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Managing port disruption through sailing speed optimization for sustainable maritime transportation

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ABSTRACT

Ports, as nodes in maritime transportation, frequently face disruptions leading to congestion, adversely affecting the efficiency and sustainability of the global supply chain. This study considers the speeding-up strategy to alleviate port congestion. We model the transportation network as a closed Jackson network and adopt a tailored mean-value analysis algorithm to solve the model. To deliver the increased sailing speed, we further put forward a bi-section search algorithm. Our numerical analysis results demonstrate the feasibility of increasing speed to alleviate port congestion. However, when port congestion exceeds a certain threshold, the system faces collapse, rendering the increase in speed ineffective. Additionally, we recommend shipping companies consider using clean energy when employing the speeding-up strategy to mitigate congestion, thus safeguarding the environment. Our study combines theoretical methodologies and analytical models, providing insights regarding speeding up the vessels. The findings of this study offer guidelines for real-world sustainable maritime practice.

1. Introduction

Maritime transportation stands as the cornerstone of global trade and economic vitality. However, disruptions occurring at ports exert a detrimental impact on the functioning of maritime transportation services. Illustratively, in May 2022, during the COVID-19 lockdown, the Port of Shanghai, the world's largest container port, faced severe congestion, with more than 130 ships queuing for services (The News Lens, 2022). Subsequently, in September 2022, Typhoon Hinnamnor prompted the closure of the Port of Waigaoqiao (Shanghai), leading to delays or cancellations for over 20 ships on international routes (ThePaper.cn, 2022). Furthermore, the labor strike at the Los Angeles and Long Beach ports in June 2023 resulted in a significant work stoppage, costing the U.S. economy nearly $500,000 daily (Los Angeles Times, 2023). Another incident in June 2023 involved a collision between a boat and a ferry, leading to the temporary shutdown of the Port of Miami and causing prolonged delays for hundreds of passengers (Port of Miami, 2022). Adding to the complexity, the simultaneous disruption of multiple ports due to natural disasters can exacerbate the challenges faced by the maritime industry (Verschuur et al., 2020). These instances underscore the criticality of addressing port congestion and disruptions to ensure the reliability and resilience of maritime transportation networks.

Port congestion encompasses various types, significantly impacting the efficiency of maritime transportation (Chinedum, 2018). These disruptions include vessel queue congestion, where a substantial number of ships await service, leading to congestion in navigational channels and anchorage areas. Cargo pileup congestion arises from inadequacies in cargo handling, causing delays as cargo processing rates lag behind arrival rates. Natural disasters, e.g., typhoons, can induce port closures, disrupting shipping schedules. Labor strikes may lead to labor stoppages, impacting port activities and economic losses. Furthermore, equipment failures, traffic congestion in the port vicinity, safety incidents, and simultaneous disruptions across multiple ports during natural disasters contribute to the complexity of port congestion scenarios. This multifaceted nature of congestion underscores the critical need for effective management and strategic planning to alleviate congestion-related challenges (Xu et al., 2022; Wang et al., 2020).

In this study, we integrate queueing theory with maritime domain knowledge to investigate whether changing sailing speed is an effective measure for mitigating port congestion. And we find that increasing sailing speed is a feasible solution. Our approach adopts the mean-value analysis (MVA) algorithm tailored for solving the closed Jackson network as outlined in Guo et al. (2023). This algorithm is abbreviated as MVATD (MVA for the network with travel time and disruptions),

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offering a holistic perspective on the complex dynamics of maritime transportation. Drawing upon our insights into the maritime domain, particularly the cubic relationship between sailing speed and fuel consumption, we establish a baseline scenario that serves as a benchmark for our analyses under disruption-free conditions. To further refine our analysis, we deploy a bi-section search algorithm. This approach allows us to systematically explore and identify the optimal sailing speed capable of effectively mitigating congestion, offering a nuanced solution to the complex challenges posed by disruptions.

Our research contributions are summarized below.

Theoretical contributions. Our study innovatively integrates the sailing speed theory (i.e., the recognized relationship between speed and fuel consumption) and queueing theory in the maritime domain, specifically, in the port management domain. We derive three valuable insights concerning the implementation of a speeding-up strategy from a theoretical perspective. Moreover, the bi-section search algorithm offers an efficient solution for calculating the ship's sailing time.

Practical contributions. The insights related to the speeding-up strategy also provide practical implications for stakeholders seeking to enhance the efficiency of their transportation networks in the face of disruptions. The stakeholders can increase the sailing speed to reduce the losses caused by port congestion. Additionally, we recommend that stakeholders consider the environmental impact of increasing vessel speed. Clean energy may present a solution in this regard. In essence, our study not only combines rigorous analytical methodologies but also interprets the findings in the context of real-world maritime challenges.

The rest of the paper is organized as follows. Section 2 summarizes the existing literature. Section 3 introduces our method in detail and provides insights into the speeding-up strategy. Section 4 reports the results of the numerical study. Conclusions are drawn in Section 5.

2. Literature review

Many scholars have delved into a comprehensive exploration of the factors influencing port congestion. In response to the port congestion risks intensified by the COVID-19 pandemic, Gui et al. (2022) effectively quantify congestion risks under diverse factors by integrating risk assessment models and leveraging fuzzy Bayesian reasoning, the Analytic Hierarchy Process (AHP), and the variation coefficient method. Their approach is validated through a real case study, which provides crucial insights for risk prevention and mitigation strategies in the context of port congestion. Bolat et al. (2020) assess the importance weights of factors contributing to port congestion. By integrating perspectives from port state control, flag state control, and independent surveyors, Bolat et al. (2020) employ the AHP method to classify and rank factors. Findings indicate that documentation procedures, port operation and management, ship traffic inputs, port structure and strategy, and government relations emerge as the foremost factors influencing port congestion. Chinedum (2018) employs the concept of ranking by inspection, utilizing ship dwell times in five African ports to assess variations in ship turnaround time and efficiency levels. Chinedum (2018) aims to discern active factors contributing to port congestion in African ports and examines the resulting implications on regional logistics and supply chains. Findings underscore that congestion in African ports is rooted in planning, regulation, capacity, efficiency, or a combination of these factors.

Some scholars proactively address the issue of port congestion by forecasting congestion or offering recommendations for port infrastructure development. Peng et al. (2023) introduce high-frequency container port congestion measures using Automatic Identification System (AIS) data. Hourly congestion statuses are determined, overcoming limitations of traditional data sources, and a Long Short-Term Memory (LSTM) neural network model is proposed for congestion prediction, demonstrating improved performance, particularly in sequence prediction, with the inclusion of congestion propagation effects. Their findings offer valuable insights and decision support for port congestion. Bai et al. (2023) introduce a novel method for measuring port congestion by examining ship behaviors in different port zones. Application of the model to 20 major container ports globally demonstrates its efficiency and practical applicability, particularly highlighted by the observed congestion surge at the Port of Los Angeles from August to December 2020. Liu et al. (2023) adopt system dynamics to evaluate container port congestion during the COVID-19 pandemic. Utilizing data from Ningbo Zhoushan Port, simulations reveal that smart regulations at a high level of epidemic prevention are most effective in alleviating congestion. Notably, increasing port investment in smart technologies yields enhanced results, particularly in scenarios with lower epidemic prevention levels. Meng et al. (2023) argue that improper fleet deployment can lead to port congestion. They presents a variational inequality model designed to optimize ship routing and allocation strategies for mitigating port congestion. Many studies on shipping route optimization and port scheduling have provided insights into how optimization algorithms can alleviate port congestion, e.g., Meng et al. (2014),Zhen et al. (2016), and Wang et al. (2018), as optimization algorithms play a vital role in decision making (Zhang et al., 2021; Wu and Xu, 2022; Bukoye and Gadiraju, 2022). Due to the focus of this paper not being on the optimization domain, it will not delve into further explanations.

From the above literature review, it can be observed that existing research predominantly focuses on identifying the factors influencing port congestion and predicting port congestion in advance. Research on alleviating port congestion often approaches the issue from an optimization perspective. To the best of our knowledge, Guo et al. (2023) is the only study that incorporates queueing theory with port congestion. Our study is inspired by Guo et al. (2023), but we consider the impact of speed on port congestion.

3. Methodology

The main symbols used in this study are summarized below.

3.1. MVATD for two ports

Let us consider a scenario where there exist a total of $N = 2$ ports, which can be regarded as servers. The service time, representing the combined duration of unloading and loading for each vessel at port i ($i \in \{1,2\}$), follows an exponential distribution with a mean of s_i. It is worth noting that the notation j ($j \in \{1,2\}/\{i\}$) is employed to represent the other port in subsequent discussions. The service time mentioned above corresponds to the total time required for unloading and loading operations at port i. The transportation system consists of a total of L vessels that travel along fixed routes between the two ports. Given L vessels within the transportation system, the average waiting time at port i, the average number of vessels encountered by an arriving vessel, and the arrival rate of vessels at port i are denoted as $w_i(L)$, $n_i(L)$, and $\lambda_i(L)$, respectively. According to Little's Law, we have:

$$n_i(L) = \lambda_i(L) w_i(L), \forall i \in \{1,2\}. \tag{1}$$

Guo et al. (2023) use the closed Jackson network to model the transportation network containing ports and vessels. And they further propose an MVATD algorithm to remedy the off-of-shelf MVA for solving the closed Jackson network to consider travel times and disruptions. In this study, referring to Guo et al. (2023), MVATD is used to model the network with two ports and L vessels. To make this study self-contained, we briefly introduce MVATD for the two ports below.

In order to address disruptions occurring at ports, we incorporate the concept of virtual ports and vessels based on the work by Ramanjaneyulu and Sarma (1989). This approach allows us to model and analyze disruptions effectively. Specifically, for each port i, we introduce a corresponding virtual port denoted as $N + i$. A virtual vessel is then introduced to simulate the disruptive event experienced by port i, traveling between port i and virtual port $N+i$. To characterize the disruptive behavior at the virtual port $N+i$, we denote the mean service time of the virtual vessel as τ_i. Similarly, the mean service time of the virtual vessel at port i during the disruption is denoted as f_i. The utilization waste of port i due to disruptions can be quantified by the expression $\rho_i = \frac{f_i}{f_i+\tau_i}$. During a disruption, the virtual vessel, having a higher priority compared to regular vessels, preempts the servicing vessel upon arrival at port i and occupies the port for an exponentially distributed duration with mean f_i. This duration represents the time required for the port to rectify the disruption and return to normal operation. Subsequently, the virtual vessel proceeds to virtual port $N+i$ and remains there for an exponentially distributed time with mean τ_i. This time interval corresponds to the average inter-arrival time of disruptions at port i. The utilization waste ρ_i provides an indication of the extent to which port i is affected by disruptions, reflecting the portion of its capacity that is rendered idle due to these events.

The waiting time expression in (1) then can be refined as follows (Guo et al., 2023):

$$w_i(L) = \frac{(1+n_i(L-1))s_i + \rho_i f_i}{1-\rho_i(1-\rho_i)}. \tag{2}$$

Assuming a fixed travel time t_{ij} for vessels traveling between port i and port j, it is important to consider the impact of travel times on the return time of a vessel to a tagged port, such as port i. When travel times are taken into account, the return time for a vessel to the tagged port is prolonged, which subsequently leads to a decrease in the arrival rate (λ_i) at that specific port. To characterize the time period from a vessel's arrival at port i, its subsequent departure, and its eventual arrival at port j, we introduce the concept of first passage time denoted as π_{ij}. This represents the duration it takes for a vessel to complete the journey from port i to port j. Notably, the special case π_{ii} signifies the first return time for a vessel to port i. By applying a first-step analysis, we can formulate the equations that describe the behavior of a system with L vessels as follows:

$$\pi_{ii} = w_i(L) + t_{ij} + \pi_{ji}, \ \forall i \in \{1,2\}, j \neq i \tag{3}$$

where

$$\pi_{ji} = w_j(L) + t_{ji}, \ \forall j \in \{1,2\} \backslash \{i\}. \tag{4}$$

Solving these equations simultaneously yields π_{ii}. If the system has L vessels, we can then write the arrival rate $\lambda_i(L)$ as

$$\lambda_i(L) = L/\pi_{ii}, \ \forall i \in \{1,2\}. \tag{5}$$

Thus, we can conclude the MVATD algorithm for two ports, which is shown as Algorithm 1.

Algorithm 1. MVATD algorithm for two ports.

Output: $w_i(L)$, $\lambda_k(L)$, and $n_i(L)$
begin
  Step 1.
    (a) Initialize $n_i(0) = 0$, $i \in \{1,2\}$.
  Step 2. for $l = 1 : L$ **do**
    (a) Calculate the mean waiting times

$$w_i(l) = \frac{(1+n_i(l-1))s_i + \rho_i f_i}{1-\rho_i(1-\rho_i)}, \quad \forall i \in \{1,2\}.$$

    (b) Calculate the arrival rates:

$$\pi_{ii} = w_i(L) + w_j(L) + t_{ij} + t_{ji}$$

$$\lambda_i(l) = \frac{l}{\pi_{ii}}, \quad \forall i \in \{1,2\},$$

    where π_{ii} is obtained from Equations (3) and (4).
    (c) Calculate the mean queue lengths:

$$n_i(l) = \lambda_i(l) w_i(l), \quad \forall i \in \{1,2\}.$$

  end
end

3.2. Baseline case

The daily fuel consumption of a ship is approximately proportional to its speed cubed (Wang and Meng, 2012), which means the fuel consumption per unit distance is approximately proportional to its speed squared. Suppose the distance between the two ports is l nautical miles (nm). The cost of sailing a ship over l in x (hours) can be written as

$$cx + \alpha la\left(\frac{l}{x}\right)^2 \tag{6}$$

where c is the fixed cost (\$/hour), α is the fuel price (\$/ton), and a is a coefficient. Based on Formula (6), we can find the economic speed (i.e., the speed that minimizes the above total cost).

We assume that, initially, shipping companies plan their decisions (i.e., number of ships L and sailing speed) without considering port disruption. Thus, they sail their ships at this economic speed, and the resulting sailing time is $t_{12} = t_{21} = \frac{x^*}{24}$ days, where x^* can be delivered from Formula (6) by taking the derivative with respect to x. Suppose that the cargo volume per year from port 1 to port 2 is Q, from port 2 to port 1 is less than or equal to Q, and thus we only focus on cargo from port 1 to port 2. Suppose that a ship capacity is q. To transport all cargo, the number of ships in the system L should be

$$L = \min\left\{L' = 1,2,\ldots | \lambda_1(L') \geqslant \frac{Q}{365q}\right\}. \tag{7}$$

For simplicity, we assume that $\lambda_1(L) = \lambda_2(L) = \frac{Q}{365q}$ (otherwise the actual speed will be slightly less than the economic speed).

3.3. Eliminating congestion by increasing ship sailing speed

From Eq. (5), we can conclude that $\lambda_1(L) = \lambda_2(L)$ is the throughput of a port, which is the ratio of the number of ships and the round-trip time, i.e., the sum of waiting time at the two ports and twice one-way travel time between the two ports. In case of disruption, to ensure all cargo can be transported, the throughput should remain the same as the one in the baseline case. However, in case of disruption, the waiting time increases. To remedy the problem, from the perspective of shipping companies, increasing sailing speed serves as a cost-effective measure.

With a given $\rho_i, i = 1, 2$, if the sailing speed increases, the travel time changes and the waiting time also changes. We need to find the speed such that the round-trip time remains unchanged (thus the throughput is unchanged). We use Algorithm 2 to conduct the bi-section search to decide the increased sailing speed. Then, we can calculate the resulting fuel consumption (it is proportional to speed squared because the number of round-trips per year is unchanged) and thus the carbon dioxide (CO_2) emissions.

Algorithm 2. Bi-section search algorithm for deciding sailing time.

```
Input: ρ1, ρ2, t* = x*/24, s1, s2, f1, f2, L
Output: t_ρ1
begin
    t_min = 0
    t_max = t*
    rt_0 ← Calculate the round trip time without the disruption by Algorithm 1
    while t_max − t_min > 10^−3 do
        t_ρ1 = (t_max + t_min)/2
        rt_1 ← Calculate the round trip time under the disruption by Algorithm 1
        if rt_1 ≤ rt_0 then  t_min = t_ρ1

        else  t_max = t_ρ1

    end
end
```

disruption (i.e., keep the overall throughput rate unchanged).

Proposition 1 (Guo et al., 2023). In a transportation system with two ports, port 1 is more efficient than port 2 (i.e., $s_1 < s_2$). Only one port has disruption at a time. And the disruptions are stochastically the same (i.e., $f_1 = f_2, \tau_1 = \tau_2$, and $\rho_1 = \rho_2$). The total round-trip time of a vessel is longer when a small port (i.e., port 2) is affected by a disruption than when a large port (i.e., port 1) is affected by the same-scale disruption.

Proof. Based on Proposition 1, which is proven in Guo et al. (2023), we know that the total round-trip time of a vessel is longer when the disruption happens to the slower port. Thus, a faster vessel speed is needed to keep the overall throughput rate unchanged.

Insight 3. It is optimal to have inbound rate and outbound travel speed equal for vessels.

Proof. We use x_1 and x_2 to denote the time (hours) spent in sailing over the distance of l_1 and l_2. According to (6), the total cost (denoted by $C(x_1, x_2)$) is:

$$C(x_1, x_2) = cx_1 + \alpha l_1 a\left(\frac{l_1}{x_1}\right)^2 + cx_2 + \alpha l_2 a\left(\frac{l_2}{x_2}\right)^2. \tag{8}$$

For minimizing $C(x_1, x_2)$, we take partial derivatives with respect to x_1 and x_2, respectively. We have

$$\frac{\partial C(x_1, x_2)}{\partial x_1} = c - 2\alpha a\frac{l_1^3}{x_1^3} = 0 \tag{9}$$

$$\frac{\partial C(x_1, x_2)}{\partial x_2} = c - 2\alpha a\frac{l_2^3}{x_2^3} = 0. \tag{10}$$

Therefore, the optimal value of x_1 and x_2 should be

$$x_1^* = l_1\left(\frac{2\alpha a}{c}\right)^{\frac{1}{3}} \tag{11}$$

$$x_2^* = l_2\left(\frac{2\alpha a}{c}\right)^{\frac{1}{3}}. \tag{12}$$

Because $l_1 = l_2$, we have $x_1^* = x_2^*$. Thus, it is optimal to have inbound rate and outbound travel speed equal for vessels.

3.4. Insights regarding speeding up the vessels

We now obtain some insights by the queueing model when disruptions occur.

Insight 1. Due to the existence of an upper speed limit for vessels, there exists an upper limit for disruption frequency (i.e., ρ_i) such that the disruption with frequency below this limit can be mitigated by solely speeding up the vessels. Suppose there is no such upper limit for vessel speed, there still exists an upper limit on disruption frequency and the disruption with frequency larger than this limit cannot be mitigated by solely speeding up vessels.

Proof. This conclusion means that, even without speed limit, speeding up cannot fully mitigate the large frequency of disruption. Suppose that the travel time is zero, then the round-trip time equals the sum of two sojourn times. As ρ_i increases to 1, the sojourn time increases to infinity. Hence, there must exists an upper limit of ρ_i so that the system with disruption ρ_i and without travel time has the same round-trip time as that of the system without disruption.

Insight 1 mainly implies that in a transport system, when determining the number of ships planned, disruption has to be considered. Otherwise, the number of ships planned may not be sufficient to fulfill the cargo transport demand in case of disruption.

Insight 2. Consider two scenarios with the same level of disruption happening to port 1 and port 2 respectively (i.e., $f_1 = f_2, \tau_1 = \tau_2$), then the scenario with disruption happening to the slower port (i.e., service time is longer) requires a faster vessel speed to mitigate the impact of

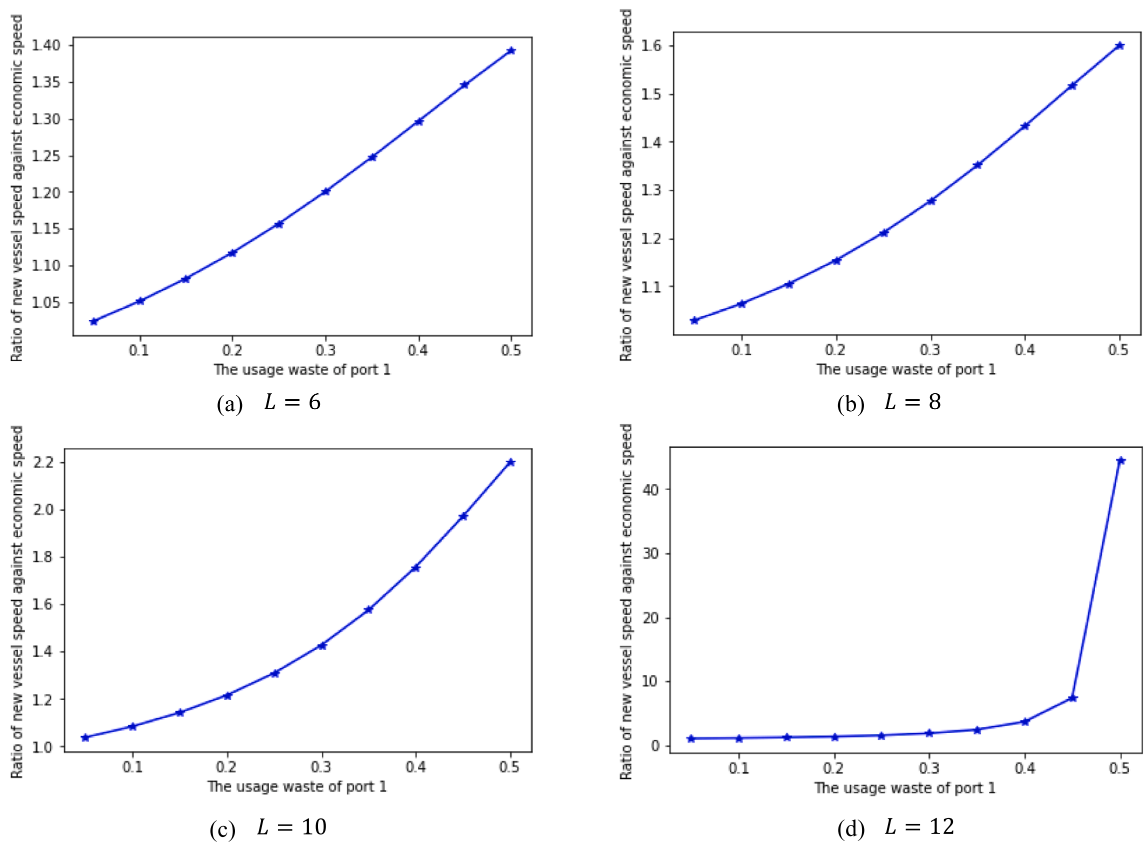


Fig. 1. The ratio of increased sailing speed as a function of the usage waste of port 1.

Table 1
Summary of key notations.

Notations	Descriptions
L	total number of vessels in the network;
t_{ij}	the travel time for vessels to travel to port j after visiting port i;
$w_i(L)$	mean waiting time at port i, given L vessels in the transportation system;
$n_i(L)$	mean number of vessels seen by a tagged arriving vessel, given L vessels in the transportation system (the tagged arriving vessel is not one of the L vessels;
$\lambda_i(L)$	arrival rate of vessels at port i, given L vessels in the transportation system;
s_i	mean service time of regular vessel of port i;
τ_i	mean service time of virtual vessel (disruption) at virtual port $N+i$;
f_i	mean service time of virtual vessel (disruption) at port i;
$\rho_i = f_i/(f_i + \tau_i)$	usage waste of port i due to disruption;
π_{ij}	the first passage time for a vessel from port i to port j;
c	the fixed cost;
x	the sailing time (hours);
Q	the cargo volume per year from port 1 to port 2.

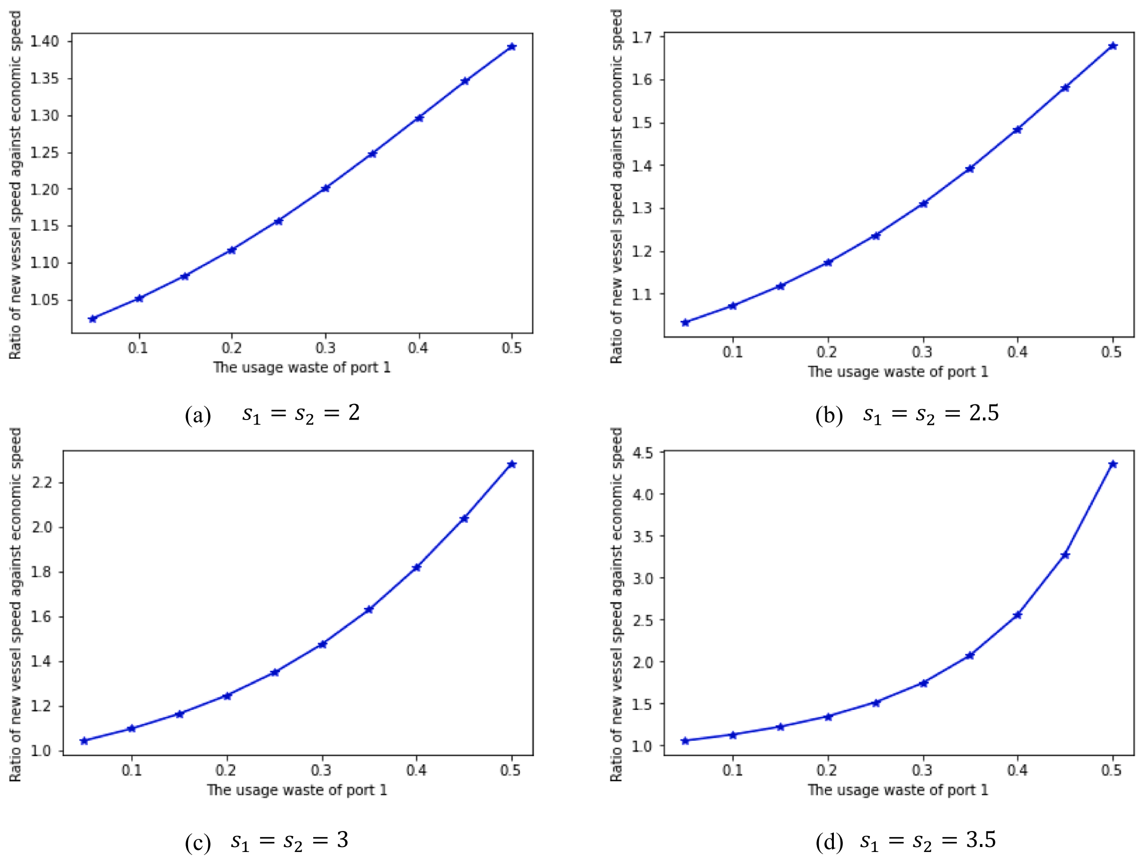
4. Numerical study

In this section, we conduct the numerical study to test Algorithm 2. Suppose that the traveling time between the two ports is 14 days. The two ports have similar capacities, indicating that in the absence of disruptions, the mean service time s_1 and s_2 are the same. We set $s_1 = s_2 = 2$ days. Without loss of generality, we assume that port 1 experiences a disruption.

In order to ensure the completion of all cargo transportation demands during disruptions, we employ Algorithm 2 to search for the optimal sailing speed under disruption. The usage waste of port 1 ranges from 0 to 0.5. The results are illustrated in Fig. 1. (see Table 1).

First, as the usage waste of the port increases, i.e., the level of congestion becomes higher, vessels need to increase their sailing speed further to meet the transportation demands. The results in Fig. 1(a)–(d) all support this opinion. For example, given that there are 8 vessels in the network, Fig. 1(b) indicates that when the usage waste of port 1 increases to 40%, the ship sailing speed also needs to increase by approximately 40% to mitigate the impact of disruption on the transportation system. Second, we find that the number of vessels in the systems plays an important role in determining the sailing speed. As the number of vessels in the system increases, ships need to increase their sailing speed even more to maintain the efficiency of the system. That is, from Fig. 1(a)(a) to Fig. 1(d), the ratio of new sailing speed against economic sailing speed increases at the same level of usage waste of port 1. For example, when the usage waste of port 1 is 0.3, the ratio of the new sailing speed is 1.2 when $L = 6$, 1.3 when $L = 8$, and 1.4 when $L = 10$. Third, Fig. 1(d) shows that when there are many vessels in the transportation system and the congestion level is high, the transportation system faces collapse. In Fig. 1(d), the ratio of new sailing speed sharply increases after the usage waste of port 1 exceeds 0.4. This indicates that beyond a certain congestion threshold, adjusting vessel speed alone is insufficient to resolve the congestion issues in the system, which also confirms the validity of insight 1. We also conduct sensitivity analysis concerning the value of service time s_1 and s_2. Results are shown in Fig. 2. The findings are the same as the above analysis.

Although increasing ship sailing speed may alleviate disruptions to some extent, it is crucial to consider its impact on CO_2 emissions. Given the number of round-trips per year is unchanged, the fuel consumption is proportional to sailing speed squared. Therefore, while addressing disruptions, it's essential to consider the environmental implications and find a balance between operational efficiency and sustainability. It is recommended that ships utilize Liquefied Natural Gas (LNG) and low-sulfur fuels to mitigate the environmental impact of increased speed.



(a) $s_1 = s_2 = 2$ (b) $s_1 = s_2 = 2.5$

(c) $s_1 = s_2 = 3$ (d) $s_1 = s_2 = 3.5$

Fig. 2. The ratio of increased sailing speed as a function of the usage waste of port 1 when $L = 6$.

Heavy fuel oil is commonly chosen as the fuel for ships due to its low cost. Therefore, when speed's impact on the environment or environmental requirements for the route is not a concern, ships typically opt for heavy fuel oil. However, in congested scenarios, employing higher-cost clean energy sources is essential to ensure the overall efficiency of the transportation network while prioritizing environmental friendliness. Although the cost of utilizing clean energy is high, it simultaneously reduces the delays caused by port congestion and protects the environment, thus enabling shipping companies to avoid losses incurred by delays and fulfill their social responsibility for environmental protection. Many vessels adopt dual-fuel systems, which also provide them with operational flexibility to select different fuels according to different scenarios.

5. Conclusion

This study investigates the viability of enhancing sailing speed as a strategy for mitigating port congestion. Incorporating MVATD, the cubic relationship between sailing speed and fuel consumption, and a bi-section search algorithm, we find that the strategy of increasing sailing speed works to address port congestion. Our proposed bi-section algorithm can deliver the optimal sailing speed under different levels of disruptions. As port congestion intensifies, there is a need to elevate speeds further; correspondingly, as the number of vessels in the system increases, the impact on ports requires balancing with higher sailing speeds. However, our results show that the transportation system faces collapse when the congestion level is too high, and thus increasing sailing speed is of no avail.

We need to emphasize that while increasing sailing speed is a means to alleviate port congestion, the adverse environmental impact should be considered, as increased sailing speed often leads to higher emissions. In such cases, we recommend shipping companies use clean energy to offset the emissions associated with increased sailing speed while maintaining the efficiency of the transportation system. Furthermore, the use of clean energy aligns with the requirements of sustainable maritime practices (Hewu et al., 2022).

Our study is not without limitations. First, due to the unavailability of real data, we do not use real-world data to conduct experiments. Second, the sailing speed is affected by many factors in maritime practice, such as weather conditions, which we do not take into account in our modeling process. Third, we do not provide a solution for alleviating extreme port congestion and modulating sailing speeds can only mitigate mild port congestion. Future research can seek real-world data and develop a more comprehensive model to capture the complex situation by considering more influencing factors.

CRediT authorship contribution statement

Summer Guo: Software, Methodology. **Haoqing Wang:** Methodology, Software, Writing - original draft. **Shuaian Wang:** Methodology, Writing - review & editing.

Declaration of Competing Interest

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

Data availability

No data was used for the research described in the article.

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