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Multi-lateral ocean voyage optimization for cargo vessels as a decarbonization method

Inkyung Sung [a,*], Haris Zografakis [b], Peter Nielsen [a]

[a] Operations Research Group, Department of Materials and Production, Aalborg University, Aalborg, Denmark
[b] Stephenson Harwood LLP, London, United Kingdom

A R T I C L E I N F O

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A B S T R A C T

To address the operational inefficiency in maritime cargo transport caused by the traditional *Sail Fast Then Wait* (SFTW) practice, we propose a systemic optimization approach that organizes vessels sailing towards the same port so that their arrival at the anchorage is synchronized with the capacity of the port to receive vessels at berth from the anchorage. A solution procedure with a quadratic program is implemented and tested using a sample of about 14,000 voyages from Automatic Identification System (AIS) data in 2018. From the analysis, the proposed approach produces 9% of fuel savings per voyage, on average, while minimizing the demand–supply imbalance levels at the ports. The proposed approach also keeps the arrival order of vessels at ports as if they had sailed with SFTW practice, which is necessary so as to encourage agreement on the proposed approach from the stakeholders in the maritime industry.

1. Energy inefficiency in the maritime industry

Maritime transportation is the backbone of global supply chain and economic development, providing low trade cost and efficient transportation (Lam, 2011). The maritime transportation industry is a key mode in the global transportation and distribution system, carrying almost 80% of international trade. The importance of the industry will be much more significant as seaborne trade demands are expected to grow by the globalization of markets and a low freight rate due to the increased vessel size and its economies of scale (Pasha et al., 2021). According to UNCTAD (2021), 2.4% of the annual growth in maritime trade is expected between 2022 and 2026.

On the other hand, the maritime transportation industry is a considerable source of Green House Gas (GHG) emissions and serious pollutants. According to IMO (2021), GHG emissions of total shipping have been increased by 9.6% from 2012 to 2018, contributing almost 3% of global anthropogenic GHG emissions (1076 million tonnes) in 2018. As a result, relevant international and domestic regulations have been introduced, imposing environmental requirements to the maritime transportation sector.

The International Maritime Organization (IMO) energy efficiency regulations mostly focus on the technical aspects of vessels, rather than the highly networked and complex interaction among the stakeholders in the maritime transportation industry (Poulsen et al., 2022). For example, in tanker and dry bulk shipping, shipowners follow the instructions of charterers, who often bear the cost of fuel consumption.

Traditionally, ocean cargo transport is a highly fragmented industry in terms of ship categories (container ships, dry bulk carriers, wet bulk carriers, general and project cargo carriers and roll-on/roll-off ships), cargoes and trades, as well as types of entities involved (Lam, 2011; Graham, 1998). Approaching shipping from the perspective of its role in supply chains, a similarly

* Corresponding author.
E-mail address: inkyung_sung@mp.aau.dk (I. Sung).

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fragmented picture emerges: the supply chains for containers are very different to those for petroleum and its products, grains and other agricultural commodities, general cargo, vehicles or industrial equipment. Vessels are often commercially employed (chartered) by entities in the supply chain that do not themselves own, buy or sell the cargo on board. Another perspective from which fragmentation is also apparent is ports; several hundreds of commercial ports operate around the world, each with its own ecosystem of terminals, tugs, pilots, stevedores and interface with other transport systems (Ascencio et al., 2014).

The common thread running through that fragmented industry and supply chains is that the ocean journeys of cargo ships are not systemically optimized, either among them as a seaborne system, or as part of the entire supply chain system. While there has been great progress in the last 30 years in satellite coverage, communications, weather forecasting, and of course data processing, all of which have enabled the development of sophisticated and effective weather routing and voyage planning systems, this has only led to the optimization of the voyages of individual ships. Optimization of cargo transport as a system (either as a seaborne system or as a wider supply chain system) remains elusive.

It is clear that the lack of a systemic approach in this highly fragmented industry has allowed cargo vessels to follow the same operational model since the age of sail; each vessel departs towards its destination at its own optimal speed (often, the service speed that is very similar to that of every other vessel in the same category), and without regard for other vessels or for the conditions at the destination. This operational model, known as *Sail Fast, Then Wait* (SFTW) or *Rush-to-Wait*, is an energy-inefficient practice.

The traditional SFTW practice is underpinned by the contractual architecture of international maritime trade in various ways (Adland and Jia, 2018):

- Bulk cargo vessels perform voyages at the instruction of their charterers, who have the right to give orders as to the commercial employment of the vessels. The relevant contracts (voyage and time charterparties) contain speed warranties and the obligations of utmost dispatch, or similar.
- Many of those charterparties contain requirements for the vessel's arrival at a loading port by a particular date (*laycan*), or else the charterer has the option to cancel the charterparty.
- In some types of charterparties (voyage charterparties), the vessel's prompt arrival at the port of destination triggers financial obligations in the form of *demurrage*, which is legally defined as *liquidated damages for delay* but, from a financial perspective, is an income stream for the shipowners.
- In other types of charterparties (time charterparties), the fuel cost falls on the charterer, meaning that shipowners have no incentive to optimize operations and, indeed, are unable to disobey charterers' operational instructions.
- The above features give rise to what is sometimes referred to as an *agency problem* or *split incentives* in charterparties. Viewed from a supply chain perspective, the contracts for sale and purchase of commodities on board the vessels also contain provisions that require prompt arrival of the vessel that has been chartered to carry the goods bought and sold in the form of laycans and demurrage (similar to provisions in charterparties) and delivery periods for the goods.
- Finally, bills of lading, the final piece in the jigsaw of maritime trade contractual architecture, also incorporate terms from charterparties, and prescribe that a vessel that operates in any way other than due dispatch is an unlawful deviation.

2. Related work

2.1. Maritime decarbonization and blue visby solution

To improve energy efficiency of a voyage, thus reduce the GHG emissions from the maritime industry, many attempts and proposals have been made in various contexts. First, advances in maritime engineering domain have been made especially for ship design optimization (Peri et al., 2001) and ship efficiency analysis (Wang et al., 2018). Environment friendly marine fuels with lower (e.g., biofuels, LNG) or zero (e.g., green ammonia, green methanol, green hydrogen) GHG emissions have also been developed and being developed to replace the currently used marine fuel oil and marine diesel oil, highly polluting distillate fossil fuels.

There has also been progress towards energy-efficient voyages from a planning and operational perspective. Together with other commercial decisions in voyage planning (e.g., routing and cargo-ship matching), speed choices have the greatest impact on GHG emission reduction (Poulsen et al., 2022). In the view of its importance, the speed of vessels has been addressed as a key decision variable in many vessel scheduling systems (Dulebenets, 2022). A speed optimization approach that seeks the most efficient travel speeds for a vehicle with a given route (Sung and Nielsen, 2020) has also been actively applied to the ship voyage optimization (Yu et al., 2021).

Importantly, in the light of the need to reduce GHG emissions, the energy-inefficient and sub-optimal utilization of vessels due to the SFTW operational practice has recently attracted the public's attention: the congestion outside Suez increased day-by-day as a result of the grounding in Suez of the container ship Ever Given, and the congestion outside various ports in China and the USA as a result of supply chain bottlenecks ashore. In both cases, congestion seemed to increase without any apparent coordination attempt among those ships to adjust their speed and adapt to the changing circumstances.

Operational optimization is no longer merely desirable, but has become an imperative in ocean maritime trade and supply chains. Decarbonization requires existing vessels to become more efficient, while all new fuels under consideration (methanol, ammonia, hydrogen) are both far more expensive and also have a much lower fuel density than present marine fuels. Therefore, future vessels powered by such new fuels will need to be operated at maximum fuel efficiency. It is in this context that resolving SFTW has become an urgent and important problem.

To address the operational inefficiency, there have been further attempts in two areas: *Virtual Arrival* (VA) and *Just-in-Time* arrival (JIT). VA attempts to deal with some of the obstacles described above especially in relation to the split incentives of charterparties.

VA is, by its nature, a bilateral contractual mechanism and does not address the wider supply chain. Similarly, it does not address the systemic optimization problem, i.e., the other vessels that are proceeding to the same port.

JIT, on the other hand, targets optimization beyond the one ship or the bilateral relationship between shipowners and charterers of one ship. However, JIT seeks to optimize port operations at a given port, rather than optimize the system of ships. Indeed, as every port is different, JIT solutions are difficult to deploy at scale.

The multilateral optimization system examined in this article (the Blue Visby Solution, BVS[1]) differs from VA and JIT because it approaches SFTW from a system optimization perspective, rather than a unilateral (voyage planning), bilateral (VA) or port/berth management (JIT) perspective. BVS consists of various elements, including the contractual aspects briefly set out above. BVS combines two concepts: (a) A novel technical and operational system to implement a reduction of the speed of bulk vessels through dynamic and environmentally optimal speed allocation to achieve synchronized arrival at defined points near, but not at ports; and (b) multilateral contractual arrangements for the observance of the aforementioned technical and operational system and the sharing of the financial costs and benefits, which adapts in a novel way the age-old maritime law concepts of general average and applies in a novel way the principle of mutuality.

This BVS concept is set out on the website (see https://bluevisby.com/how-does-it-work/) and has also been discussed in the submissions by Blue Visby to the Environment Committee of the UK Parliament (see https://committees.parliament.uk/work/1408/net-zero-aviation-and-shipping/publications/). The research described in this article deals with the mathematical formulation of BVS and expected performance of the solution in an ideal environment, i.e., not in actual operating conditions at sea.

2.2. Analogies with systemic optimization problems in other industries

When viewed through the lens of system optimization, the SFTW operational practice in maritime transport has similarities with analogous problems encountered in other industries. The maritime transportation industry is a system where multiple chains of operations (sailing–preparations for cargo handling–cargo handling and loading–sailing–cargo handling and discharging–etc.) are performed by a large number of entities (or actors or servers including the vessels, the charterers, the cargo sellers and buyers, terminal and ports, as well as many others).

For example, JIT manufacturing (also known as lean manufacturing) focuses on minimizing waste in manufacturing systems to deliver economies and efficiencies. In terms of methodology and terminology, waste is defined as anything that cannot bring values to a system and customers. Following the definition, anchorage waiting time of vessels, caused by SFTW practice and the resulting imbalance between demands and capacity of port operations, can be described as systemic *waste* in the maritime transportation industry.

Theory of Constraint (TOC) is another methodology that can be used to analyze (and help resolve) the waste in the maritime transportation system. TOC aims to increase the throughput of a system by focusing efforts on the constraint (bottleneck) of the system. Port operations is a constraint of the maritime transportation industry (Mulyono and Achmadi, 2016). Applying the principles of TOC, it is clear that pacing up the non-bottleneck operations (i.e., sailing with SFTW practice) cannot improve the throughput of the system, and only increase costs, inventories, and waste (waiting vessels).

Research across various industries have improved the understanding of the system-wise dynamics fostered by the paradigms in the system optimization and management methodologies. Various mathematical approaches have been proposed and implemented in order for various systems to improve their performance from planning and scheduling perspectives. One of the most relevant examples is a supply chain network design problem (Hamta et al., 2015). A supply chain is an integrated network of several organizations such as suppliers, manufacturers, distributors, transporters and customers, where the balance between the organization is the key to optimize the performance of the supply chain. Another relevant approach can be found in an assembly line, special flow-line production systems. For an assembly line, the workload balance between servers in the line is important to minimize the resources required to produce products at a desired rate (Boysen et al., 2007).

It should be noted that attempts for applying such a system optimization and management methodologies to the maritime transportation industry have been rarely made. This may be due to the fact that the high degree of fragmentation in the maritime industry complicates a systemic approach. It is also possible that the maritime industry presents an additional complicating factor; fragmentation is accompanied by competing commercial business models and contractual structures that are bilateral in nature, rather than systemic or multilateral. While a systemic approach, which considers the interactions between operational components of the maritime shipping and seeks collaborative agreements between the components, can be found in the context of liner shipping (Dulebenets et al., 2021), the key difference to this study, which focuses on tanker and dry cargo shipping sectors, is the availability in liner shipping of global voyage schedules as a governing factor. In liner shipping, container ships are deployed following fixed routes and schedules (Wang and Wang, 2021), which makes it easy to apply a systemic approach, whereas, in tanker and dry cargo shipping, vessels rarely follow a fixed schedule (Jia et al., 2017).

[1] Blue Visby and Blue Visby Solution are trademarks and the Blue Visby Solution has patent pending status.

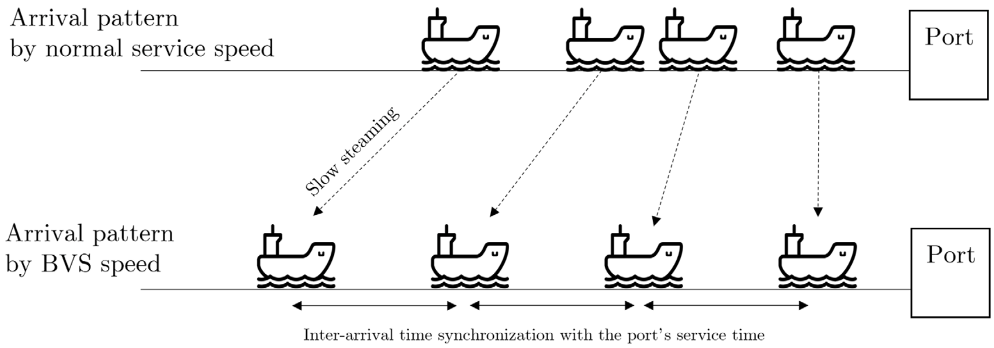

Fig. 1. Adjustment of vessels' arrival time at a port by BVS.

2.3. Gaps in the literature: Barriers in the VA and JIT application

VA has been studied mainly based on scenario-based analysis to identify the expected benefits by VA. The VA studies in the literature are focused on what-if analysis (for example, what if a waiting time at berths is reduced by 50%) mainly using real vessel trajectory data. Johnson and Styhre (2015) analyze the sources of vessel's unproductive time at a port based on Statements of Facts and Voyage Reports available for a short sea dry bulk shipping in the North and Baltic Seas. Upon the findings, they evaluate the potential benefits of sailing speed reduction of vessels under a scenario where turnaround time at a port is reduced. Andersson and Ivehammar (2017) identity ships anchored at ports in the Baltic Sea on 40 occasions in 2015 from Automatic Identification System (AIS) data. Based on the data, they estimate potential savings of VA under different scenarios, where a sailing speed reduction percentage and the time when the speed reduction is applied during a journey are varied. Jia et al. (2017) investigate potential benefits of VA at a global scale focusing on the oil tanker markets. In the study, 5066 voyages performed by Very Large Crude Carriers (VLCCs) were considered and expected fuel savings from the voyages were calculated under several scenarios where the port waiting time is reduced by different scales.

The JIT-based studies have been conducted mainly from the port/berth optimization perspective. In particular, a traditional Berth Allocation Problem (BAP) that allocates berths to vessels based on their fixed arrival time has been extended by the JIT concept. Golias et al. (2009) formulate the BAP with vessel arrival times at berths as a decision variable to minimize the total waiting time and delayed departures of vessels. A simulation–optimization hybrid approach has also been used for solving the BAP. Lang and Veenstra (2010) investigate the impact of an arrival planning system for terminal and vessel sailing operations using a simulation model. Similarly, Alvarez et al. (2010) develop a simulation to represent vessels' and port resources' (berths and land-side equipment) behaviors, into which an optimization algorithm is embedded to determine optimal speed of vessels based on the resource availability.

Approaching the VA and JIT publications from the perspective of system optimization, it is clear that the scenario-based approach lacks systematic and mathematical aspects on how to achieve the scenarios assumed for their analysis. On the other hand, the BAP-based approaches have been addressed in a relatively small-scale due to the complexity of the formulations and methodologies involved. They also assume full control of ports and vessels, which is methodologically simplistic, as one of the key constraints is the fragmentation in both the vessel usage and the port usage systems, both in terms of multiplicity of competing actors, as well as the absence of multilateral contracts.

3. Proposed Blue Visby Solution: Keeping queue numbers of voyages

We examine a novel concept, BVS, which differs from both VA and JIT. BVS comprises many elements, but the focus of this article is purely mathematical optimization analysis. In BVS, sailing speeds of vessels heading to the same destination port are dynamically determined to meet an expected service rate of the port, while keeping a given arrival order of the vessels. The arrival order is determined by vessels' *notional* arrival time at the port, the estimation of a vessel arrival time using its normal service speed. According to BVS, vessels' actual arrival order at the port is retained as if they had sailed with the utmost despatch practice. In addition, BVS aims to determine sailing speed of the vessels such that the arrival rate of the vessels can be kept as close as the service rate of the port. The concept of the BVS optimization problem is illustrated in Fig. 1.

An optimization problem involved in BVS can be formally described as follows. At the moment of BVS initiation, a total of n vessels sail towards a destination port. Queue numbers of the vessels are assigned by their notional arrival time at anchorage points of the port. The vessels are indexed by i according to their queue numbers. The voyage distance of vessel i is denoted by d_i. The operational speed range of vessel i is given as $[\alpha \cdot v_i, v_i]$ where v_i is the service speed of vessel i and α is the speed conservation factor that controls the degree of slow steaming by BVS. The arrival time window of vessel i at an anchorage point, $[e_i, l_i]$, is then calculated by d_i divided by the operational speed range of the vessel. With the notation, the optimization problem for BVS, $\mathcal{P}_{BVS}$, which is to set the arrival time of vessel i (t_i, $\forall 1 \le i \le n$), can be written by

$$(\mathcal{P}_{BVS}) \qquad \min \sum_{i=1}^{n-1} \left(t_{i+1} - t_i - \rho\right)^2 \tag{1}$$

$$t_i \le t_{i+1} \qquad \forall\ 1 \le i \le n-1, \tag{2}$$

$$e_i \le t_i \le l_i \qquad \forall\ 1 \le i \le n, \tag{3}$$

where ρ is the target inter-arrival time of vessels, which will be set based on the port's service rate. Objective function (1) minimizes the sum of squares of the deviations of the inter-arrival time between two consecutive vessels, $t_{i+1} - t_i$, from ρ. Constraint (2) guarantees that vessels arrive at the port keeping the arrival order calculated. Constraint (3) ensures that vessels' arrival time at their anchorage points are set within their feasible arrival time windows.

According to the arrival time of the vessels found by solving $\mathcal{P}_{BVS}$, the BVS speed is calculated and the vessels will continue their voyages according to the BVS speeds until they arrive at the destination port or a new vessel starts its journey to the same port. In the latter situation, $\mathcal{P}_{BVS}$ will be re-initiated to derive new BVS speeds for the vessels incorporating up-to-date information. The BVS process where solving $\mathcal{P}_{BVS}$ is embedded to get the BVS speed is described in the procedure description below.

---

procedure BVS PROCESS
Step 1. A new voyage to a port is registered.
Step 2. Identify a set of vessels on their journeys to the same port
Step 3. Compute the notional arrival time of the vessels based on their original positions and operational sailing speeds.
Step 4. Sort the vessels according to their notional arrival time at the port in ascending order, assigning them a queue number.
Step 5. Solve $\mathcal{P}_{BVS}$ to derive BVS speeds for the vessels.
Step 6. Assign BVS speed to the vessels.
end procedure

---

4. Experimental setting

4.1. Dataset

The feasibility and expected benefits of BVS are analyzed using the AIS sample data for tanker and dry bulk carrier trajectories in 2018. As oil tankers and dry bulk carriers do not follow a fixed departure or arrival schedule, they have more flexibility in adjusting their sailing speed and thus arrival time (Jia et al., 2017). Following this, we acquire AIS data for voyages performed by the vessel types with more than 50,000 Dead Weight Tonnage (DWT) to target voyages with a relatively long duration. To minimize noises in the dataset, we exclude the voyages that anchored more than 100 km away from their destination ports, or sailed either slower than 1 knot or faster than 50 knots. As a result, we identify the target dataset $\mathcal{D}_{AIS}$ with a total of 14,452 voyages to 975 destination ports. The distributions of DWT of the voyages in $\mathcal{D}_{AIS}$ are shown in Fig. 2.

For each voyage in $\mathcal{D}_{AIS}$, we approximate the service speed of the vessel (v_{AIS}) by the distance between the origin port and the anchorage point at the destination port (d_{AIS}) divided by the time gap between its departure and anchorage arrival (t_{AIS}). The haversine formula is used to calculate the sailing distance. With the data, the original total fuel consumption of a voyage (F^{AIS}) is estimated by

$$F^{AIS} = \left\{B \cdot (v_{AIS})^3\right\} \cdot t_{AIS}, \tag{4}$$

where B is a vessel-specific constant (Smith et al., 2011).

4.2. BVS implementation

We implement a simulation model according to the BVS process that represents vessels and ports behaviors. In the simulation model, the following assumptions are applied:

- A voyage route between two locations is a straight line between the locations and its length is computed by haversine formula.
- Vessels have the same fuel consumption profile.
- Weather conditions do not affect the fuel consumption of a vessel.
- A vessel's berth waiting time and service time at a port are not considered for fuel consumption computation.

With the assumptions, the simulation model sequentially generates voyages according to their departure schedules as in $\mathcal{D}_{AIS}$ and performs the BVS process (Step 1–6) when a new voyage starts. The simulation model then updates the positions of the vessels

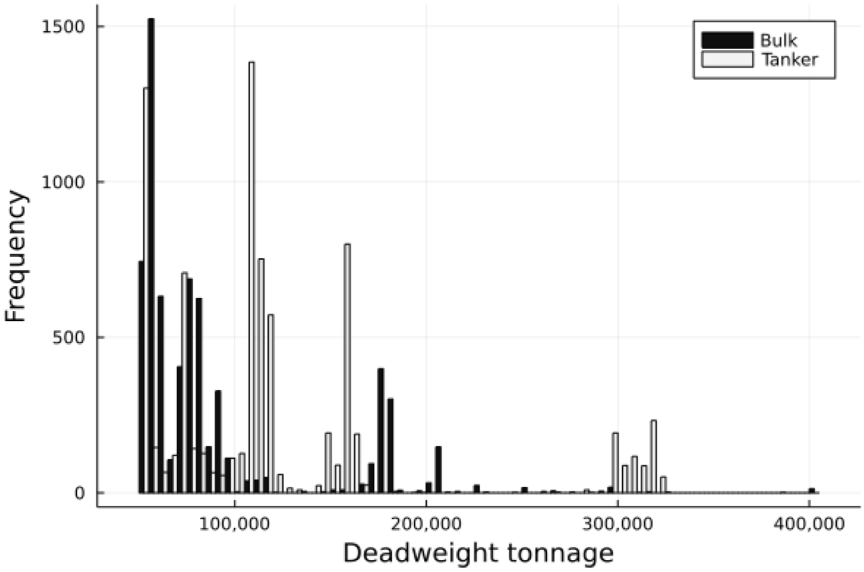

Fig. 2. A histogram of deadweight tonnage of the voyages in $\mathcal{D}_{AIS}$.

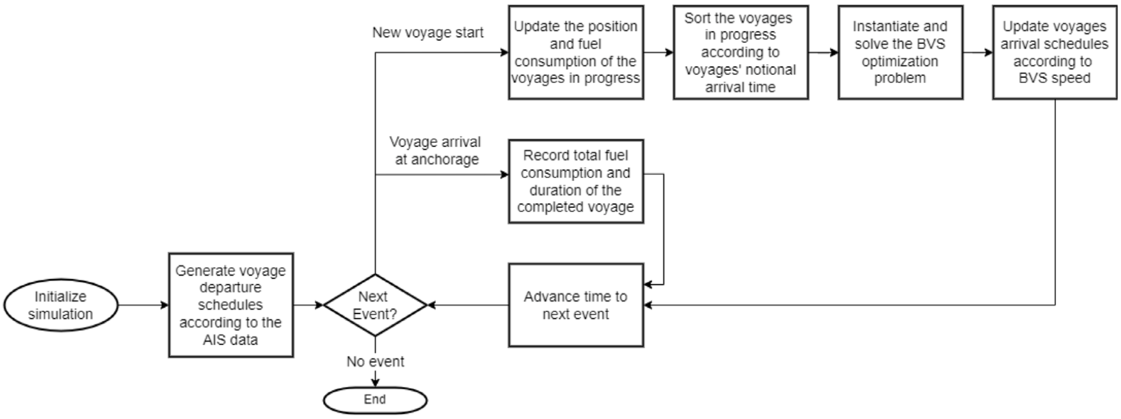

Fig. 3. The flow chart of the simulation model.

according to BVS speeds for the vessels, i.e., the outcome of the BVS process. Upon the arrival of a vessel at its anchorage point, the simulation model records the voyage time and total fuel consumption of the voyage (F^{BVS}) by

$$F^{BVS} = \sum_{z=1}^{Z} B \cdot (v_z)^3 \cdot t_z, \tag{5}$$

where Z is the total number of updates on the speed during the voyage, and v_z and t_z are the BVS speed assigned and corresponding voyage duration of the vessel between the zth and $(z+1)$th speed update. The flow chart of the simulation model implemented is described in Fig. 3.

In the simulation implemented, we set the parameters of $\mathcal{P}_{BVS}$ as follows. We first estimate the target inter-arrival time of vessels at a destination port (ρ in hours) by 168 h (a week) divided by the median number of vessels discharged by the port per week in $\mathcal{D}_{AIS}$. Next, the service speed of the vessel v is estimated by v_{AIS} and the speed conservation factor α is set by 0.9. Lastly, the earliest and latest arrival times for a vessel at its anchorage point are set by the remaining sailing distance in the simulation divided by the operational speed range $[\alpha \cdot v_{AIS},\ v_{AIS}]$. With the parameter setting, $\mathcal{P}_{BVS}$ instances created during the simulation are solved using IpOpt nonlinear optimization problem solver. Note that $\mathcal{P}_{BVS}$ is a quadratic program that is to optimize a quadratic objective function (Eq. (1)) subject to linear constraints. IpOpt is a well-recognized nonlinear and quadratic programming solver that implements a primal–dual interior-point method. For the mathematical details of the implementation, please refer to Wächter and Biegler (2006).

Table 1
Descriptive statistics for fuel savings by BVS.

Fuel savings per voyage (%)				Fuel savings per voyage (tonnes) with $B = 0.03$			
Mean	Median	Std.	Max	Mean	Median	Std.	Max
7.47	3.03	9.35	98.48	4.76	0.07	12.76	247.29

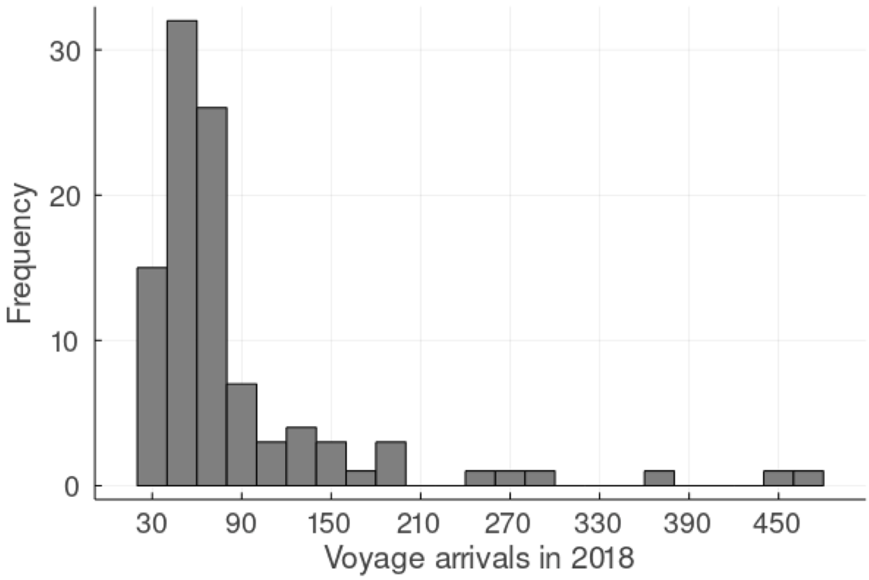

Fig. 4. A histogram of voyage arrivals to the top 100 busiest ports.

Table 2
Descriptive statistics for fuel savings by BVS for the top 100 busiest port.

Fuel savings per voyage (%)				Fuel savings per voyage (tonnes) with $B = 0.03$			
Mean	Median	Std.	Max	Mean	Median	Std.	Max
8.75	6.77	9.40	99.72	5.35	0.33	13.28	246.07

5. Experimental results: The benefits of BVS

5.1. How much fuel savings can be achieved by BVS?

Let us first investigate how much fuel savings can be expected by applying BVS. We calculate the percentage of the fuel savings per voyage by BVS using

$$100(\%) \times \left(1 - \frac{F^{BVS}}{F^{AIS}}\right),$$

where F^{AIS} is the estimated original fuel consumption of a voyage calculated by Eq. (4), and F^{BVS} is the simulated fuel consumption of the same voyage with BVS, calculated by Eq. (5).

To give a pragmatic perspective on the scale of the expected fuel savings, we also estimate the absolute fuel savings per voyage ($F^{AIS} - F^{BVS}$) by applying the VLCCs vessel-specific constant, $B = 0.03$, to the fuel consumption functions (4) and (5) (Smith et al., 2011). The results are summarized in Table 1.

With BVS, 7.5% and 4.8 tonnes of fuel savings are expected to achieve, on average. From the median perspective, the fuel savings seems relatively marginal (a median of 3%). This marginal improvement may be contributed by including the voyages heading to the ports with very few vessel arrivals. By the nature of BVS, those voyages are rarely benefited from BVS. Note that $\mathcal{P}_{BVS}$ is not even specified with a single voyage (minimum two voyages required).

Based on this idea, we identify 8679 voyages to the top 100 busiest ports in $\mathcal{D}_{AIS}$ (see Fig. 4 for a distribution of the number of voyage arrivals to the top 100 busiest ports in the dataset) and compute the corresponding fuel savings. The fuel savings of the voyages to the top 100 busiest ports by BVS are summarized in Table 2.

As presented, when narrowing down the scope of the dataset to the voyages heading to the top 100 busiest ports, BVS shows substantial fuel savings (8.8% fuel savings on average). From our analysis on $\mathcal{D}_{AIS}$, the JIT arrival of voyages at anchorage points

Table 3
Descriptive statistics for the demand–supply imbalance in the top 100 busiest ports.

Without BVS (as-is)				With BVS			
Mean	Median	Std.	Max	Mean	Median	Std.	Max
34.90	36.46	0.16	72.57	29.66	32.39	0.17	69.50

(i.e., zero anchorage time) is expected to bring 33.6% of average fuel savings with a median of 21.1% per voyage. While the dataset used is different, the work of Jia et al. (2017) reports 19.3% of average fuel savings when port waiting time is reduced by 100%. Considering that BVS does not involve the complexity in berth management for JIT arrivals, it can be concluded that BVS brings significant and comparable fuel savings to the JIT solutions.

5.2. How many voyages can be completed by BVS, keeping their queue numbers?

One of the key aspects of BVS, important to encourage involvement from the stakeholders of the maritime transportation industry, is to keep the arrival order of voyages at a port the same as the one with SFTW practice. This condition is incorporated into BVS by imposing constraint (2) to $\mathcal{P}_{BVS}$. However, it is not always possible to satisfy this constraint because of different configurations of voyages (origin/destination ports, departure time, etc.) and different operational speeds of vessels. In other words, keeping the desired arrival order of vessels at a port might be infeasible to achieve.

Therefore, it is important to check if the voyages with BVS can be completed while keeping their notional arrival orders. To examine this, we sort the voyages to the same port by their notional arrival time and compare the resulting order to the simulated voyage arrival order with BVS. Considering the fact that from a voyage perspective, receiving a higher queue number than the one the voyage is supposed to take under the SFTW practice is a problem (as this may bring delays in port admission), we count the voyages that experienced such a queue number increase.

As a result, 769 voyages (around 5% of the total voyages) are identified and these voyages encounter average 2.4 queue number increase. A median of the queue number increase is one. In other words, only 2.5% of the total voyages experienced the queue number increase greater than one. Based on the results, it can be concluded that BVS can keep the queue numbers of voyages as if they had sailed with SFTW practice, which is critical to encourage agreement on BVS from the stakeholders in the maritime transportation industry.

5.3. Improved balance between voyage arrivals and port services by BVS

Considering a port as the bottleneck of the maritime supply chain, the main function of BVS is to balance the voyage arrivals to a port and the service capacity of the port so that the berth waiting time of the voyages as well as fuel consumption during their voyages can be minimized. Given this, it is important to see how much the voyage arrival process is synchronized with the service capacity of a port by BVS.

To examine the degree of the vessel-port synchronization by BVS, we compute medians of the voyage inter-arrival time to the top 100 busiest port in $\mathcal{D}_{AIS}$ (termed *without BVS*) and compute the same from the simulation results (termed *with BVS*). With these two sets of results, the imbalance between the voyage arrival and the port capacity is measured for each set by

$$100(\%) \times \frac{\rho - \tilde{I}}{\rho},$$

where ρ is the ideal voyage inter-arrival time for a port, determined based on the approximated port capacity, and $\tilde{I}$ is the median vessel inter-arrival time to the port computed from the considered result dataset. Descriptive statistics of the imbalance measurements between with and without BVS scenarios are presented in Table 3.

As presented, BVS improves the imbalance measurement (around 5% average reduction). While the inter-arrival time of voyages to ports cannot be fully synchronized with ports' service time (note that we allow maximum 10% of speed reduction in the optimization problem and the demands for ports are often far exceeding ports' capacity), the imbalance reduction level achieved by BVS seems sufficient to bring the significant energy efficiency improvement as we observed in the previous experimental results.

To clearly visualize the vessel-port synchronization by BVS, we plot the inter-arrival differences for the top 20 busiest port in Fig. 5. The figure shows the voyage inter-arrival time gap for each port by the line between the current median inter-arrival time (a cross mark) and the one updated by BVS (a triangle). The target inter-arrival time (ρ) is plotted with a star mark in the figure. With the setting, the improvement on the vessel-port imbalance by BVS can be represented as an arrow towards the target inter-arrival rate.

From the figure, one can first observe that the current inter-arrival rate of voyages to the ports is far greater than the ports' service rate, which explains high congestion levels at the ports. Next, the figure clearly shows that the inter-arrival time of voyages to the ports becomes close to the target inter-arrival time by applying BVS. This is critical to synchronize the voyage arrival and discharge processes, and in turn, to minimize the waiting time of the voyages at anchorages and the congestion level of the ports.

On the other hand, one may notice that the median value of the voyage inter-arrival time at the port of *Ust-Luga* is decreased by BVS. However, when we take a close look at the results, BVS indeed resolves the imbalance between the voyage arrivals and the port capacity by avoiding the voyages with very short time intervals. See Fig. 6 where two histograms of the voyage inter-arrival time at the port of Ust-Luga – one from the AIS data and the other with BVS – are presented. The voyage arrivals with a short interval cause surge in demand, and this, combined with dynamics in port operation, is likely to lead severe port service delays.

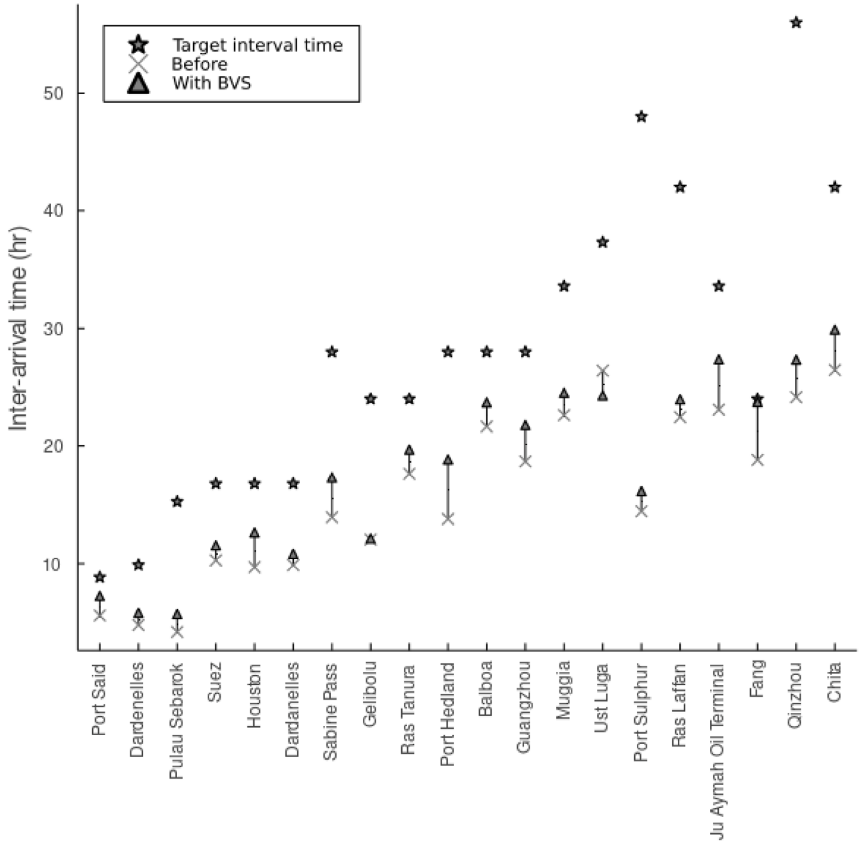

Fig. 5. The voyage inter-arrival time adjustment by BVS.

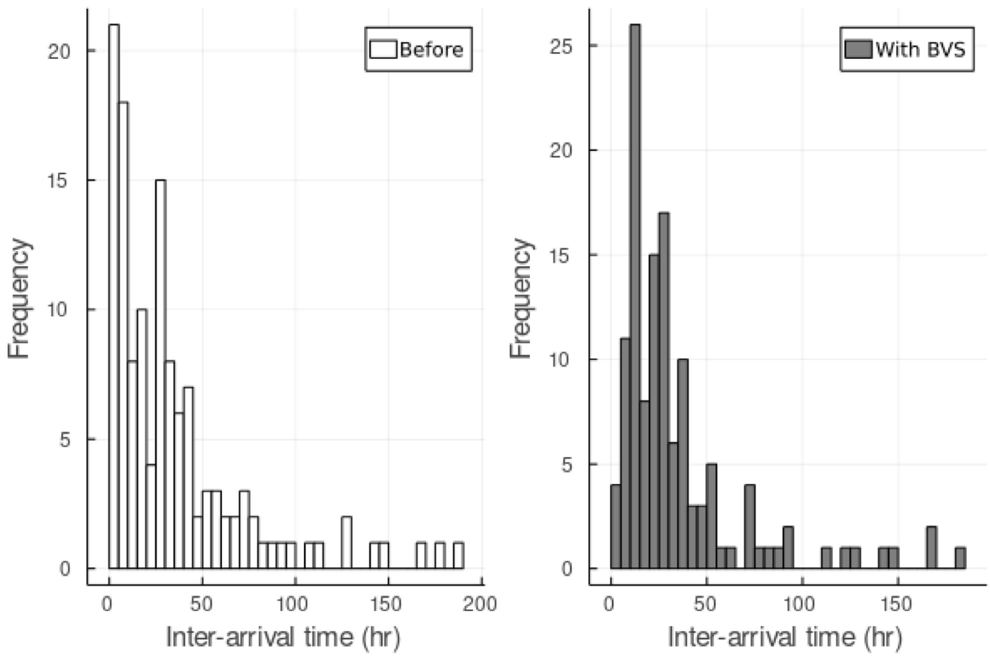

Fig. 6. Histograms of the voyage inter-arrival time for the port of Ust-Luga.

Table 4
Descriptive statistics on the voyage prolongation by BVS.

Mean	Median	Std.	Max	95%
5.64	3.83	15.07	562.60	11.11

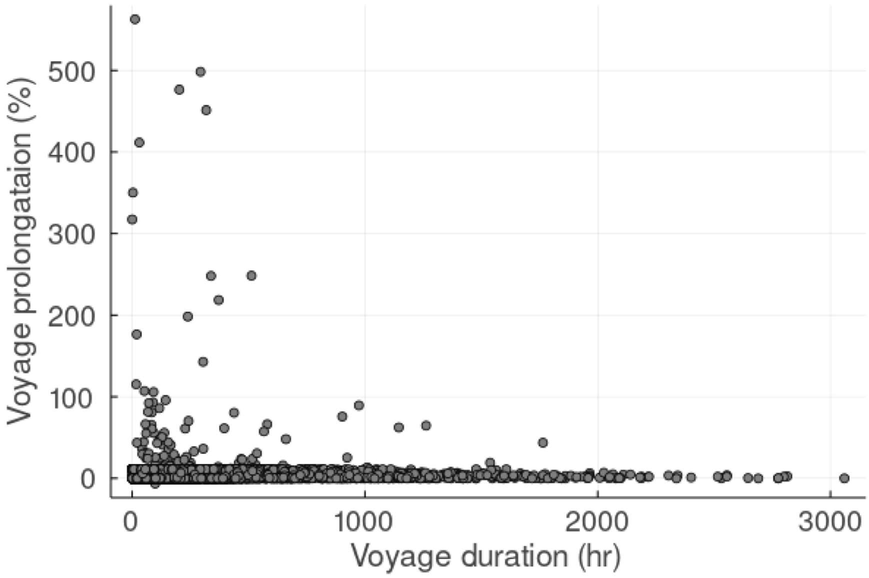

Fig. 7. The relation between voyage duration and prolongation by BVS.

5.4. How much delay is expected for voyages by BVS?

While slow steaming following BVS can save fuel consumption of voyages, this would bring additional cost by the increased voyage duration (e.g., additional hiring cost for ship crews and operator). To measure this negative impact of BVS, we compute the prolongation level of the voyages to the top 100 busiest ports by

$$100\ (\%) \times \left(\frac{T^{SIM}}{T^{AIS}} - 1\right),$$

where T^{SIM} is the simulated voyage duration of a vessel by BVS and T^{AIS} is the voyage duration of the vessel recorded in $\mathcal{D}_{AIS}$. Descriptive statistics of the voyage prolongation level are presented in Table 4.

As presented, the voyage prolongation level by BVS is marginal (around 6% on average). The majority of voyages experience less than 4% delays in their duration and the 95th percentile of the prolongation is 11%. While significant delays are observed from the result (maximum 562%), those delays are mainly occurred at the voyages with relatively short duration. This means that an absolute scale of the prolongation by BVS may not be significant. The observed relationship between the voyage duration (x-axis) and the prolongation scale (y-axis) by BVS is plotted in Fig. 7.

6. Conclusion

We have approached SFTW as a system optimization problem that addresses the maritime transportation industry as a supply chain system and improves the imbalance between demands (voyage arrivals) and supply (port capacity). We have conducted a mathematical and simulation analysis of BVS from the perspective of system optimization.

Specifically, we have taken a large sample of AIS data for tankers and dry bulk carriers in 2018 (14,452 voyages) and have observed substantial operational efficiencies that can lead to considerable fuel savings and GHG emissions reduction. From the results, BVS shows around 9% of fuel savings for the voyages to the top 100 busiest ports, on average. This saving is comparable to that observed by Jia et al. (2017) in a sample of 5066 voyages performed by VLCCs, which was 19% fuel savings by 100% port time reduction (i.e., JIT arrival). The results also demonstrate the BVS function that synchronizes voyage arrivals to a port with the port's service capacity, while keeping queue numbers of the voyages. In brief, these findings show that it is possible to resolve the SFTW operational inefficiency by taking a systemic optimization approach that does not involve the complexities in JIT of port and berthing management.

Based on the results, the contribution of this study can be noted as follows. We demonstrate the mathematical foundation of BVS that aims to synchronize voyage arrival at a port with the port's service capacity in a multilateral manner. BVS shows that the service order of the voyages at a port can be kept as if they had sailed with SFTW practice, while reducing the fuel consumption of the voyages as well as the congestion level at the port. This is essential for encouraging agreement on the proposed approach from the maritime industry stakeholders.

However, this study simplified the characteristics of vessels and operational environments, the key parameters of the voyage fuel consumption. We assumed simple routes between origin and destination ports, neglecting different configurations of ships and dynamics in the oceans. The fuel consumption of a voyage is indeed determined by many factors including ship's specification (size, type, propeller, etc.) and weathers. The fuel type (especially in terms of the sulphur content ration in the fuel oil) for voyages also depends on the location of ships. Importantly, the fidelity of the operational environments assumed for the BVS performance test is key to estimate the actual benefits of BVS, and thus to derive general agreement on the necessity of a system optimization approach for the maritime industry. To address the limitation of this study, BVS will be tested under a realistic operational environment to evaluate the BVS benefits more accurately.

Specifically, the work described in this article will be followed by a further proof-of-concept study. A more detailed analysis of a larger AIS dataset with dynamic and real operating conditions will be performed to examine realistic BVS benefits. Upon the detailed and realistic results, the practicality of BVS will also be examined by a consortium, in which a number of companies and institutions test BVS from multiple aspects of the maritime industry.

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