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Sailing Speed Optimization Model for Slow Steaming Considering Loss Aversion Mechanism

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This paper analyses loss aversion mechanism (LAM) of the shipping company's decision-makers about the risk-based decision (RBD) for slow steaming and generalizes a novel optimization model for the sailing speed through the trade-off between fuel consumption, SO_x emissions and delivery delay. The value functions against the benchmark speed were constructed based on physiological expected utility (PEU) to reveal the features of loss aversion, and the objective function was derived from these value functions with the aim to optimize the sailing speed. After that, a Genetic Algorithm (GA) solution with fitness function and special operators was built to solve the proposed model. Finally, the model was applied to pinpoint the PEU for the optimal sailing speed against the benchmark speed, and the sensitivity of the model was discussed with different benchmark speeds, value function weights and input parameters. The analysis shows that the proposed model can assist the slow steaming RBD based on the inner feelings of the shipping company's decision-makers, offering a novel tool for sailing speed optimization.

1. Introduction

Maritime transport carries more freight than any other mode of transport. It is the lifeline of trade and economic cooperation around the world. The environmentally sustainable operations in maritime shipping, essential to the health of maritime supply chains [1], are bottlenecked by the uncontrolled emissions of sulphur oxides (SO_x). According to the International Maritime Organization (IMO), the average annual global fuel consumption of maritime shipping was 325 million tons in 2007–2012, resulting in 13% of the total annual SO_x emissions [2]. To curb the air pollution from ships, the IMO issued the *MARPOL Annex VI–prevention of air pollution from ships* in 2005, and delineated sulphur emission control areas (SECAs): the SO_x emissions must be reduced from 1% to 0.1% by 2015 in such SECAs as the Baltic Sea, the North Sea, and the North American Area (coastal areas of the United States and Canada) and to 0.5% globally by 2020. Similarly, China established SECAs in its coastal areas in 2015, imposing a sulfur limit of 0.5%. However, considering the currently insufficient supply networks of low sulfur fuel oil and overwhelmed shipyard capacity of retrofitting scrubbers, the shipping companies may fail to use compliant fuel occasionally

and therefore violate the regulations. In order to deter potential violaters, there have been penalty policies reflecting the seriousness of the violation in the SECAs. For instance, the penalty against SO_x emissions in China can be up to 100 thousand RMB. Suffice it to say that complying to the limits of SO_x emissions is a strategic task for the shipping company involved in maritime supply chains.

Recent years has seen an increasing interest in the creation of sustainable maritime supply chains from the operation perspective. For the shipping company offering transport services between different ports, slow steaming is an effective way to improve the operational level. This operation has been practiced on all kinds of commercial ships, ranging from tankers, bulk carriers to containerships [3]. Considering the nonlinear relationship between sailing speed and fuel consumption [4], a ship moving at a slow speed enjoys low fuel consumption and SO_x emissions. For instance, a Maersk Triple E-class containership, designed to move at a speed (17.8 knots) below the normal range of 22–25 knots, emits 50% less SO_x than the average level on the Asia-Europe trade lane [5]. However, the sailing speed cannot fall below a certain threshold, or the ship's main engine may stall. As a result, the sailing speed of a ship has a rather complex impact on operating cost and SO_x

TABLE 1: Implementation plan for SO_x emissions control in China SECAs.

Ports in SECA	In force	Sulphur limit	Application
Key ports in Yangtze River delta	2016.4.1	<0.5% m/m	All ships—change over to low sulphur fuel after the berthing before the departure.
Key ports in Pearl River delta	2016.10.1	<0.5% m/m	All ships—change over to low sulphur fuel after the berthing before the departure.
Key ports in Circum-Bohai sea area	2017.1.1	<0.5% m/m	All ships—change over to low sulphur fuel after the berthing before the departure.
All ports in above 3 SECAs	2018.1.1	<0.5% m/m	All ships—change over to low sulphur fuel prior to the berthing.
All ports in above 3 SECAs	2019.1.1	<0.5% m/m	All ships—change over to low sulphur fuel prior to entering any SECA.

emissions. The sailing speed also affects the round-trip time of the ship route [6]. Suppose the round-trip time of a containership route is 48d at the sailing speed of 22 knots. That time might surpass 48d if the containership sails at a lower speed. Therefore, when a shipping company decides to reduce fuel consumption and SO_x emissions through slow steaming, the sailing speed reduction could exert an adverse impact on the punctuality of shipment delivery, leading to poor service level and customer dissatisfaction [7]. To sum up, the sailing speed is a key decision variable in slow steaming [8], in addition to fuel price, SO_x emissions, delivery schedule, cargoes onboard, etc.

To optimize the sailing speed, the shipping company must make a trade-off, or risk-based decision (RBD), between different operational objectives, such as fuel consumption, SO_x emissions, and delivery delay. The empirical studies have shown that loss aversion is ubiquitous for real-world RBDs in various uncertain conditions, which goes against the rational agent hypothesis in expected utility theory or axioms of preference [9]. The concept of loss aversion first appeared in "Prospect theory: an analysis of decision under risk" [10] and has been applied in many studies focusing on the RBDs in different domains. In addition, neuroeconomics provides a new theoretical framework for the human decision-making process, using modern techniques and tools in brain science. Both the related literature and the physiological findings make it possible to analyse the loss aversion mechanism (LAM) of the shipping company's decision-makers and give a logical explanation to the RBD in slow steaming.

1.1. Objectives. Hailed as the world factory, China is an important link in maritime supply chains. The ships entering and leaving the ports along China's coastline both bring cargoes and exacerbate the air pollution in and around the ports. The *NRDC White Paper on Prevention and Control of Shipping and Port Air Emissions in China* states that the daily emissions of a medium or large containership using fuel oil with 3.5% sulphur are comparable to those of 500,000 trucks that conform to China IV emission standards and drive 164 km per day. Considering the cost-effectiveness of the

SECAs in emission control, the Chinese Ministry of Transport released the *Implementation Plan for SECAs in the Waters of Pearl River Delta, Yangtze River Delta, and Circum-Bohai Sea Area (Beijing-Tianjin-Hebei)* in December 2015, which lays down an increasingly strict standards or alternative measures on sulphur content in fuel oil for ships engaging in port-based operations (Table 1).

In the quest for environment friendly solutions, slower sailing speed is a common answer to the reduction of total SO_x emissions. However, the slowdown of sailing speed may cause the delay of shipment delivery. The resulting inventory cost can be viewed as a loss, which should not be overlooked if punctuality is required. Hence, it is necessary to make a trade-off between fuel consumption, SO_x emissions, and delivery delay in sailing speed optimization problem. In general, the previous models for this problem only pursue the minimal fuel consumption, SO_x emissions or delivery delay (e.g., penalty charges), failing to treat the minimal total cost as an explicit objective [11]. Such an approach could leave a negative impact on post-optimization analysis. Therefore, this paper aims to determine the optimal sailing speed of the ship on a fixed route considering the trade-off between fuel consumption, SO_x emissions, and delivery delay.

An often neglected, yet essential concept is the inner feeling as the shipping company's decision-makers in slow steaming operations. In many cases, the company has thought of an empirical sailing speed before the decision-making process. The functional magnetic resonance imaging (fMRI) study by Breiter et al. [12] demonstrates that the human nervous system carries the neurological feature of physiological expected utility (PEU) in the calculation and evaluation for RBD. It could be enlightening to take the loss aversion model in prospect theory as a PEU function before exploring the LAM of the shipping company's decision-makers with different degrees of personal preference in the RBD for slow steaming [13]. The existing studies on sailing speed optimization problem seldom examine practical issues like the PEU against the benchmark speed of slow steaming. Thus, this paper also attempts to disclose the LAM of the shipping company's decision-makers, considering such three

operational objectives in slow steaming as fuel consumption, SO_x emissions and delivery delay, and determine its impact on the RBD of the shipping company.

1.2. Contributions. The main contributions of this paper to environmentally sustainable operations in maritime shipping are as follows:

(1) An analytical framework was established to examine the LAM of the shipping company in the RBD for slow steaming, with the aim to maximize the PEU against the benchmark speed.

(2) This paper enables the shipping company to determine the optimal sailing speed of the ship on a fixed route based on the trade-off between fuel consumption, SO_x emissions and delivery delay.

(3) The proposed sailing speed optimization model for slow steaming (SSOM-SS) was verified in a case study on the RBD for slow steaming of the Orient Overseas Container Line (OOCL) containership operating between Dalian and Kaohsiung across the SECA in Chinese coastal regions.

The rest of the paper is organized as follows: Section 2 reviews the previous studies on the research topic; Section 3 presents the PEU-based value function that reflects the LAM about the RBD for slow steaming; Section 4 creates a mathematical model for the RBD on sailing speed and proposes a solution based on genetic algorithm (GA), considering the conflicting objectives of fuel consumption, SO_x emissions and delivery delay; Section 5 applies the proposed model to simulate the RBD for slow steaming of the OOCL containership operating between Dalian and Kaohsiung; Section 6 wraps up this paper with some meaningful conclusions.

2. Literature Review

2.1. Slow Steaming: Concepts and Models. Slow steaming is the most popular and most effective decision-making method for environmentally sustainable operations in maritime shipping [14]. In 2007, Maersk Line, the world's largest containership company, conducted slow steaming trials on its 110 containerships, proving that it is safe to reduce the sailing speed to as low as 10%. Three years later, Maersk Tankers reduced the speed of their very large crude carriers (VLCCs) by half. China Ocean Shipping Company (COSCO), together with its partners in the OCEAN Alliance were also reported to introduce slow steaming on certain ship routes.

Several conflicting operational objectives need be considered for slow steaming. For example, the minimal SO_x emissions, an indicator of environmental sustainability, cannot be achieved simultaneously with the minimal operating cost and minimal inventory cost, two economic metrics often realized by lowering fuel consumption and improving service level. Fuel consumption, operating cost, and SO_x emissions are non-linearly correlated with the sailing speed. In fact, the daily fuel consumption is a cubic function of sailing speed [15] for most types of ships, such as tankers, bulk carriers, and containerships. However, this relationship does not apply to some large

containerships or near-zero sailing speed. Obviously, SO_x emissions are proportional to the fuel burned, and the ratio depends on the type of fuel [16]. A simple way to determine the ratio is to multiply the sulphur content (e.g., 3.5% for heavy oil and <0.5% for low-sulphur oil) with the daily fuel consumption. The operational objectives of slow steaming are easily to meet if there is no penalty for delivery delay or reward for timely delivery. In real-world slow steaming problems, the decision-maker must carefully weigh between the minimal fuel consumption, minimal SO_x emissions and minimal delivery delay.

As stated earlier, the sailing speed is a key decision variable in the expressions of fuel consumption, SO_x emissions, and delivery delay. Many scholars have examined the sailing speed and its impacts on various factors, including but not limited to Wang et al. [17], Wen et al. [18]. More recently, Psaraftis and Kontovas [8] summed up the existing sailing speed optimization models, most of which take the sailing speed as an input to the decision-making problem [19, 20]. Otherwise, the optimal sailing speed can only be determined empirically. According to the Pareto frontier, the empirical value may only bring a marginal benefit in some areas at the cost of other objectives. Here, the Pareto frontier is treated as a surface as in a hypothetical sailing speed decision problem. It should be noted that all the models in the literature on sailing speed have not considered the utility of decision maker. The previous studies adopted minimizing total cost as the objective of the model, however, they neglected that the aversion of cost is derived from the inner feelings of the decision-makers. Directly charactering utilities and attitudes of the decision-makers, as used in this paper, may be superior in selecting the choice that best fit the preferences of shipping companies.

2.2. Loss Aversion: Prospect Theory and Application. Loss aversion is one of the anomalies that economists first discovered that human behaviour logic is inconsistent with positivists' mathematical logic. Kahneman and Tversky [10] held two views in their prospect theory. First, the reference point determines the attitude of the decision-maker for the RBD. The decision-maker is interested in the gains or losses of the benchmark decision, rather than the absolute amount of profit or cost. The value function is concave in the case of gains, indicating that the decision-maker is risk-avert, and convex in the case of losses, indicating that the decision-maker is risk-loving. This goes against the axioms of preference about gains or losses in neoclassical economics. Secondly, the decision-maker is loss-averse. When the RBD leads to losses against the reference point, the decision-maker react more fiercely than the case if the RBD leads to gains against the reference point, that is, the losses bring greater pain to the decision-maker than the pleasure from an equal amount of gains. Thus, the value function of the decision-maker is steeper in the loss region than the gain region. Based on the properties above, Tversky and Kahneman [21] put forward a two-part power value function, which can be expressed as:

$$v(w) = \begin{cases} (w - w_0)^\alpha, & \text{if } w \geq w_0, \\ -\lambda(w_0 - w)^\beta, & \text{if } w < w_0, \end{cases} \quad (1)$$

Table 2: Gains or losses generated by main risk factors of slow steaming.

Risk factors	Potential failure effects	Potential failure mode
Fuel consumption	Increase operation cost (−)	Weight inexperience of risky decision-making in slow steaming operations; improper decision on sailing speed
SO$_x$ emission	Emit unnecessary SO$_x$ and violate the regulation (−)	
Delayed of shipment delivery	Vessel delay and decrease customer dissatisfaction (−)	

where w_0 is the benchmark decision, i.e., the reference point of the decision-maker; α and β are risk attitude coefficients ($\alpha < 1$, $\beta < 1$); λ is the loss aversion coefficient ($\lambda > 1$) [22]. The decision-maker will be pleasant if there are gains against the benchmark decision and painful if there are losses. The value function with convexity in loss and concavity in gain may not be applicable to all individuals, however, it can be confirmed at an aggregate level, i.e., at least fit for the mean or median values of all the individuals [21, 23]. Furthermore, Fang and Niimi [24] reveals that the importance of loss aversion is beyond the mean. In fact, their results show that loss aversion exists as a panel quantile regression results, indicating that the effect is at least valid for the majority.

The studies above have demonstrated the commonly loss-averse attitudes of decision-makers towards gains and losses of money, and the value function stated has been widely adopted in the research of assets management [25, 26]. The value function of loss aversion can also be used to describe the attitude towards various things in other domains, if the gains and losses can be designated with amounts of money. For example, Bleichrodt and Pinto [27] measured the utilities of health outcomes, which may seem greatly different from financial assets though, by converting the health states to monetary outcomes of gains and losses. It turns out that the parameters of the value function in Tversky and Kahneman [21] also fit the utilities of health states well, which indicates that the prospect theory and the classical monetary value function are widely applicable and can be used in different domains [22].

As result, there is an emerging trend in introducing loss aversion of decision-making to the research field of transportation. Masiero and Hensher [28] estimated the asymmetric preferences in freight transportation and demonstrated the existence of loss aversion when making choices among different transportation alternatives. Others proposed behaviour models by incorporating the notion of LAM and aimed at investigating some useful relationships between human choices and various factors. Fetene et al. [29] found charging decisions of electric vehicle owners are influenced by electricity price using the behaviour models based on LAM. However, the literature on transportation applying LAM is still poor, especially the maritime sector. This paper enriched the literature mainly in the combining of LAM with the RBD of slow steaming practice for shipping companies. It is one of the few attempts to investigate the decision-making process of shipping companies with the consideration of the decision-makers' utilities, and more studies of maritime transportation focusing on inner feelings of decision makers are in need to spring up.

3. Slow Steaming Objectives Based on LAM

3.1. LAM of Slow Steaming Operations. Both the automatic processing and emotional processing of the human brain enables the decision-maker to maximize his/her preferences under constraints. In the RBD for slow steaming, the PEU about gains or losses is affected by three risk factors, i.e. fuel consumption, SO$_x$ emissions, and delivery delay (Table 2). The potential failure effect indicates the type of gains or losses generated by each risk factor, while the potential failure mode describes the possible failure scenarios for each risk factor. The three risk factors, together with their priority, importance, and impact, were adopted to measure the PEU about gains or losses. Unlike the expected utility in positivists' decision-making theory, the PEU in value-based choice exists as the computing and comparison between value functions.

As stated in Section 2.2, although the classical studies on loss aversion are based on the experiment over outcomes of money rather than the three risk factors listed in Table 2, we can designate amounts of money to the risk factors. For example, in practice, the risk factors are usually measured as fuel cost, the penalty against SO$_x$ emissions and the compensation to consumer. In this way, the subjective feelings of the shipping company about the gains/losses of slow steaming are quantified by monetary outcomes. Since the prospect theory and loss aversion have been demonstrated as widely existed for the attitude towards money, they can also be valid for the risk factors linked with monetary outcomes.

The previous fMRI test results on slow steaming were adopted to further verify the rationality of the loss aversion features of the RBD for the sailing speed under the risk factors of fuel consumption, SO$_x$ emissions, and delivery delay. The previous research has shown that different types of decision-making information are processed by different nervous systems [30]. Specifically, Brodmann area (BA) 9, BA10 and the like mainly perform cognitive functions like thinking, intuition, information processing, and emotion interpretation. These regions are closely related to the marginal part of the forebrain. The positive emotions are generated and adjusted by the left dorsal lateral prefrontal cortex, while the negative emotions by the right dorsal lateral prefrontal cortex. In the case of gains (+), the decision-maker always tends to choose the risk-avert strategy with the increase of fixed gains; the blood oxygen level near the left dorsal lateral prefrontal cortex of the decision-maker is obviously suppressed. In the case of losses (−), the decision-maker generally tends to be risk-loving but turns to risk-avert when the losses exceed a certain threshold; the blood oxygen level near the right dorsal lateral prefrontal cortex is obviously suppressed. It is easy to conclude

that, the dramatic difference in Brodmann areas of the shipping company's decision-makers with varied preferences facing the gains/losses of slow steaming can characterize the LAM about the RBD for slow steaming [31, 32].

3.2. PEU-Based Objective Function.

The previous analysis proves that the PEU $U(^{*})$ can characterize the RBD on sailing speed in slow steaming, provided that the latter carries loss aversion features. Let p be the fuel price ($/ton), f be the penalty against SO_x emissions ($/ton), and c be the compensation to consumer ($/d·ton), i.e., the inventory cost. Then, derived from Tversky and Kahneman [21], the value functions of the three risk factors fuel consumption U_1, SO_x emissions U_2 and delivery delay U_3 can be expressed as:

$$U_1(p, F(V), F(V_0))$$
$$= \begin{cases} p^{\alpha}(F(V_0) - F(V))^{\alpha}, & \text{if } F(V) \leq F(V_0), \\ -\lambda p^{\beta}(F(V) - F(V_0))^{\beta}, & \text{if } F(V) > F(V_0), \end{cases} \quad (2)$$

$$U_2(f, E(V), E(V_0))$$
$$= \begin{cases} f^{\alpha}(E(V_0) - E(V))^{\alpha}, & \text{if } E(V) \leq E(V_0), \\ -\lambda f^{\beta}(E(V) - E(V_0))^{\beta}, & \text{if } E(V) > E(V_0), \end{cases} \quad (3)$$

$$U_3(c, S(V), S(V_0))$$
$$= \begin{cases} c^{\alpha}(S(V_0) - S(V))^{\alpha}, & \text{if } S(V) \leq S(V_0), \\ -\lambda c^{\beta}(S(V) - S(V_0))^{\beta}, & \text{if } S(V) > S(V_0). \end{cases} \quad (4)$$

As suggested by Tversky and Kahneman [21] and testified by various studies (e.g., [22, 27]), the risk attitude coefficients α and β were set to 0.88 and the loss aversion coefficient λ to 2.25. The value functions with the provided parameters are sufficient in describing most of the preferences of shipping companies. Then, the sailing speeds V (knot) were determined by RBD considering the PEUs of U_1, U_2, and U_3, respectively, and contrasted with the benchmark speed V_0 (knot), i.e., the reference point. In this way, the author obtained the deviation of each sailing speed from the benchmark speed. In the above equations, $F(V_0)$ and $F(V)$ are the fuel consumption (ton) before and after slow steaming, respectively; $E(V_0)$ and $E(V)$ are the SO_x emissions (ton) before and after slow steaming, respectively; $S(V_0)$ and $S(V)$ are the delivery delays (d) before and after slow steaming, respectively.

The goal of slow steaming is to find the optimal sailing speed that maximizes the cost-effectiveness and environmental friendliness in terms of PEU. The objective function is the weighted average of the above three value functions:

$$\text{Max}_{V} U(V) = w_1 U_1(F(V), F(V_0)) + w_2 U_2(G(V), G(V_0))$$
$$+ w_3 U_3(S(V), S(V_0)), \quad (5)$$

where w_1, w_2, and w_3 are the empirical weights for the trade-off between the three objective functions ($w_1 + w_2 + w_3 = 1$); V is controlled between the maximum speed V_{max} (knot), i.e., the design speed V_d (knot) and the minimum speed V_{min} (knot).

4. SSOM-SS

4.1. Assumptions and Modelling.

The proposed SSOM-SS targets a ship on a fixed route between port A and port B. The ship route is predetermined during the route design and fleet deployment. The entire route is divided into multiple legs between the origin port, the destination port, and the intermediate ports. The ship visits all these ports following a preset sequence. Let $N = \{1, 2, \ldots, n\}$ be the set of all ports on the route, $D_{ij(i \in N, j \in N)}$ (nautical mile) be the inter-port distances, Q_{ij} (ton) be the cargoes onboard from port i to port $j(j \neq i)$, and the T_{ij} (day) be the agreed delivery schedule from port i to port j. It is assumed that the set of cargoes onboard is fixed and each cargo is an indivisibles distinct commodity. Under these assumptions, it is necessary to decide on the proper sailing speed V (knot) for slow steaming.

4.1.1. Fuel Consumption Function.

The fuel consumption function is a cubic function between fuel consumption and sailing speed [15]. Thus, the daily fuel consumption per ship $F_d(V)$ can be expressed as:

$$F_d(V) = F_M \left(\frac{V}{V_d}\right)^3 + F_A. \quad (6)$$

The total fuel consumption of the ship $F(V)$ operating at $24\,V$ nautical miles per day across the route can be expressed as:

$$F(V) = \sum_{i \in N, j \in N} \left(F_d(V) \times \frac{D_{ij}}{24V}\right) \quad (7)$$
$$= \frac{1}{24} \sum_{i \in N, j \in N} D_{ij} \left(\frac{F_M}{V_d^3}V^2 + \frac{F_A}{V}\right),$$

where V_d is the design speed of the ship; F_M (ton/d) and F_A (ton/d) are the daily fuel consumption of the main engine(s) and the auxiliary engine(s), respectively.

4.1.2. SO_x Emissions Function.

The SO_x emissions is linearly proportional to fuel consumption. The proportionality is known as the actual sulfur content $\sigma(\%)$. The regulations or SECAs on SO_x emissions are different from country to country. Here, the volume difference of SO_x emissions between port i and port j, $E_{ij}(V)$ is expressed as:

$$E_{ij}(V) = (\sigma - \overline{\omega}_{ij}) \times F_d(V) \times \frac{D_{ij}}{24V}, \quad (8)$$

where $\overline{\omega}_{ij}$ is the sulfur limit, an indicator of regulation strictness on SO_x emissions between the two ports. The value of this indicator is negatively correlated with the strictness. Then, the total SO_x emissions across the route $E(V)$ can be expressed as:

$$E(V) = \sum_{i \in N, j \in N} (E_{ij}(V))$$
$$= \frac{1}{24} \sum_{i \in N, j \in N} (\sigma - \overline{\omega}_{ij}) D_{ij} \left(\frac{F_M}{V_d^3}V^2 + \frac{F_A}{V}\right). \quad (9)$$
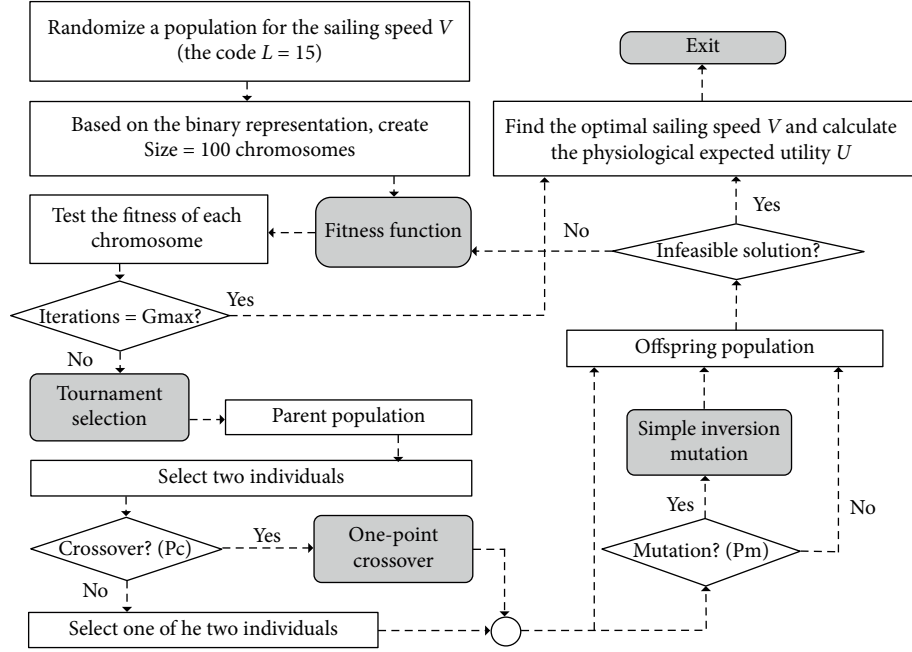
FIGURE 1: Flowchart of the proposed GA.

4.1.3. Delivery Delay Function. Delivery delay, an indicator of service level, is defined as the product between the total time delay (d) and the cargoes onboard, with the time delay being the difference between the actual sailing time $D_{ij}/24V$ and the agreed delivery schedule T_{ij} between port i and port j. Hence, the delivery delay function can be established as:

$$S(V) = \sum_{i \in N, j \in N} \left(\left(\frac{D_{ij}}{24V} - T_{ij} \right) \times Q_{ij} \right). \tag{10}$$

It is natural to see that the time delay is nonnegative. If the port operation time and time delay are negligible, the agreed delivery schedule T_{ij} equals the $D_{ij}/24V_d$ at the design speed, that is:

$$\frac{D_{ij}}{24V} \geq T_{ij} = \frac{D_{ij}}{24V_d}. \tag{11}$$

Hence, the maximum sailing speed $V_{\max}$ can be determined as

$$V \leq V_{\max} = V_d. \tag{12}$$

4.1.4. Mathematical Model. In light of the PEU-based objective function, *the SSOM-SS can be formulated as a nonlinear programming model:*

$$\underset{V}{\text{Max}} \, U(V) = w_1 \max\left\{0, p^{0.88}(F(V_0) - F(V))^{0.88}\right\}$$

$$- w_1 \max\left\{0, 2.25 p^{0.88}(F(V) - F(V_0))^{0.88}\right\}$$

$$+ w_2 \max\left\{0, f^{0.88}(E(V_0) - E(V))^{0.88}\right\}$$

$$- w_2 \max\left\{0, 2.25 f^{0.88}(E(V) - E(V_0))^{0.88}\right\}$$

$$+ w_3 \max\left\{0, c^{0.88}(S(V_0) - S(V))^{0.88}\right\}$$

$$- w_3 \max\left\{0, 2.25 c^{0.88}(S(V) - S(V_0))^{0.88}\right\}$$

$$\text{s.t.} \qquad 0 < V \leq V_d. \tag{13}$$

4.2. GA-Based Solution. Inspired by the process of natural selection [33], the GA was adopted to solve the SSOM-SS because it can express multiple solutions, unlike simulated annealing or tabu search and has been successfully applied to sailing speed optimization. The fitness function and special operators were combined to ensure the solution feasibility in the reproduction phase. Figure 1 shows the flow of the proposed GA, including solution representation, fitness calculation, selection, crossover, mutation, and infeasible solution adjustment.

Step 1. Solution representation: Considering the features of the decision variable, the chromosome for the SSOM-SS was subjected to binary representation. In other words, the solution was encoded as strings of zeros (0) and ones (1); then, each binary string was converted into a decimal number by Equation (14) and normalized to a real number V in the specified interval by Equation (15):

$$(b_1 b_2 \cdots b_{\text{CodeL}})_2 = \left(\sum_{s=1}^{\text{CodeL}} 2^s b_s \right)_{10} = y^t, \tag{14}$$

$$V = \text{Min}V + y^t \frac{(\text{Max}V - \text{Min}V)}{2^{\text{CodeL}} - 1}. \tag{15}$$

Step 2. Fitness function: Each solution meeting the constraints was viewed as a chromosome. If the reciprocal of the objective function serves directly as the fitness function, there will not be enough distinction in the selection probabilities of different chromosomes, which may weaken the selection operator of the GA. Since the SSOM-SS is a maximization problem, the fitness function was subjected to linear calibration by Equation (16) and the fitness is maintained as a positive number.

$$U'(V) = U(V) - \min(U(V)) + \xi, \tag{16}$$

where $\xi = 1$.

Step 3. Selection: Selection is the driver of genetic search. The fitness function needs to be transformed for proportionate roulette selection. To avoid the transformation, the tournament selection was adopted to select the best individuals in the current population and keep them in the next generation.

Step 4. Crossover: Crossover is a genetic operation that exchanges two individuals. First, the parent population meeting the crossover probability P_c was selected; then, the crossover segments were randomly determined in the parent population; after that, the genes in these segments were exchanged by one-point crossover, forming the off-spring population.

Step 5. Mutation: Mutation determines the local search ability of the GA and ensures the diversity of the population. Here, the simple inversion mutation is performed to generate new individuals at the mutation probability P_m.

Step 6. Infeasible solution adjustment: If the solution (chromosome) is infeasible after crossover and mutation, Steps 2–5 should be repeated until the termination condition is satisfied.

5. Computational Results and Sensitivity Analysis

5.1. Parameter Settings. This section evaluates the applicability of the SSOM-SS and the efficiency of the GA using a real-world case of the OOCL. The evaluation is followed by the sensitivity analysis involving the benchmark speed V_0, the value functions U_1, U_2, and U_3 and their weights w_1, w_2, and w_3. The object of the case study is the OOCL containership service between Dalian and Kaohsiung. The ports along the fixed ship route include: (1) Ningbo, (2) Dalian, (3) Tianjin, (4) Qingdao, (5) Lianyungang, (6) Kaohsiung, (7) Taichung, and (8) Keelung. The inter-port distances D_{ij} and the limits on SO_x emissions $\overline{w}_{ij}$ for the ports within China's SECAs are shown in Figure 2. The daily fuel consumption of main engine(s) F_M, the daily fuel consumption of auxiliary engine(s) F_A and the design speed of the ship V_d were configured according to those of 10,000 TEUs containership. Moreover, the fuel price p, the penalty against SO_x emissions f, the compensation to consumer c, and the actual sulfur content σ are listed in Table 3. The agreed delivery schedule T_{ij} was calculated based on the $D_{ij}/24V_d$ and cargoes onboard Q_{ij} from port i to port j (Table 4). To output a realistic representation, the inherent structure of the real case data was maintained despite a few perturbations.

5.2. Sensitivity Analysis. The first step of the sensitivity analysis is to explore the SSOM-SS performance at different benchmark speeds V_0. Specifically, the PEU-based objective function $U(V)$ was solved by the proposed GA with Matlab R2013 running on a personal computer (Quad Core 3.7 GHz Processor; 8 GB RAM). According to IMO [34], the average service speed for the size category where the tested ships located is 16.3 knots. Any deviation from the current speed
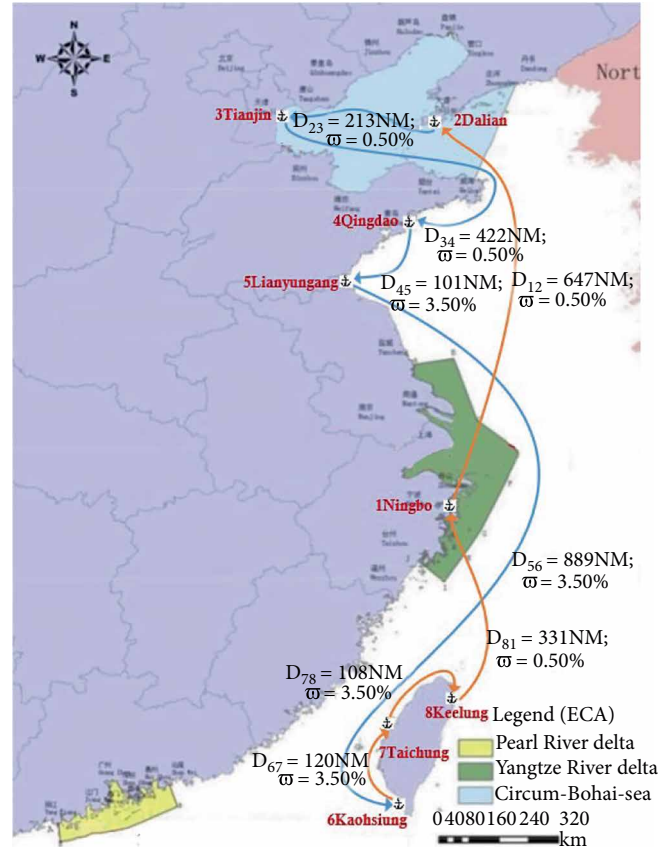

FIGURE 2: The OOCL containership service between Dalian and Kaohsiung.

will lead to a change in the utilities of decision-makers. Therefore, the benchmark speed V_0 is set as 16.3 knots at first, and then changed within the range between 25.5 knots (the design speed V_d) and 8 knots (the minimum sailing speed V_{min}) for sensitivity analysis. As shown in Figure 3, the value of the objective function $U(V)$ climbed up as the V_0 increasing from 16.3 knots to V_d; the value of $U(V)$ decreased with V_0 and reached the minimum of -0.010 at the V_0 of 14 knots, and then increased drastically when the V_0 decreased to 8 knots. It can also be seen that the optimal sailing speed V was equal to or approximated the V_0, when the latter was 14 knots and 15 knots; in other cases, V stayed near 16 knots and less than V_0, when V_0 fell within $\{16.3, 17, 18, 19, 20, 21, 22, 23, 24, 25.5\}$ knots, or near 13 knots and greater than V_0 if V_0 was below 14 knots ($V_0 = \{8, 9, 10, 11, 12, 13\}$ Knots). The results reveal that slow steaming decisions should be made within a small interval based on the benchmark speed, perhaps due to the effects of conflicting objectives. It is intuitive that the value functions U_1 and U_2 for fuel consumption and SO_x emissions are synchronized and negatively correlated with the PEU U_3 for delivery delay. Following this train of thought, the huge increase of the objective function $U(V)$ and great deviation between the optimal sailing speed V and the benchmark speed V_0 with the decrease in the benchmark speed V_0 demonstrate that the shipping company is more sensitive to delivery delay of slow steaming when the reference sailing speed is relatively slow.

TABLE 3: Containership information and other parameters.

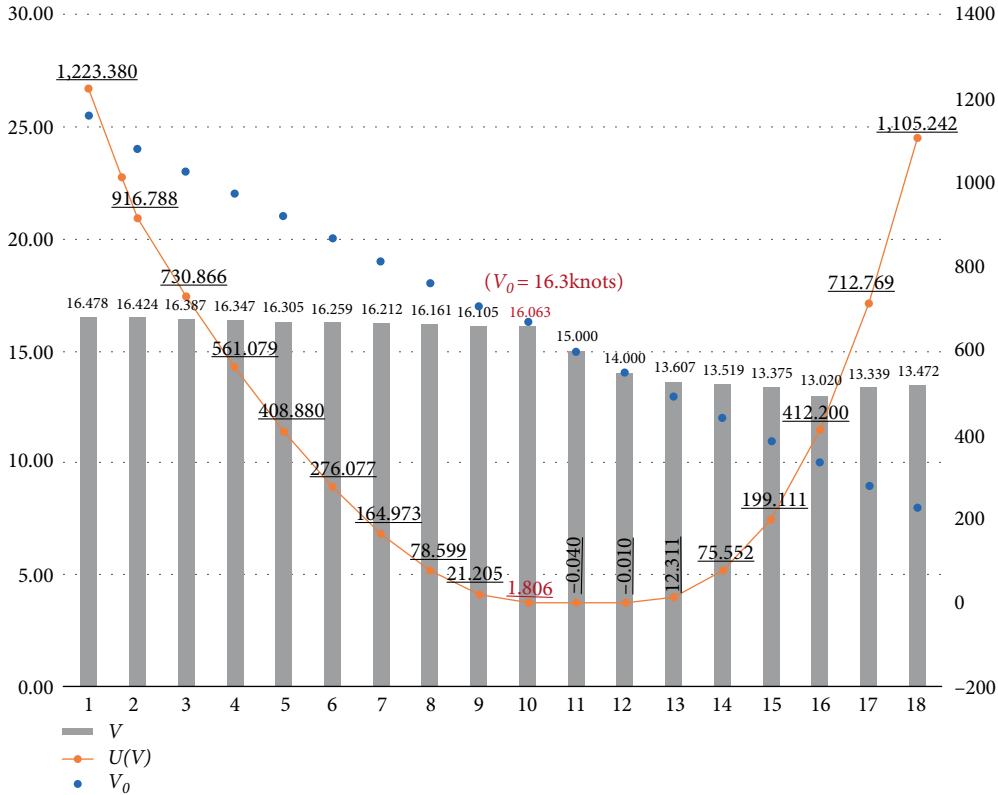| Parameter	Value	Unit	Source
F_M	24.4	ton/d	IMO [34]
F_A	4.5	ton/d	IMO [34]
p	366.49	$/ton	Fuel price: IFO380, 2018-03-29
f	200	$/ton	Environmental protection tax: SO_x, 1.2RMB/0.95 kg
c	0.13	$/d ton	Psaraftis and Kontovas [8]
V_d	25.5	knot	IMO [34]
σ	3.50	%	Qian et al. [16]

FIGURE 3: Sensitivity analysis at different benchmark speeds V_0.

TABLE 4: Agreed delivery schedule and cargoes onboard.

T_{ij} (day)	Value	Q_{ij} (TEU)	Value
T_{12}	1.926	Q_{12}	7000
T_{23}	0.634	Q_{23}	8000
T_{34}	1.256	Q_{34}	9000
T_{45}	0.301	Q_{45}	9000
T_{45}	2.646	Q_{56}	10000
T_{56}	0.357	Q_{67}	6000
T_{67}	0.321	Q_{78}	8000
T_{78}	0.985	Q_{81}	10000

In the above analysis, fuel consumption, SO_x emissions and delivery delay are treated as equally important, i.e., the three factors share the same weight $w_1 = w_2 = w_3 = 1/3$. In actual operation, the shipping company can adjust the weights according to factors like fuel price, limits on SO_x emissions,

delivery schedule, and cargoes onboard. Here, the objective function $U(V)$ and the optimal sailing speed V are determined at different combinations of w_1, w_2, and w_3 for values functions U_1, U_2, and U_3 with the benchmark speed of $V_0 = 16.3$ knots.

As shown in Figure 4, the optimal sailing speed V was 11.52 knots when w_1 and w_2 reached the maximum of 1, indicating that the shipping company enjoyed the greatest PEU. Besides, when w_3 reached the maximum of 1, the optimal sailing speed V equalled the maximum speed V_{max}, i.e., the design speed $V_d = 25.5$ knots. Comparing the objective function $U(V)$ values of the two weight sets (1/2, 1/4, 1/4) and (1/4, 1/2, 1/4), it is clear the shipping company is more sensitive to fuel consumption than to SO_x emissions.

Next, the sensitivity of the SSOM-SS was analysed using other input parameters, such as the fuel price p, the penalty against SO_x emissions f, the compensation to consumer c, the limits on SO_x emissions $\overline{\omega}_{ij}$, cargoes onboard Q_{ij}, inter-port distances D_{ij}, and agreed delivery schedule T_{ij}. For demonstration
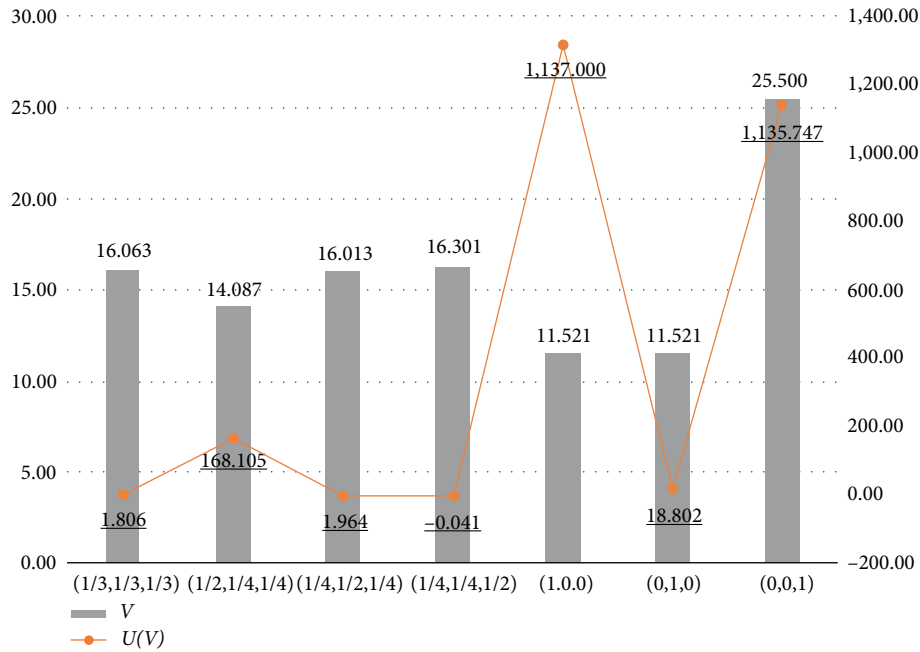
FIGURE 4: Sensitivity analysis using different weights of the value functions.

TABLE 5: Sensitivity analysis on other parameters.

Parameter changed	−50%		−20%		20%		50%	
	V	$U(V)$	V	$U(V)$	V	$U(V)$	V	$U(V)$
p	16.300	−0.030	16.300	−0.009	15.522	19.396	14.932	66.840
f	16.086	1.480	16.072	1.675	16.054	1.940	16.042	2.138
c	14.263	97.205	15.400	21.674	16.300	−0.008	16.300	−0.026
$\overline{\omega}_{ij}$	16.033	2.270	16.051	1.989	16.075	1.625	16.096	1.352
Q_{ij}	14.263	97.205	15.400	21.674	16.300	−0.008	16.301	−0.026
D_{ij} and T_{ij}	16.063	0.981	16.063	1.484	16.063	2.120	16.063	2.580

purpose, the weights were set as $w_1 = w_2 = w_3 = 1/3$ and the benchmark speed V_0 as 16.3 knots. During the analysis, one of the six input parameters was changed at a time, while the others were kept constant. The analysis results are recorded in Table 5.

It can be seen from Table 5 that the objective function $U(V)$ was extremely sensitive to the variation in c and Q_{ij}, moderately sensitive to that in p, slightly sensitive to that in f and $\overline{\omega}_{ij}$, and insensitive to D_{ij} and T_{ij}; the optimal sailing speed V is positively correlated with c, $\overline{\omega}_{ij}$ and Q_{ij}, and negatively with p and f. These results offer a preliminary guide for the reaction of the shipping company to the variation in one of the six parameters during slow steaming: the optimal sailing speed V for slow steaming should increase when the compensation to consumer (inventory cost) and cargoes onboard increase or the limits on SO_x emissions are violated; meanwhile, optimal sailing speed V should decrease when the fuel price or the penalty against SO_x emissions increase.

It is observed that the objective function $U(V)$ and the optimal sailing speed V followed similar trends with the variation in the set of the six parameters. The similarity reveals that the PEU for the RBD on sailing speed tends to grow with the decrease of the compensation to consumer or cargoes onboard and with the increase of the fuel price. However, the

objective function $U(V)$ was not so sensitive to the variation in the other parameters. To sum up, the shipping company is recommended to implement slow steaming at a high fuel price, low compensation to consumer or few cargoes onboard.

6. Conclusions

Slow steaming is an effective way for the shipping company to reduce SO_x emissions and build sustainable maritime supply chains. It is a RBD under the risk factors of fuel consumption, SO_x emissions, and delivery delay. In this paper, the LAM for personal preferences of RBD makers is investigated at different gains/losses in slow steaming, the PEU-based value functions against the benchmark speed were constructed to reveal the features of loss aversion about the RBD for sailing speed of the ship on a fixed route, and the objective function was derived from these value functions with the aim to maximize the sailing speed. Then, the SSOM-SS was put forward to assist the slow steaming RBD based on the inner feelings of the shipping company. This model is sufficiently flexible to include other indices of environmentally sustainable maritime operations, offering a novel tool for sailing speed optimization. After that,

a GA solution with fitness function and special operators was built to solve the SSOM-SS, trying to determine the optimal sailing speed based on fuel consumption, SO_x emissions and delivery delay. Finally, the model was applied to pinpoint the PEU for the optimal sailing speed against the benchmark speed, and the sensitivity of the SSOM-SS was discussed with different benchmark speeds, value function weights, and input parameters (e.g., fuel price, inventory cost, cargoes onboard, agreed delivery schedule, and limits on SO_x emissions). The proposed model enables the shipping company with loss aversion to determine the optimal sailing speed for slow steaming in the face of the rising fuel price, increasingly strict environmental regulations and excess available capacity of commercial ships. In addition, the model can be applied to reduce fuel price and mitigate SO_x emissions for various types of ships, and to eliminate the hidden hazards of low consumer satisfaction and delays in shipment delivery. For the few shipping companies that may bear loss neutral or other different properties of preferences, only the risk attitude coefficients and the loss aversion coefficient of the value function need to be changed, and the methodology in this paper still works well.

In future research, additional constraints and random factors (e.g., berthing availability and speed reduction policy of SECAs) will be included to develop sailing speed decision models for slow steaming, making it possible to prepare flexible route design and deploy fleets for various services. Meanwhile, the GA will be compared with the GAMS on various instances to provide insight on its performance.

Data Availability

The data used to support the findings of this study are currently under embargo while the research findings are commercialized. Requests for data, 12 months after publication of this article, will be considered by the corresponding author.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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