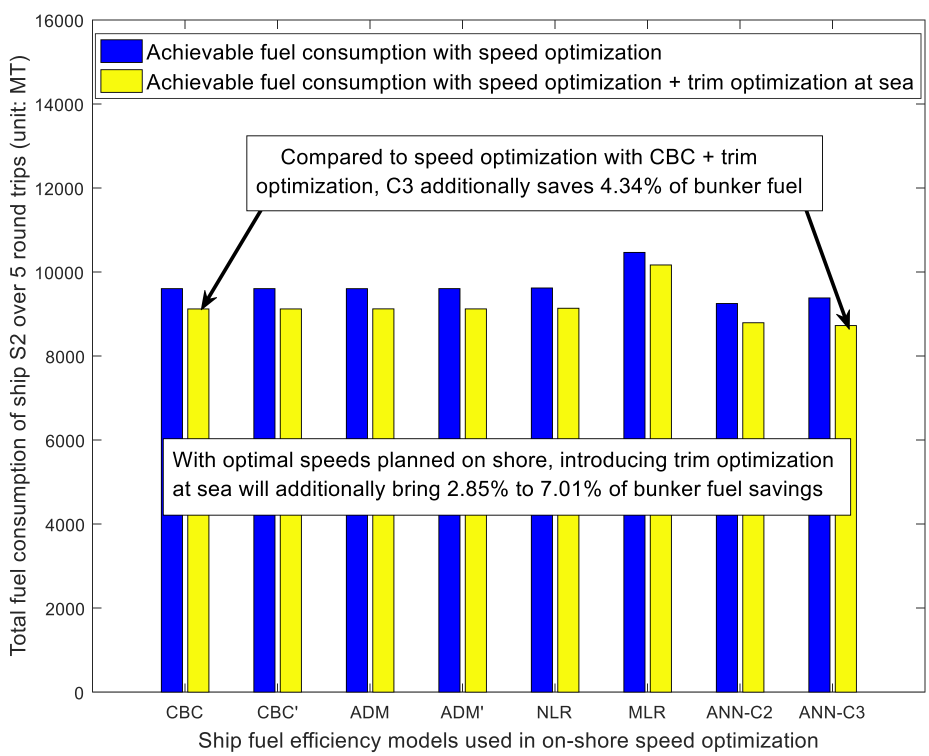
Fig. 14. Influence of ship fuel efficiency model choice on on-shore speed optimization results

Table 6. Achievable bunker fuel consumption with optimal speeds based on different ship fuel efficiency models and optimal trim settings via C1 (unit: MT)

Ship	Trip	CBC	CBC'	ADM	ADM'	NLR	MLR	ANN (C2)	ANN (C3)
S1	1	2150.16	2150.16	2150.14	2150.16	2148.38	2483.66	2149.54	2142.61
	2	2213.24	2213.24	2213.24	2213.24	2223.30	2424.90	2207.83	2187.59
	3	2218.44	2218.44	2218.44	2218.44	2225.34	2486.49	2208.28	2204.80
	4	2277.22	2277.22	2277.22	2277.22	2278.42	2514.55	2278.06	2260.01
	5	2444.42	2444.42	2444.42	2444.42	2443.56	2627.64	2426.30	2406.93
	6	2245.17	2245.17	2245.17	2245.17	2244.47	2477.80	2223.86	2207.55
	7	2350.37	2350.37	2349.99	2350.37	2351.55	2559.64	2328.35	2314.22
	Overall	15899.01	15899.01	15898.61	15899.01	15915.03	17574.68	**15822.22**	**15723.72**
S2	1	2176.24	2176.24	2179.04	2176.24	2187.95	2195.20	2009.87	1989.20
	2	2030.92	2030.92	2029.15	2030.92	2034.00	2122.69	1941.93	1903.70
	3	1903.95	1903.95	1903.86	1903.95	1903.35	2171.87	1852.37	1848.27
	4	1581.10	1581.10	1581.10	1581.10	1581.87	1920.00	1566.22	1564.84
	5	1429.14	1429.14	1429.88	1429.88	1430.25	1758.03	1422.33	1419.04
	Overall	9121.35	9121.35	9123.02	9122.09	9137.43	10167.80	**8792.72**	**8725.04**



(a) Ship S1 over 7 round trips



(b) Ship S2 over 5 round trips

Fig. 15. Benefits of introducing trim optimization at sea (C1)

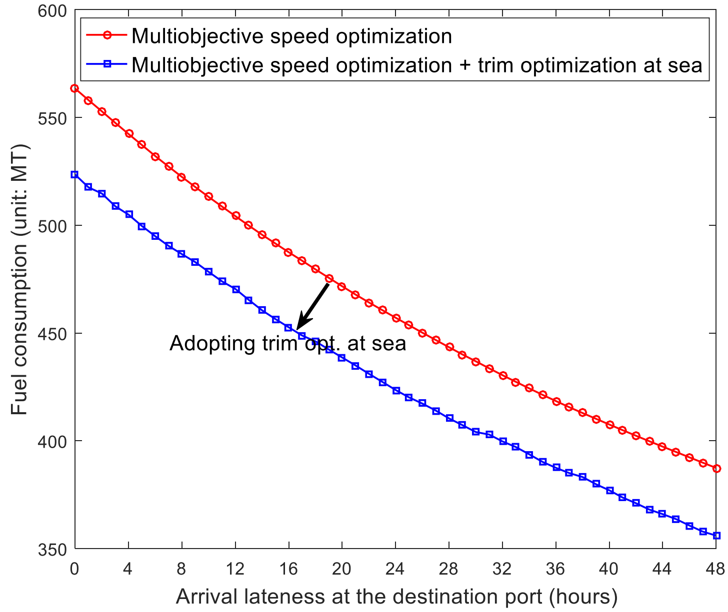
It can be seen from Fig. 15 that when compared to speed optimization alone, the application of trim optimization at sea can save an additional 3.94% (4.03% if [MLR] is excluded) to 4.72% of bunker fuel for ship S1, and save 2.85% (4.95% if [MLR] is excluded) to 7.01% of bunker fuel for ship S2. This further demonstrates the benefits of trim optimization at sea.

Fig. 15 also shows the superiority of conducting complicated simultaneous speed and trim optimization on shore with an accurate ship fuel efficiency model (ANN). The achievable fuel consumption with C3 is 1.10% (ship S1) and 4.34% (ship S2) lower than that obtained by speed optimization with [CBC] plus trim optimization at sea. This finding justifies the value of adopting the methodology in C3.

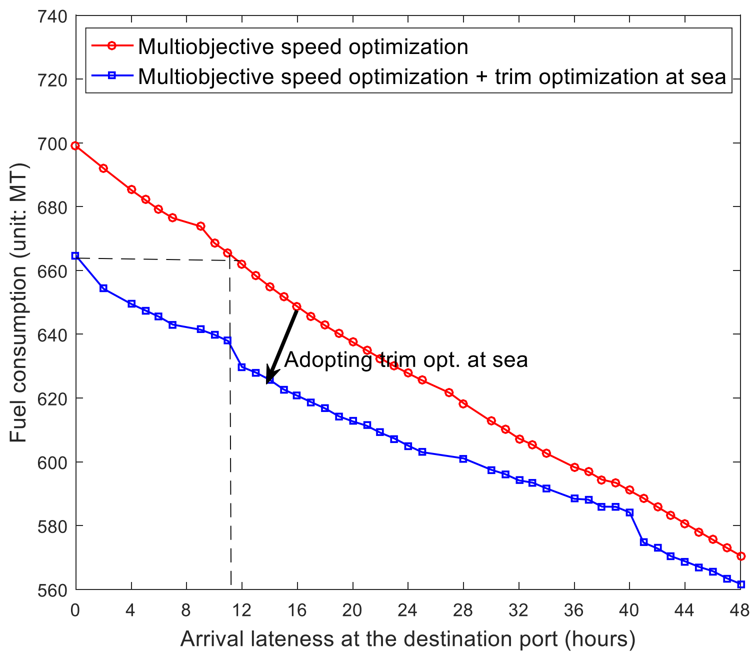
4.3. Multiobjective Onshore Speed Optimization

Mansouri et al. (2015) noted the necessity of considering multiple objectives in shipping operations to enhance environmental sustainability while maintaining certain levels of shipping service. Lee et al. (2018) further developed stepwise service level functions to reflect port operators' tolerance of ships' arrival delays when addressing ship speed optimization over a round service. Our speed optimization models ([DP^{SPEED}] and [$DP^{SPEED\text{-}TRIM}$]) can be retrofitted to include multiple objectives by using the ε-constraint approach.

To illustrate this, model [DP^{SPEED}] is retrofitted to construct a bi-objective speed optimization model that considers both bunker fuel consumption and the ship's arrival delays at the destination port. Two long-haul voyages are used as numerical examples: Voyage 1 represents one of ship S1's journeys from Jebel Ali to Singapore (3466 nm, 8.6 days), and Voyage 2 represents one of ship S2's journeys from Singapore to Jebel Ali (3479 nm, 7.6 days). Fig. 16 shows the Pareto frontiers of these two voyages. For bunker fuel consumption, the optimal objective of speed optimization and the fuel consumption of speed optimization plus trim optimization at sea are both illustrated.



(a) Voyage 1 (ship S1): Jebel Ali to Singapore



(b) Voyage 2 (ship S2): Singapore to Jebel Ali

Fig. 16. Pareto frontier of multiobjective speed optimization

The shipping company could balance its interests in fuel consumption and arrival lateness (delay) at the destination port through the Pareto frontier. The Pareto frontier for Voyage 1 is quite smooth. By contrast, the Pareto frontier for Voyage 2 shows that ship S2 could save 7.00 MT of bunker fuel if it arrives at Jebel Ali 2 hours after the ETA. If arrival delays of 4, 6, and 8 hours are allowed, these bunker fuel savings increase to 13.78, 19.94, and 22.56 MT, respectively. These arrival delays might be acceptable in practice as long as the arrival time does not deviate excessively from the contracted time window. Fig. 16 further illustrates the benefits of adopting trim optimization at sea, compared to speed optimization alone. Fig. 16(b) shows that if trim optimization is also adopted at sea, ship S2 can nearly fulfil the fuel savings corresponding to an arrival delay of 11 hours, while still maintaining ETA.

5. Conclusions and Discussion

This study introduces to the academic community the ship speed and trim optimization problem over a voyage. To address the industry requirements for this problem, two ANN models for ship fuel efficiency are constructed to enable us to predict a ship's fuel consumption rate given its sailing speed, displacement, trim, and weather and sea conditions, with or without directional information of wind, waves and sea currents. With this prediction capability, we propose three optimal solution countermeasures in a two-phase planning framework for this speed and trim optimization problem: sailing speeds are optimized in an on-shore planning phase, while trim optimization is conducted dynamically by the captain in real time when the actual weather and sea conditions at sea are observed. Trim optimization with [ANN1] in the real-time phase can be easily solved by the enumeration method, which represents our first countermeasure (C1). The other two countermeasures (C2 and C3) adopt C1 for real-time trim optimization at sea, and also include speed optimization on shore. In onshore speed optimization, C2 ignores the possible influence of trim on ship fuel efficiency by fixing the trim at zero, which makes a DP model workable in terms of both solution effectiveness and efficiency. To allow more informed speed decisions, it is necessary to optimize speed and trim simultaneously in the onshore speed planning phase due to their closely interwoven influences on ship fuel efficiency. C3 addresses this simultaneous speed and trim optimization problem with a two-step global optimization algorithmic procedure that combines DP and a state-of-the-art simulation-based optimization approach. The models and solution algorithms in this study are all driven by the black-box characteristic of the ANN ship fuel efficiency models. Hence, this is evidently a data-driven optimization study (Simchi-Levi, 2013) and could not have been conducted without the voyage report data provided by our industry collaborators.

Our methodological contributions to the literature on ship speed optimization are twofold. (a) This study introduces a highly accurate ANN model for ship fuel efficiency analysis to the problem of ship speed optimization. Compared to existing studies, adopting ANN in speed optimization (C2) for one thing makes the estimated fuel consumption much closer to the actual achievable fuel consumption in reality, and for another may create the possibility of remarkable bunker fuel savings via speed optimization. (b) This study takes the initiative to factor the influence of trim on ship fuel efficiency into speed optimization, by considering the closely interwoven influences of speed and trim on ship fuel efficiency. Numerical experiments have shown that simultaneous speed and trim optimization will enable onshore officers to make more informed speed decisions.

As far as the contribution to existing studies of ship trim optimization is concerned, this study overcomes the drawbacks of trim tables and charts, upon which the trim optimization literature focuses, in the sense that trim tables and charts are unable to reflect consideration of weather and sea conditions. Numerical experiments have also revealed that no matter what data model is adopted for ship fuel efficiency analysis in onshore speed optimization, the additional application of dynamic trim optimization at sea (C1) would always be beneficial and bring considerable bunker fuel savings.

The experimental results of the three countermeasures compared to the real situation are extremely encouraging. Experiments with two 9000-TEU containerships show that (a) C1 saves 4.96% and 5.83% of bunker fuel for the two ships, compared to the real situation; (b) C2 increases the bunker fuel savings to 7.63% and 7.57%; and (c) C3 further enhances the savings to 8.21% and 8.29%. These bunker fuel savings and the resulting mitigation of CO_2 emissions are significant. This study is highly consistent with IMO's promotion of *improved voyage planning* as a fuel-efficiency measure (IMO, 2012), and with the appeals of ClassNK, a leading ship classification society, for the evolution from *eco-ships* to *eco-shipping*, which highlights the roles of data analytics and managerial approaches in improving ship fuel efficiency (Nakamura, 2015).

The most important insight of this study for the shipping industry is the discovery that the proposed two-phase optimal solution countermeasures can considerably improve the industry status quo in ship speed and trim optimization over a voyage, leading to remarkable fuel cost savings and emission reductions. Such an insight is not yet apparent to the industry. At the same time, we note that the shipping industry is very conservative. A new initiative taken by a shipping company may be resisted not only by the internal pressure of the company, but also by ship owners, port operators, and shippers. Shipping companies are thus reluctant to share data, which has led to the dearth of data-driven research (Christiansen et al., 2013; Fransoo and Lee, 2013; Meng et al., 2014; Lee and Song, 2017). For this reason, our three countermeasures are introduced in an incremental manner. As a first step, we will work with the shipping company regarding field implementation of C1, which requires the least change of the state-of-the-art shipping practices. After that, C2 and C3 will be implemented gradually, and we envision that they will be implemented using a *rolling horizon*, with the speed for each segment updated each day to compensate for uncertainties in future weather and sea conditions.

However, this does not mean that these three countermeasures will be adopted in the shipping industry very soon. First, providing a technical solution does not mean overcoming cultural barriers. The implementation of speed optimization in C2 or C3 requires that captains adopt the daily speed suggestion from the onshore officers. This would cause resistance from captains because this new practice erodes their authority as endowed by the long history of commercial shipping. Second, communication between the various players in the shipping industry is accompanied by complicated issues of autonomy and mutual trust. For instance, the IMO noted that trim optimization is ignored in the great majority of cases in shipping practice and more companies have opted out of trim optimization in the recent development of energy efficiency regulations, because the fuel-saving performance of the trim tables or curves estimated by the CFD approach is not convincing to captains at sea (IMO, 2016). We face a similar issue in voyage speed optimization. Some WISPs and/or ship classification societies have actually begun to provide the commercial service of fine adjustments to daily sailing speeds over a voyage to save bunker fuel. However, the fuel efficiency estimation behind these services is also based on ship motion models and hydrodynamics and aerodynamics calculations in computers, which still provokes skepticism from captains about the reliability and economic value of these services. This study provides a complementary solution to the existing industry solutions and practices based on voyage report data (which should be more convincing from the perspective of shipping companies), but confirmation of its performance in sea trials will take considerable time. It is also possible for

WISPs to implement the models in this study in their software and promote them throughout the industry.

In the era of eco-shipping, multiple sources of data related to ship fuel efficiency are available, such as voyage report data, data returned by advanced sensors around the ship, and detailed weather and sea information from WISPs or other organizations. Exploring the methods and benefits of combining these data sets in ship voyage management would emerge as a promising beam of research in the community of maritime studies (Coraddu et al., 2017; Fujitsu, 2016; Yoshida, 2017). For instance, the information on weather and sea conditions contained in each voyage report data entry is a snapshot of the whole day, and this should be corrected as the average condition on the corresponding day. The data correction in this study was performed manually by our industry collaborators with the data from their WISPs. This may be improved by a data parser in the form of a software package suggested by Lee et al. (2018) that can parse and process the weather information from publicly accessible data sets (e.g., Copernicus data). Certainly, studies of data analysis and optimization models based on these separate and/or combined data sets are also important.

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