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Article

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Original Article

Exploring the factors influencing the cost-effective design of hub-and-spoke and point-to-point networks in maritime transport using a bi-level optimization model

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ABSTRACT

Hub-and-spoke (HS) networks are cost-effective because they allow the realization of economies of density. However, the cost of point-to-point (PP) networks may be lower than that of HS networks when certain conditions, such as cargo demand, bunker price, vessel size, and the shippers' value of time change. This study explores the factors that influence the cost-effectiveness of HS and PP networks. We developed a mixed-integer programming model that allows for bi-level optimization between shipping lines and shippers. As a case study, we applied it to Chinese and Japanese ports, with both HS and PP networks. We found that high cargo demand increases the use of PP networks while enlarging vessel size increases the use of HS networks. These findings enable us to predict the occurrence of hubbing—shifting from a PP to an HS network—and de-hubbing—shifting from an HS to a PP network.

1. Introduction

There are two main types of maritime transport networks: hub-and-spoke (HS) and point-to-point (PP). In PP networks, carriers transport cargo directly between the origin and destination ports. In HS networks, carriers aggregate cargo in an intermediate port, called a hub, and then distribute the cargo to the destination ports, called spokes. HS networks require additional navigation distance, navigation time, and port charges compared to PP networks because the cargo that originates in a spoke must be transported via a hub (Hsu & Hsieh, 2005). On the other hand, HS networks can connect origin and destination ports through fewer shipping services than PP networks; accordingly, their configuration can reduce network construction costs—aggregation can more easily yield economies of scale and density (O'Kelly & Miller, 1994). However, Tran and Haasis (2015) and Fan and Luo (2013) demonstrated that larger vessels are not always economically effective in HS networks because economies of density may not be present; along these lines, HS networks can be less cost-effective than PP networks in some conditions. Wilmsmeier and Notteboom (2011) indicated that the identification of shipping networks contributes to regional shipping market analyses because it allows the current market situation and its future development to be classified. However, since the appropriate container port developments for regional economies are different for HS and PP networks, HS and PP network designs need to be identified.

While studies have been conducted on maritime network designs, the existing literature is primarily focused on the cost-effectiveness of HS network designing. Kavirathna et al. (2018) analyzed hub port selection by shipping line based on quantitative and non-quantitative criteria. Chen et al. (2020) considered how shippers' path choice behaviors affect network design and hub location. These studies focused only on the cost-effectiveness of HS network and analyzed the influence of the various factors related to shipping line and shipper. On the other hand, the comparison studies between HS and PP networks only discussed the importance of cargo flow. For example, Hsu and Hsieh (2005) stated the importance of container flow between origin and destination ports for PP network design. There is a research gap of the lack of evaluating the influential factors that determine the cost-effectiveness of HS and PP networks. To bridge this gap, this study explores the cost-effective designs of HS and PP networks.

We used a mixed-integer programming model based on the model developed by Zheng et al. (2015) to capture the bi-level optimization between shipping lines and shippers and the influencing factors and considered several constraints on network design, such as vessel capacity and cargo demand increases. As a case study,

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we examined routes between Japan and China, where, despite the development of the Busan port as a hub with strong competitiveness in the Asian maritime network, both HS and PP networks exist. We compared the ratio of the transshipment and direct shipment cargo of the routes as an HS and a PP network, respectively.

The rest of this paper is structured as follows. In Section 2, we review the existing literature on maritime network design. In Section 3, we present the mixed-integer programming model. In Section 4, we present the quantitative analysis of the case study. In Section 5, we conclude the paper and discuss directions for further research.

2. Literature review

Previous studies have been conducted on maritime network designs in the context of the cost-effectiveness of HS network designing. Ji et al. (2015) examined the routing optimization problem in HS networks. They demonstrated that the time deadline, container vessel capacity, and cargo handling capacity of each port significantly influence the total cost and number of routes. According to Kim et al. (2019), shipping routing is affected by the sea freight rate. Shibasaki and Kawasaki (2019) focused on the international intermodal container cargo shipping network in South Asia and mentioned the importance of network capacity. Mulder and Dekker (2014) solved the combined fleet-design, ship-scheduling, and cargo-routing problem as a network design problem. Kavirathna et al. (2018) showed the dominant performance of Singapore as hub port in many criteria such as frequency of vessel visit and port capacity. Jiang et al. (2019) argued that the transshipment capacity of hub ports improves the capacity performance of the port shipping network. These studies focused on how several factors related to shipping lines can affect HS network design in maritime transport.

Several researchers have also analyzed how shipping networks affect the behavior of shippers. For example, Angeloudis et al. (2016) and Wang et al. (2014) used game theory to analyze the effect of competition between the shipping lines a shipper may choose to use. Chen et al. (2020) analyzed path choice behavior of shippers, the liner network and the hub port location along the West African coast. Talley (2014) demonstrated that carriers, shippers, and ports have both direct and indirect effects on shippers' path choices. Kawasaki et al. (2020) pointed out the importance of considering the perspective of several maritime transport stakeholders, such as shippers and port management bodies. These studies demonstrated that various factors related to shipping lines and shippers can influence the network design.

As for studies that have compared HS and PP networks, Imai et al. (2009) compared HS and PP networks as multi-port-calling and stated the cost-effectiveness of multi-port-calling considering container management issues, including empty container repositioning. Notteboom et al. (2019) demonstrated that a difference in throughput volatility exists in ports with high transshipment cargo (HS network) and ports with high gateway cargo (PP network). Hsu and Hsieh (2005) analyzed the trade-off between shipping cost and inventory cost in HS and PP networks. They indicated the cost-effectiveness of PP network in high container flow between origin and destination ports. These studies compare the cost-effectiveness of HS and PP networks focused on container flow.

In summary, container flow affects the selection between HS and PP networks. However, the impact of various factors considered in previous studies focusing only on HS network has not been verified for the selection between HS and PP networks. The significance of this study lies in suggesting the cost effectiveness of HS and PP networks with various factors related to shipping line and shipper changings.

3. Methods and material

3.1. Model development

3.1.1. Factor selection and model requirements

Hsu and Hsieh (2005) indicated the importance of container cargo volume in a PP network design. Given the difficulty of making a profit on the service, we should consider cargo volume first. Additionally, a higher bunker price can affect the shipping route (Wang & Meng, 2012a) and may increase costs for HS networks because the total navigation distances are longer through the hub port. Subsequently, shipping lines deploy larger sized vessels in ports with berths deep enough for larger sized vessels to call, because larger sized vessels can achieve lower unit costs (Ng & Kee, 2008). The vessel size expansion can affect the network, such as more aggregation to hub ports to realize higher slot utilization of the larger vessels. Moreover, shipping lines consider the shippers' demand for lower transit times in designing networks (Notteboom, 2006). PP networks, which have lower navigation times than HS networks, are selected when shippers place greater value on time. Thus, four factors—cargo demand, bunker price, vessel size, and the value of time of shippers—can influence the cost-effectiveness of HS and PP networks. Therefore, in this study, we focused on how the changes in these four factors influence the costs of HS and PP networks.

We developed a model that focuses on whether cargo in several ports is transported directly or through a hub port. We categorized several ports as port set N and other origin, destination, and hub ports as port set M. We considered the bi-level optimization model that includes two decision-makers—shippers and shipping lines—making their own decisions by interacting with each other. Fig. 1 illustrates the structure of the bi-level optimization model. The shipping line constructs a shipping network by combining shipping services between ports in sets N and M. The shipper decides whether to transport via hub port in an HS network or directly transport in a PP network. Wang et al. (2015) demonstrated the importance of chance in the shipper choosing one of these alternatives, and the proposed bi-level optimization between shipping lines and shippers, that considers the demand uncertainty of each network, which Zheng et al. (2015) did not consider.

We prepared two assumptions to simplify the calculations. First, we assumed that the transported cargo volume in one service is proportionally assigned to each vessel by the vessel size deployed in the service. For example, when the total cargo volume between one OD is 120 TEU and two services, namely 500 and 1000 TEU vessels, are deployed, the volume of cargo transported by the 500 and 1000 TEU vessels is 40 and 80 TEU, respectively. We determined this assumption based on the strong correlation between the container port throughput and the capacity of the vessels calling at the port (Ducruet, 2016). Second, we assumed that the freight rate in a service is simply calculated to prevent the shipping line from being in a deficit; this means that we did not consider any freight rate uncertainty, such as that which may emerge with competition between shipping lines. The notations for the simulation model are illustrated in Appendix A.

3.1.2. Shipping line

The shipping line selects the variables deployed in vessel type (e) and shipping service (r)to minimize its total cost (Cs). Vessel type is the selection and deployment to the service chosen of a vessel type from the set of vessel types (E). Each vessel type has specific values for two characteristics: navigation speed (v^e) and vessel size (s^e). The service is chosen from a set of services (R) that consists of port n chosen from a set of ports (N) and port m chosen from a set of ports (M).

One of the decision variables of the shipping line is a binary variable (y_r^e), which takes a value of 1 if vessel type e is used for ser-

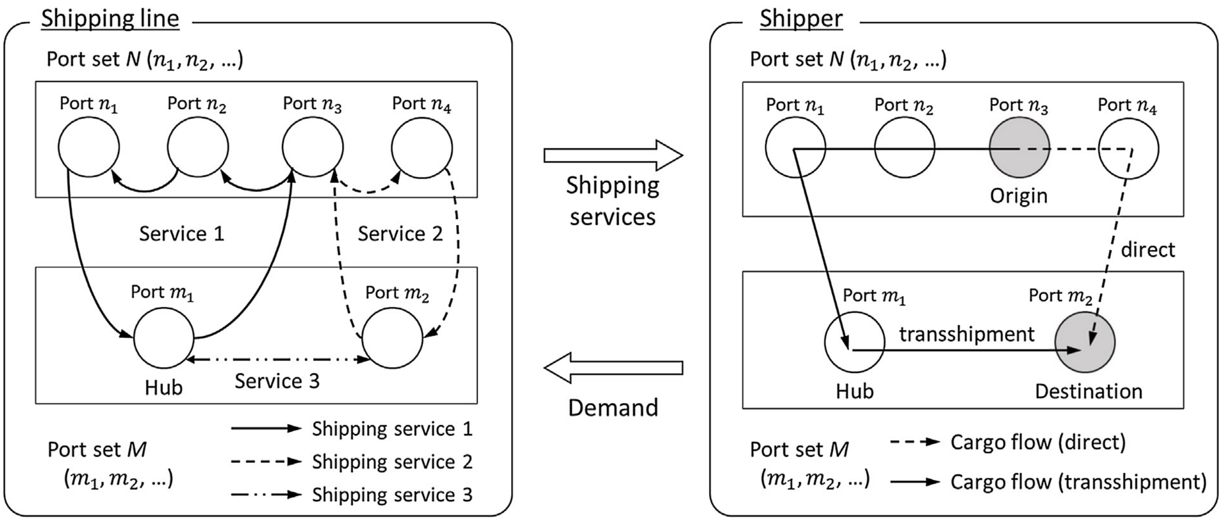

Fig. 1. Structure of the bi-level optimization model.

vice r and 0; otherwise, it is grouped in a vector, $\boldsymbol{y}$. Vector $\boldsymbol{y}$ indicates the services and types of vessels the network includes, and, given the assumption mentioned above, the cargo volume in the service depends on the vessel size. Therefore, the cargo volume in the service can be obtained from vector $\boldsymbol{y}$. The obtained cargo volume from ports m to n in service r $\left(\hat{q}_r^{m,n}\right)$ and the cargo volume from ports n to m in service r $\left(\tilde{q}_r^{n,m}\right)$, which includes exports and imports for port n, respectively, are grouped in vector $\boldsymbol{q}$.

As illustrated in Eq. (1), the total cost is the sum of the cost of each service (C_r^e), which consists of all operations between ports n to m and the cost to transport the transshipment cargo to or from port m via the hub port. Eq. (2) illustrates the cost of each service. According to Hsu and Hsieh (2005), operation costs can be divided into three parts: capital and operating costs, fuel costs, and port charges. Capital and operating costs represent the total expenses paid for vessel operation each day. In this study, we refer to these costs as vessel cost (vc^e), which consists of the chartering vessel and maintenance costs, among others. Regarding the vessel cost, the shipping line pays for the cost of the total voyage time. Total voyage time includes navigation time, which can be expressed in terms of navigation distance and navigation speed $\left(d_r^{i,i+1}/v^e\right)$, and waiting time, which includes pilotage and loading or unloading in ports n $\left(Lt_n^e\right)$ and m (Lt_m^e). Fuel cost $\left(fc^e\right)$ is the expense related to fuel consumption. As Wang and Meng (2012b) demonstrated, fuel consumption per day is the third power function of navigation speed (v^e). To consider sailing time, we multiplied fuel consumption by navigation time $\left(d_r^{i,i+1}/v^e\right)$. Port charges can be divided into charges for the vessel and cargo. In this study, we name the former "port charge" (pc_m^e), which includes servicing charges in port, such as pilotage. We name the latter "handling charge" (hc_m), which consists of fees paid for cargo handling in the container yard. These are charged per container; thus, we multiplied cargo volume to obtain the total cost of handling cargo. Eqs. (3) and (4), which we calculated based on the equations obtained from Tran (2011), Kim et al. (2019), and Gkonis and Psaraftis (2009), demonstrate the vessel cost (vc^e) and fuel cost (fc^e), respectively. In these studies, the equations are estimated using several methods, such as the least-squares method using observed data on container vessels. The term BP indicates bunker price, and the term μ is a coefficient that allows the analysis of different scenarios. We used the observed values of the port charge (pc_m^e) and handling charge (hc_m) from each port website. Eq. (5) illustrates the total transshipment cargo volume to or from port m (tQ_m). The equation represents volume using cargo volume $\left(Q_k^{m,n}\right)$ and a binary variable $\left(x_k^{m,n}\right)$, which takes 1 if the port k is the same as port m and otherwise 0. We use the term k to distinguish between transshipment and direct transport. Note that the meaning of k differs for exports and imports. For exports, port k is where the cargo was first unloaded. Thus, if ports k and m (destination) are different ports, the loaded cargo on board is transshipped in port k. In contrast, for imports, port k is where the cargo was last loaded. If ports k and m (origin) are different ports, then the cargo on board is transshipped in port k. The transshipment cost (tc_m) includes costs, such as loading costs in the hub port.

$$Cs = \sum_{e\in E}\sum_{r\in R} y_r^e \cdot C_r^e + \sum_{m\in M} tc_m \cdot tQ_m \tag{1}$$

$$\begin{aligned} C_r^e = {} & vc^e\left(\sum_{p_{ri}\in P_r}\frac{d_r^{i,i+1}}{v^e} + \sum_{n\in Pn_r} Lt_n^e + \sum_{m\in Pm_r} Lt_m^e\right) \\ & + \sum_{p_{ri}\in P_r} fc^e\left(v^e\right)^3\frac{d_r^{i,i+1}}{v^e} + \sum_{m\in Pm_r} pc_m^e \\ & + \sum_{n\in Pn_r} pc_n^e + \sum_{m\in Pm_r}\sum_{n\in Pn_r}\left(hc_m + hc_n\right)\left(\hat{q}_r^{m,n} + \tilde{q}_r^{n,m}\right) \\ & \forall r \in R,\ \forall e \in E \end{aligned} \tag{2}$$

$$vc^e = 108.05\left(s^e\right)^{0.6257} + 0.948 s^e + 4120\ \forall e \in E \tag{3}$$

$$fc^e = \mu \cdot BP\left(0.0392 s^e + 5.582\right)/\left(5.4178\left(s^e\right)^{0.1746}\right)^3\ \forall e \in E \tag{4}$$

$$tQ_m = \sum_{n\in N}\sum_{k\in M}\left(\hat{x}_k^{m,n}\cdot\hat{Q}_k^{m,n} + \tilde{x}_k^{n,m}\cdot\tilde{Q}_k^{n,m}\right)\ \forall m \in M \tag{5}$$

We formulated the network design problem by applying a mixed-integer programming model. Eq. (6) illustrates the objective function to minimize the shipping line's cost. Notably, the constraints of the model are presented in Eqs. (6) through (14). Eqs. (7) and (8) illustrate the amount of transported cargo in each service as assumed in Section 3.1.1 regarding service cargo volume and a guarantee that the services will transport all the cargo. Term $z_r^{n,m}$ is a binary variable, which takes 1 if service r includes ports n and m and 0 otherwise. Eq. (9) defines cargo volume on board (u_{ri}) during navigation within port n, and we calculated it by removing import and adding export cargo to/from port n. Eq. (10) defines cargo volume on board during navigation within port m. Eq. (11) is the capacity constraint, which ensures that the total cargo on board in each service does not exceed the capacity of the vessel size and slot utilization (γ). Term p_{ri} denotes port i within service r. The sets of ports n and m that are included in service r are indicated by terms Pn_r and Pm_r, respectively. The total set of ports that are included in service r is indicated by term P_r, which is the combination of Pn_r and Pm_r ($P_r = Pn_r \cup Pm_r$). The case where the set Pn_r contains port p_{ri} implies navigating in port n. Constraint 12 limits each service to at most one vessel type. Constraint 13 denotes non-negative constraints. Constraint (14) denotes y_r^e as a binary variable.

$$\min Cs(\boldsymbol{y}, \boldsymbol{q}) \tag{6}$$

subject to:

$$\hat{q}_r^{m,n} = \sum_{e \in E}\sum_{k \in M} \hat{Q}_k^{m,n} \frac{y_r^e \cdot s^e}{\sum_{e \in E}\sum_{r \in R} \hat{z}_r^{m,n} \cdot y_r^e \cdot s^e} \quad \forall m \in M, \forall n \in N, \forall r \in R \tag{7}$$

$$\tilde{q}_r^{n,m} = \sum_{e \in E}\sum_{k \in M} \tilde{Q}_k^{n,m} \frac{y_r^e \cdot s^e}{\sum_{e \in E}\sum_{r \in R} \tilde{z}_r^{n,m} \cdot y_r^e \cdot s^e} \quad \forall m \in M, \forall n \in N, \forall r \in R \tag{8}$$

$$u_r^{i,i+1} + \sum_{m \in Pm_r} \hat{q}_r^{m,i} = u_r^{i-1,i} + \sum_{m \in Pm_r} \tilde{q}_r^{i,m} \quad \forall i \in \left\{ i | p_{ri} \in Pn_r \right\}, \forall r \in R \tag{9}$$

$$u_r^{i,i+1} + \sum_{n \in Pn_r} \tilde{q}_{ri}^{n,i} = u_r^{i-1,i} + \sum_{n \in Pn_r} \hat{q}_r^{i,n} \quad \forall i \in \left\{ i | p_{ri} \in Pm_r \right\}, \forall r \in R \tag{10}$$

$$u_r^{i,i*1} \le \sum_{e \in E} y_r^e \cdot \gamma \cdot s^e \, \forall i \in \left\{ i | p_{ri} \in P_r \right\}, \quad \forall r \in R, \forall e \in E \tag{11}$$

$$\sum_{e \in E} y_r^e \le 1 \quad \forall r \in R \tag{12}$$

$$\hat{q}_r^{n,m}, \tilde{q}_r^{n,m} \ge 0 \quad \forall r \in R, \forall n \in N, \forall m \in M \tag{13}$$

$$y_r^e \in \left\{0, 1\right\} \quad \forall r \in R, \forall e \in E \tag{14}$$

3.1.3. Shipper

The shipper determines if their shipping is transshipped or directly transported to the destination through a logit model, which represents a stochastic user equilibrium based on the generalized cost. We obtained import and export cargo to and from port n from Eqs. (15) and (16), respectively. Term λ is a coefficient for cargo demand ($\mathcal{D}^{m,n}$ and $D^{n,m}$), which allows analysis of different scenarios, and term θ_m is a scale parameter. We calculated the generalized cost of import and export to and from port n separately in Eqs. (17) and (18). Eq. (17) consists of the freight rate $\left(\delta^{k,n}\right)$ and time cost $\left(\alpha \cdot T^{k,n}\right)$ from ports k to n. Eq. (18) consists of the freight rate $\left(\delta^{n,k}\right)$ and time cost $\left(\alpha \cdot T^{n,k}\right)$ from ports n to k. Term ρ is a coefficient for the value of time, which allows for the analysis of different scenarios. The cost for transshipment includes the required time $\left(tT^{m,k}\right)$ and a parameter $\left(\xi_k\right)$ that indicates other costs.

$$\mathcal{Q}_k^{m,n} = \lambda \cdot \mathcal{D}^{m,n} \frac{\exp(-\vartheta_m \cdot \mathcal{GC}_k^{m,n})}{\sum_{k \in M} \exp(-\vartheta_m \cdot \mathcal{GC}_k^{m,n})} \tag{15}$$

$$Q_k^{n,m} = \lambda \cdot D^{n,m} \frac{\exp(-\theta_m \cdot GC_k^{n,m})}{\sum_{k \in M} \exp(-\theta_m \cdot GC_k^{n,m})} \tag{16}$$

$$\mathcal{GC}_k^{m,n} = \delta^{k,n} + \rho \cdot \alpha \cdot T^{k,n} + \mathcal{X}_k^{m,n}\left(\rho \cdot \alpha \cdot tT^{m,k} + \tilde{\xi}_k\right) \tag{17}$$

$$GC_k^{n,m} = \delta^{n,k} + \rho \cdot \alpha \cdot T^{n,k} + x_k^{n,m}\left(\rho \cdot \alpha \cdot tT^{k,m} + \xi_k\right) \tag{18}$$

Eqs. (19)–(23) illustrate the components of the generalized cost of imports. Note that we can calculate the components for exports by reversing the order of the index. As illustrated in Eq. (19), we calculated the freight rate per TEU by the cost and cargo volume in the service after the assumption in Section 3.1.1 that the per-service freight rate is simply determined to not be in a deficit. This means that the value of the freight rate depends on the cargo volume. However, we determined the cargo volume based on the service choice of the shipper, which is heavily affected by the freight rate. This means that these two variables are interdependent. The determination of freight rate by shipping line affects the shipper's choice and vice versa. We solved the game by determining a Nash equilibrium to obtain optimum values, such that neither player has an incentive to unilaterally change strategies. We demonstrate the detailed equilibrium conditions in Section 3.1.4. Meanwhile, Eq. (20) defines transport time for the cargo between ports k and n $\left(T^{k,n}\right)$, which consists of waiting time in ports (Wt_k), average waiting time for the vessel to arrive $\left(7/2f^{k,n}\right)$, navigation time $\left(St^{k,n}\right)$, and loading or unloading time (Lt_k^e). Transshipment time, defined in Eq. (21), consists of navigation time $\left(td^{m,k}/tv\right)$ and loading or unloading time in the hub port. The frequency of voyages for each port is the sum of the number of services aligned to unit 1, which means service r is once a week (Eq. (22)) and is multiplied. As illustrated in Eq. (23), we determined navigation time by averaging the navigation time of each service.

$$\delta^{k,n} = \frac{\sum_{e \in E}\sum_{r \in R} z_r^{k,n} \frac{y_r^e \cdot C_r^e}{\sum_{m \in Pm_r}\sum_{n \in Pn_r}\left(\tilde{q}_r^{n,m} + q_r^{n,m}\right)}}{\sum_{e \in E}\sum_{r \in R} z_r^{k,n} \cdot y_r^e} \tag{19}$$

$$T^{k,n} = \frac{\sum_{e \in E}\left(Wt_k + \frac{7}{2f^{k,n}} + Lt_k^e + St^{k,n} + Lt_n^e + Wt_n\right)}{\sum_{e \in E}\sum_{r \in R} z_r^{k,n} \cdot y_r^e} \tag{20}$$

$$tT^{m,k} = \frac{\sum_{e \in E}\left(\frac{td^{m,k}}{tv} + 2Lt_k^e\right)}{\sum_{e \in E}\sum_{r \in R} z_r^{m,k} \cdot y_r^e} \tag{21}$$

$$f^{k,n} = \sum_{e \in E}\sum_{r \in R} z_r^{k,n} \cdot y_r^e \cdot 1 \tag{22}$$

$$St^{k,n} = \frac{\sum_{e \in E}\sum_{r \in R}\sum_{p_{ri} \in P_r} z_r^{k,n} \cdot y_r^e \frac{d_r^{i,i+1}}{v^e}}{\sum_{e \in E}\sum_{r \in R} z_r^{k,n} \cdot y_r^e} \tag{23}$$

3.1.4. Solution algorithm

The optimum vectors $\boldsymbol{y}$ and $\boldsymbol{q}$ need to be determined to solve the mixed-integer programming model. We can uniquely determine vector $\boldsymbol{q}$ by vector $\boldsymbol{y}$, given Constraints (7) and (8) and Eqs. (16)–(24). The solution for vector $\boldsymbol{q}$ must involve an optimum freight rate δ that represents a Nash equilibrium outcome between the shipping line and shipper, as mentioned in Section 3.1.3. Thus, this study used bi-level optimization to determine vector $\boldsymbol{y}$ and freight rate δ.

We used the algorithm proposed by Zhang et al. (2018) to obtain the Nash equilibrium freight rate δ. In this algorithm, the two players make repeated calculations based on the last iteration. Specifically, one player calculates using initialization, and the other player calculates using determination. After that, the first player calculates their rule based on the determination of the other player. This calculation is then iterated until the stopping criterion is reached. Note that the first player can be either the shipping line or the shipper, and initialization depends on the first player. In this study, we set the shipper as the first player and the freight rate as δ in the initialization. If we set the shipping line as the first player, we must include the vector $\boldsymbol{q}$ in the initialization. The stopping criterion is the point in time when a player chooses the best response that has been determined as the best response. At that

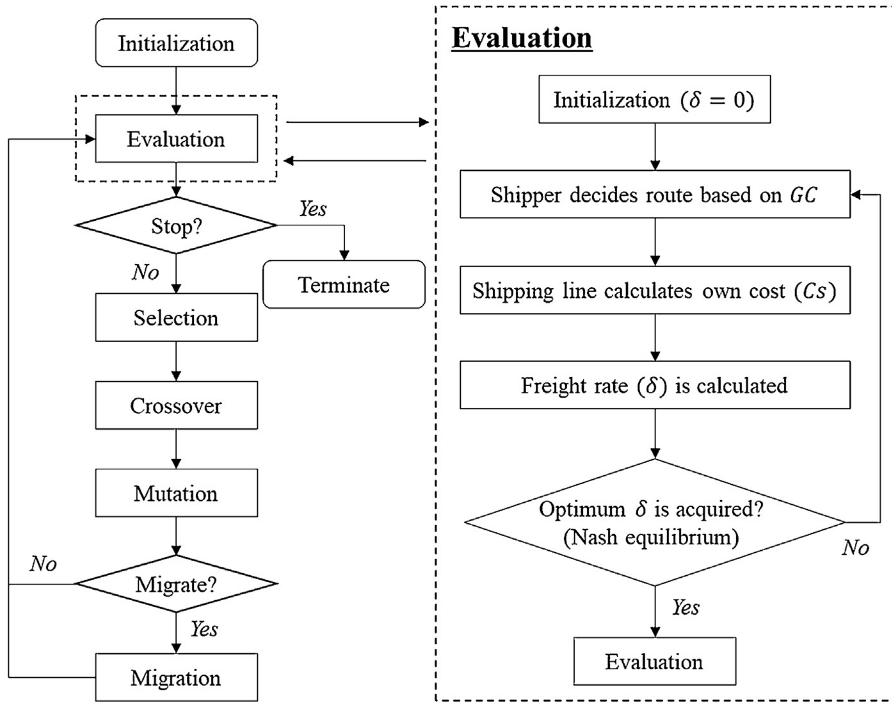

Fig. 2. Solution algorithm of the proposed PGA.

time, we obtain the following two cases. In the first case, the best response would be the same as the one in the previous response. In this case, the other player would also choose the same strategy. Thus, the strategies are the best responses for both players, and we can obtain the Nash equilibrium. In the second case, one player's best response is the same as the former response except for the previous response, which would cause an endless loop, and the Nash equilibrium would not be obtained.

For vector $\boldsymbol{y}$, the difficulty of obtaining an optimum value depends on the number of candidates for port n. If the number of candidates for port n is κ, there are $2^{\kappa} - 1$ different services to call port n, and we should consider at least $2^{2^{\kappa}-1}$ combinations in the network design. An exhaustive search cannot solve the optimization problem for network design within a realistic computation time. To solve the problem due to computational complexity, we must apply a meta-heuristic method. Therefore, we applied the genetic algorithm, proposed by Ge et al. (2003) and Zheng et al. (2015), to solve the network design problem in parallel. The parallel genetic algorithm (PGA) has more robustness and is less prone to find only a sub-optimal solution than a sequential genetic algorithm (Alba and Troya, 1999). Specifically, we divided the population, which contains tentative solutions through a genetic algorithm, into sub-populations called islands. Each island independently performs a large amount of computation to evolve. Migration is carried out, after a certain number of iterations of the islands, to exchange information for improving population diversity (Xiao et al., 2021). We can regard each binary variable (0 or 1) in vector $\boldsymbol{y}$ as a chromosome composed of individual y. It is then possible to obtain the optimum individual y with the PGA within realistic computation time. In the evaluation phase in the PGA, we set a higher fitness value, which indicates its suitability as the optimum solution, for individual y with the lower shipping line cost. Additionally, we lowered the fitness value for individual y for which we could not obtain a Nash equilibrium of the optimum freight rate δ within 100 iterations. The procedure of the proposed algorithm can be described as follows:

Step 0. Initialization: randomly generate individuals

Step 1. Evaluation

Step 1.1. Initialization: freight rate set as 0 USD/TEU

Step 1.2. Shipper: shippers decide if their cargoes are transshipped or directly transported based on Eqs. (15)–(23). Cargo volume in each service is outputted.

Step 1.3. Shipping line: based on cargo volume in each service, shipping companies calculate their cost (Eqs. (1)–(5)). Subsequently, the freight rate is calculated.

Step 1.4. Stop: if a stopping criterion of freight rate is fulfilled, go to Step 1.5. Otherwise, go to Step 1.2.

Step 1.5. Evaluation: to find fitter individuals, calculate the cost of services for each individual and evaluate whether the individuals satisfy Constraints (7)–(14).

Step 2. Stopping the simulation: if a stopping criterion of generation is fulfilled, then terminate, and output the fittest individual as the best solution. Otherwise, go to Step 3.

Step 3. Generation

Step 3.1. Selection: based on the fitness of individuals obtained in Step 1, the following two selections are implemented.

Step 3.1.1 Elite: the fittest individuals of each island are preserved until the next generation.

Step 3.1.2 Tournament: a few individuals are chosen at random, and two parents are chosen from them based on their fitness.

Step 3.2. Crossover: a uniform crossover method, in which each bit is chosen from either parent with equal probability, is implemented.

Step 3.3. Mutation: with a mutation probability, each bit in all the services can be changed.

Step 3.4. Stop: if all candidate individuals are generated, go to Step 4. Otherwise, go to Step 3.1.

Step 4. Migration: if a criterion of mitigation is fulfilled, individuals are randomly migrated to another island. Go to Step 1.

This study considered 240 individuals, four islands (each island has 60 individuals), and 100 generations. Mitigation was implemented every ten generations, and the limit of the calculation to obtain a Nash equilibrium in the sub-model was fifty. The proposed PGA was coded in MATLAB and run on an Intel® Core™ i5-8265U

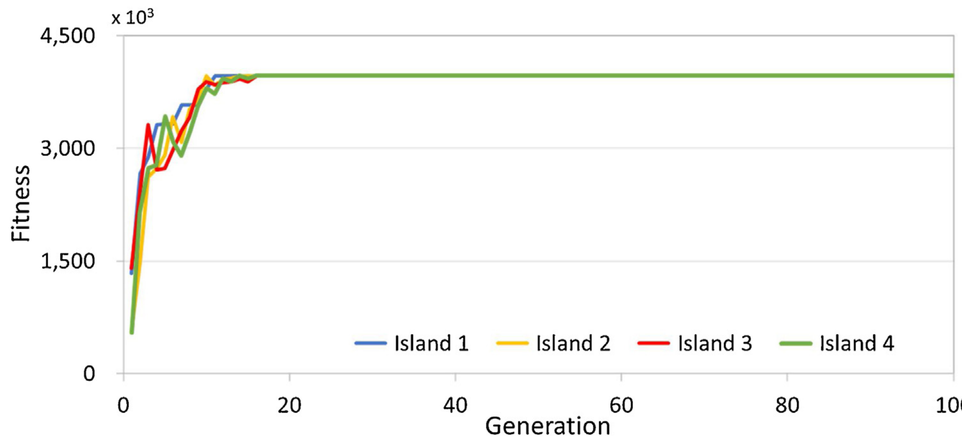

Fig. 3. Convergence of the proposed PGA.

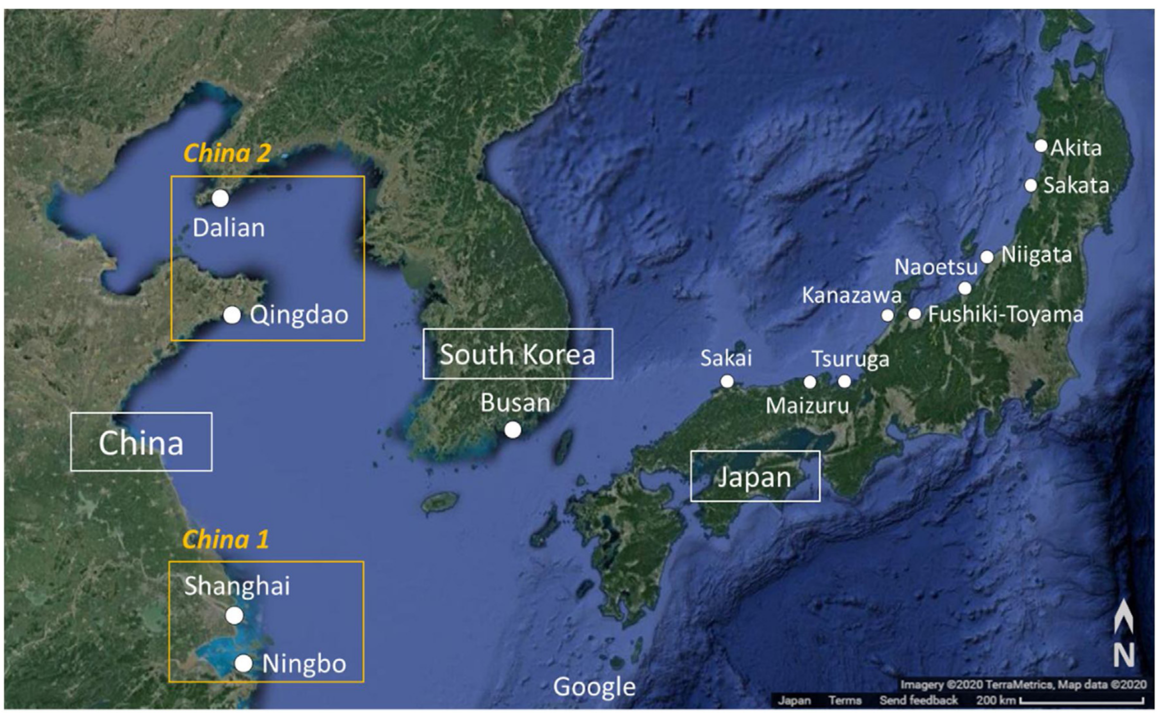

Fig. 4. Research area for the case study.

processor with 8 GB of RAM. The procedure and convergence of the proposed PGA are illustrated in Figs. 2 and 3, respectively.

3.2. Numerical analysis

3.2.1. Basic information of the study area

As illustrated in Fig. 4, we chose nine local Japanese ports facing the Sea of Japan and four Chinese ports as the research area for the case study. We chose the nine Japanese ports as port set N and the four Chinese ports and the Busan port, which is in the middle of Japan and China, as port set M in the model. As for the four Chinese ports, we treated the Shanghai and Ningbo ports as one port (China-1) and the Qingdao and Dalian ports as one port (China-2) for simplicity. Tables 1 and 2 illustrate the service and share of the cargo, respectively, in the study area in November 2018. We treated Ulsan and Kwang ports in South Korea as one port (Busan) for some services, as illustrated in Table 1. We have omitted some services and cargo in Tables 1 and 2, because the services include the nine Japanese ports but account for more than half of the rest of the Japanese ports. In Table 2, imports are shipments from trade partners (China-1, China-2, or the rest of the world) to Japanese ports, and exports are shipments from Japanese ports to trade partners. The rest of the world is cargo transshipped via Busan or China-1, which comes from other origins or goes to other destinations, such as other Asian ports. Since almost all the cargo trade with the rest of the world is transported via Busan or China-1 ports, we considered the cargo as part of the cargo of Busan or China-1 in the simulation. Since the volume of cargo traded with the rest of the world through China-2 was small, this port was omitted from the rest of the world column in Table 2. As illustrated in Table 2, the volume of both direct and transshipment cargoes is relatively balanced. Both networks exist in this area even though the Busan port is a hub port with strong cost competitiveness. Consequently, we can explore the influential factors on the cost-effectiveness of both networks by focusing on the ratio of direct and transshipment cargoes in this area. Note that transshipment is implemented only via Busan when the trade partner is China-1 or China-2.

Table 1
Information about observed services in the research area.

Service	Frequency (vessel/week)	Average vessel size (TEU)
China-1/Busan/Japan/Busan/China-1	1	1009
China-2/Busan/Japan/Busan/China-2	2	1166
China-2/China-1/Japan/China-1/China-2	1	1020
Busan/Japan/Busan	8	690
China-1/Japan/China-1	1	698

Source: Ocean Commerce (2018).

Table 2
Import/export cargo volume of the nine Japanese ports.

Trade partner	China-1		China-2		Rest of the world	
Direct/Transshipment	Direct	Busan T/S	Direct	Busan T/S	China-1 T/S	Busan T/S
Import to Japan [freight ton]	64,018	19,460	25,254	30,409	5898	139,023
Export to Japan [freight ton]	13,545	17,322	7834	7534	7186	186,282

Source: MLIT (2018).

Table 3
List of vessel types.

Vessel type (e)	1	2	3	4	5	6
Vessel size [TEU] (s^e)	300	500	800	1000	1500	2000
Navigation speed [knot] (v^e)	10.6	11.4	12.2	13.0	13.8	14.6
Loading/unloading time [hour] (Lt^e_m)	10	12	14	18	20	24
Loading/unloading time [hour](Lt^e_n)	8	10	12	14	16	20

Source: WAVE (2011) and Ocean Commerce (2018).

3.2.2. Adaptation of the model to the case study area

We considered the following two assumptions to adapt the model. First, the upper limit of the frequency of each service is once per week. In this study, we considered five types of services that consist of one or two ports m and several ports n, which are the same as the observed services illustrated in Table 1. Second, shipping lines choose ports to call in as one loop to ensure a total voyage duration in Japanese ports within seven days. We added Eq. (24), limiting the total voyage time from port n to one week or less, to the constraints in the model. We established these two assumptions because there is no observed service that exceeds seven days for the transport within Japanese ports or operates two times per week.

$$y_r^e\left(\sum_{p_{ri}\in Pn_r}\frac{d_r^{i,i+1}}{v^e}+\sum_{n\in Pn_r}Lt_n\right)\le 7\quad \forall r\in R, \forall e\in E \tag{24}$$

Several input values were required to implement the numerical analysis. Each vessel type (e) has its own values for vessel size (s^e), navigation speed (v^e), and loading or unloading time $\left(Lt^e_m\right)$, as illustrated in Table 3. As for vessel type, shipping lines choose the vessel from the set of vessel types (E), which is limited to four types of vessels (types 1–4). This means that the maximum vessel size in this area is 1000 TEU even though vessels larger than 1000 TEU are utilized in some services, especially the services of Busan and China-2, as illustrated in Table 1. Those services include ports other than the nine Japanese ports in the case study. Since we did not consider these ports, the maximum vessel size in this area can be regarded as about 1000 TEU. Note that we used vessel types 5 and 6 in the scenario analysis of vessel size expansion.

Table 4 illustrates the other required input values. Transshipment cost (tc_m) is the shipping cost based on the observed vessel size in this area. Bunker price is the average price in 20 global ports from July 31, 2018, to August 29, 2019, as obtained from Ship & Bunker. We selected the smaller freight rate, than real-world freight rates, because we did not consider all costs, such as land transportation costs, in this simulation. Therefore, the value of time (α), which

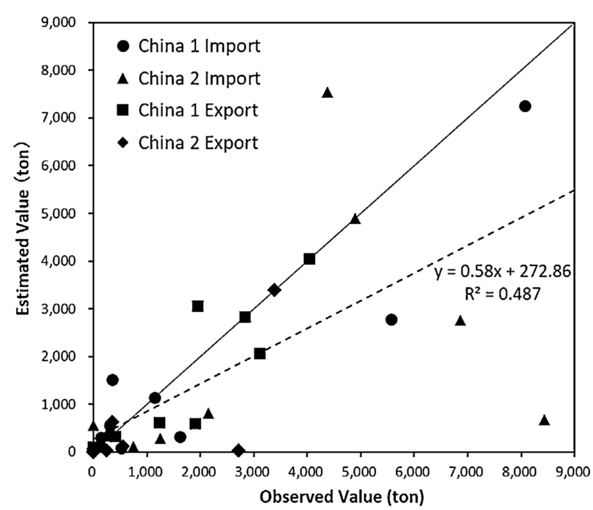

Fig. 5. Reproducibility of the simulation about transshipped cargo via Busan (solid line: forty-five degree line, dot line: approximate line from the observed data).

we obtained from WAVE (2011), is too large. We multiplied this by 0.05 to obtain a more realistic value. We estimated three other variables (hc_{ri}, Wt_a, *and* γ) using the observed values obtained from Ocean Commerce (2018). Unknown parameters (θ_m)and transshipment costs $\left(\xi_m\right)$were determined using maximum likelihood estimation to minimize the gap between estimated and observed values (see Table 5). The cargo demand values ($D^{m,n}$ and $D^{n,m}$) we used are observed values obtained from MLIT (2018). The data consisted of freight tons of cargo demand in November 2018; therefore, the term used in the simulation is one month. We converted 15.58 freight tons to one TEU based on the observed value obtained from WAVE (2011). Fig. 5 illustrates the comparison between the observed and estimated values of cargo transshipped via Busan. Although there is a gap between the observed and estimated values, overall trends fit the observed and estimated values. Therefore,

Table 4
Input values.

		Busan	China-1	China-2	Japan
Cost of the shipping line to transport the transshipment cargoes from/to Busan to/from port *m* [USD/TEU]	tc_m	–	200	300	–
Handling charge in port *l* within service *r* [USD/TEU]	hc_{rl}	100	110	120	100
Bunker price [USD/ton]	BP		387.5		
Waiting time in ports *n* and *m* [day]	$Wt_n + Wt_m$		4		
Value of time of shipper [JPY/hour-TEU]	α		1400		
The ratio of maximum carrying capacity	γ		0.8		

Source: WAVE (2011), Ocean Commerce (2018), and calculated by authors.

Table 5
Estimated parameters.

	Deviation parameter		Cost required to tranship	
	Import ϑ_m	Export θ_m	Import $\tilde{\xi}_m$	Export ξ_m
China-1	0.00174	0.00947	1002.5	95.1
China-2	0.0111	0.0209	164.8	180.0

Table 6
Changes in the share of direct cargo in response to changing factors.

	Base	Cargo demand		Bunker price		Vessel size expansion	Value of time	
		Low	High	Half		Double	Half	Double
China-1 [%]	74.6	71.8	75.9	74.3	75.5	48.5	70.4	71.8
China-2 [%]	64.6	73.8	74.3	64.6	74.6	66.1	77.7	65.0

we adopted the proposed model that includes input values and estimated parameters as the base case for the following analysis.

3.2.3. *Setting the input values*

As detailed in Section 3.1.1, this study focused on four factors: cargo demand, bunker price, vessel size, and the value of time. We varied the value of cargo demand by using coefficient (λ) values of 0.5, 1.0, and 1.5 to represent low, base, and high demand, respectively. The base values of bunker price and time were halved and doubled by changing the coefficients ($\mu, \rho = 0.5,\ 2.0$). Maximum vessel sizes in Japanese ports were expanded from 1000 to 2000 TEU vessels by changing the set of vessels from which shipping lines could choose. We contend that these factors influence the network design independently and in combination, given that vessel size expansion is effective for high cargo demand due to the economy of density. Therefore, we consider individual factors, which focus on changes in only one factor, and multiple factors, which focus on the 54-factor combinations of the four factors, including the base values of cargo demand, bunker price, the value of time, and whether the vessel size is expanded. We illustrate several of these results in the next section and include the rest in Appendix B.

4. Results and discussion

4.1. *Individual factors*

Table 6 illustrates the changes in the share of direct cargo, which indicate the share of the PP network in this area, in response to changes in each factor. The share of direct cargo in the high demand scenario (China-1: 75.9%; China-2: 74.3%) was the highest among all the scenarios illustrated in Table 6 because improving slot utilization increases the number of profitable direct services. This is consistent with the results of Hsu and Hsieh (2005), who found that direct routing tends to be optimal as demand increases. High demand is an influential factor in selecting PP networks. The share of direct cargo when the bunker price doubles was also high (China-1: 75.5%; China-2: 74.6%). This is because the total navigation distance in HS networks, which operate through hub ports, is longer. PP networks with shorter navigation distances are regarded as optimum networks when bunker prices are higher.

When vessel size can expand, the share of direct cargo in China-1 decreased from 74.6% to 48.5%. This is because shipping lines aggregate cargo in Busan to benefit from the economy of density. There is a high volume of transshipment cargo via Busan between the nine Japanese ports and other areas. When transporting a certain amount of cargo to China-1 or China-2 with transshipment via Busan, shipping lines can lower their costs by using larger vessels in the network. Thus, shipping lines design networks to aggregate cargo going to or coming from China-1 in the hub. However, the share of direct cargo in China-2 increased from 64.6% to 66.1%. We could not determine the reason shipping lines do not aggregate cargo going to or coming from China-2; however, there might be enough cargo volume to establish a PP network due to the slot utilization in this condition. Note that there are some cases where shipping lines aggregate China-2 cargo, such as low demand, the base bunker price, and the base value of time (see Appendix B). Consequently, vessel size expansion results in the aggregation of China-1 or China-2 or both cargoes in Busan, and it is an influential factor in selecting an HS network.

We expect that, as the value of time increases, the share of direct shipping should increase because PP networks are superior to HS networks in terms of lead time. However, there was no clear tendency toward this expected outcome in the results. This is because network design is mainly performed by shipping lines—the upper decision-makers in network design—who focus on minimizing costs. Shipping lines consider the shipper as the lower decision-maker. Ducruet and Notteboom (2012) observed that networks that are more efficient for the shipping line tend to be less convenient for shippers. Therefore, a shipper can affect the shipping line's decision-making, which is not always beneficial to the shipper. It is difficult to demonstrate the clear conditions for network design from the shipper's point of view.

4.2. *Multiple factors*

Fig. 6 illustrates the distribution of the share of direct cargo for the 54 simulated combinations of the four factors (i.e., cargo

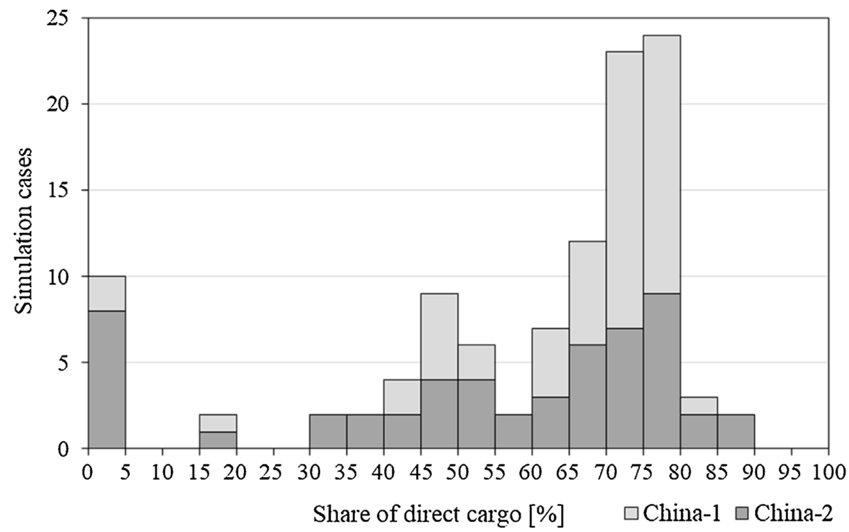

Fig. 6. Distribution of simulation cases for the share of direct cargo in China-1 and China-2.

Table 7
Frequency distribution table of simulated conditions in China-1 or China-2.

Share of direct cargo	Cargo demand			Bunker price			Vessel size		Value of time		
	Low	Base	High	Half	Base	Double	Base	Expansion	Half	Base	Double
Base or less	31	21	12	23	19	22	26	38	21	19	24
More than base	5	15	24	13	17	14	28	16	15	17	12
Bottom 10	18	1	1	2	5	13	8	12	6	3	11
Top 10	1	4	15	9	6	5	14	6	9	4	7

The underlined values are the largest for each factor.

Table 8
The influence of each factor in designing an HS or a PP network.

Network design	Strong influential		Synergistic	
	Demand	Vessel size	Bunker price	Value of time
HS network	Low	Expansion	Double	Double
PP network	High	Base	Half	Half

demand, bunker price, vessel size, and value of time). Compared to the individual factors in previous sections, there were several cases where the share of direct cargo drastically changed, including outcomes with 0% direct cargo share. The synergy between the factors strongly influences the choice between HS and PP networks.

Table 7 illustrates the frequency distribution of each factor for less and more than the base and the bottom and top ten direct cargoes in China-1 and China-2. Note that we separately counted China-1 and China-2 in the same factor; thus, we considered 108 results from the 54 simulated conditions. Compared with the base levels of the variables, the share of direct cargo decreased with low cargo demand and vessel size expansion and increased with high cargo demand. This means that cargo demand and vessel size expansion strongly influence the choice between HS and PP networks.

However, the cases that resulted in the bottom ten shares of direct cargo included two or more of the following four factor values: low demand, double bunker price, vessel size expansion, and double value of time. These four factor values tend to increase the use of HS networks. The cases that resulted in the top ten shares of direct cargo included two or more of the following four factor values: high demand, half bunker price, no expansion, and half value of time. These four factor values tend to increase the use of PP networks. The results of bunker prices in the individual analysis were opposite to that of the multiple factor analysis. Specifically, doubling the bunker price caused a low share of direct cargo when demand was low, or vessel size expansion was allowed (bottom ten in Table 7); however, it was associated with a high share of direct cargo when demand was at the base level, and vessel size was limited (Table 6). This demonstrates that the influence of bunker price on network design changes based on other factors, such as cargo demand and vessel size. A similar pattern can be observed for the value of time. The share of direct cargo increased as the value of time decreased in the multiple factor analysis (bottom and top ten in Table 7), but the individual factor analysis did not demonstrate any specific tendency. In short, in considering bunker price and the value of time, the focus should be on their synergy with other factors, such as cargo demand and vessel size expansion. Consequently, we can regard cargo demand and vessel size as strong influential factors and bunker price and value of time as synergistic factors.

4.3. Discussion and implications

Table 8 summarizes the important outcomes obtained from the simulation. Cargo demand and vessel size expansion influenced the choice of HS and PP networks as the strong influential factors while, bunker price and value of time influence the choice of HS and PP networks as the synergistic factors. The cost-effective HS or PP networks were different for each factor's value.

These results can be utilized for future network design; the network changing from PP to HS, which is known as hubbing, or from HS to PP, which is known as de-hubbing (Redondi, 2012). De-hubbing would occur because of the introduction of autonomous vessels that can navigate independently using next-generation technology (Munim, 2019). According to Allal et al. (2018), autonomous vessels improve fuel consumption because the elimination of the onboard crew results in a reduction of the ship's weight. Such fuel improvements may yield lower bunker prices. Introducing autonomous vessels in a high cargo demand area would increase de-hubbing, because de-hubbing can occur when there is high cargo demand and low bunker price, as illustrated in Table 8. Therefore, measures directly related to autonomous ship equipment, such as charging equipment, and precautionary measures to prevent de-hubbing, such as lowering port charges in hubs, need to be considered.

In summary, our results contribute to predict for future network changings such as hubbing and de-hubbing. Policymakers engaged in port management can develop effective port strategies to take precautionary measures for the network changings by focusing on each factor's value.

5. Conclusions

In this study, we used a mixed-integer programming model to solve a bi-level optimization problem between shipping lines and shippers to identify factors that affect the cost-effectiveness of PP and HS networks. This was achieved by focusing on four factors: cargo demand, bunker price, vessel size, and the value of time. The proposed bi-level optimization considered the demand uncertainty of each network according to changes in the four factors. As a case study, we applied the model to observed shipping between Japanese and Chinese ports, which are organized as both PP and HS networks. This study can assist policymakers engaged in port management to take precautionary measures for future network changings such as hubbing or de-hubbing by focusing on changing the four influential factors based on the following results.

First, as cargo demand increased, improving slot utilization increased the number of profitable direct services; consequently, the share of direct cargo increased. High cargo demand tended to favor PP networks, while low cargo demand led to the selection of HS networks. In particular, a synergy between low demand and other factors, such as high bunker price and high value of time, increased the share of HS networks.

Second, to realize economies of density, shipping lines aggregate their cargo in hub ports and deploy larger vessels. Thus, in the vessel size expansion scenario, shipping lines tended to aggregate cargo from China-1 or China-2 in Busan. Thus, increasing vessel size tended to favor the selection of HS networks. These two factors, which include cargo demand and vessel size, influenced cost-effective network design without the influence of other factors.

Third, depending on other factors, a high bunker price can cause either a high or low share of direct cargo. Bunker price is not a definite and influential factor but synergizes with other factors, such as cargo demand and vessel size. Fourth, the optimum network was not always convenient for the shipper because the shipper works as a lower decision-maker in the network design. In the networks with a shipper with a high value of time, the number of direct shipping services did not always increase, and thus, the share of direct cargo did not always increase. The value of time was not an influential factor by itself; instead, it was a synergistic factor, like cargo demand, which is the same as bunker price. Notably, a high value of time can be an influential factor in selecting HS networks when cargo demand is low, and the range of vessel sizes is expanded; moreover, the low value of time was an influential factor for selecting PP networks when demand was high. These two factors, which include bunker price and value of time, influenced cost-effective network design in combination with other factors, such as cargo demand and vessel size.

Finally, compared to the changes in one of these factors, changes in two or more factors strongly influenced the network design selection of HS or PP networks. Specifically, the share of direct cargo was lower in cases that included two or more of the four factors, that is, low demand, doubled bunker price, vessel size expansion, and doubled value of time. In these cases, HS networks were selected because they are the most cost-effective. However, the share of direct cargo was higher in cases that included two or three of the following factors: high demand, half bunker price, and half value of time. PP networks were selected as the most cost-effective network in these cases. Hence, we confirm the importance of the synergy of these factors in network design selection.

One of the major limitations of this study is that our model does not consider the uncertainty of freight rate caused by the competition between shipping lines. The other limitation is that this study focuses only on the routes between Japan and China. Geographical conditions, such as navigation distance, also affect the HS and PP network designing. It is preferable to consider other routes (e.g., the Asia–Europe route) for exploring the effect of different geographical conditions, therefore, these should be investigated in future research.

Declarations of interest

None.

Acknowledgment

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Appendix A. Notations

e	Vessel type	$\hat{q}_r^{m,n}$	Cargo volume from port m to port n within service r [TEU]
r	Liner service	$\check{q}_r^{n,m}$	Cargo volume from port n to port m within service r [TEU]
n	Ports focused on the cargo volume in this study	$\hat{Q}_k^{m,n}$	Cargo volume from port m to port n via port k [TEU]
m	Other origin, destination, and hub ports	$\check{Q}_k^{n,m}$	Cargo volume from port n to port m via port k [TEU]
k	First unloading port for exports and last loading port for imports	tQ_m	Cargo volume of transshipment cargo from/to port m [TEU]
E	Set of vessel types	$\hat{D}^{m,n}$	Cargo demand from port m to port n [TEU]
R	Set of liner services	$\tilde{D}^{n,m}$	Cargo demand from port m to port n [TEU]
N	Set of ports focused on the cargo volume in this study	$u_r^{i,i+1}$	Cargo volume on board from i th port to i+1 th port within service r [TEU]
M	Set of other origin, destination, and hub ports	$d_r^{i,i+1}$	Navigation distance from i th port to i+1 th port within service r [nm]
P_r	Set of ports within service r	$\widehat{GC}_k^{m,n}$	Generalized cost of shipper from port m to port n via port k [USD/TEU]
Pn_r	Set of ports n within service r	$\widetilde{GC}_k^{n,m}$	Generalized cost of shipper from port n to port m via port k [USD/TEU]
Pm_r	Set of ports m within service r	Lt_k^e	Waiting time of shipping line using vessel type e at port k
p_{ri}	i th port within service r	$T^{k,n}$	Required time from port k to port n [day]
Cs	Total cost of shipping line [USD]	$tT^{m,k}$	Required time for transshipping from port m to port k [day]
C_r^e	Cost of the shipping line within service i by vessel type e [USD]	$\delta^{k,n}$	Average freight rate from port k to port n [USD/TEU]
v^e	Navigation speed of vessel type e [knot]	Wt_k	Waiting time in the terminal of port k [day]
s^e	Vessel size of vessel type e [TEU]	$St^{k,n}$	Average shipping time from port k to port n [day]
vc^e	Vessel cost of vessel type e [USD/day-times]	$f^{k,n}$	Frequency from port k to port n [vessel/week]
fc^e	Fuel cost of vessel type e [USD/day-times]	α	Value of time of shipper [USD/hour]
tc_m	Cost of transshipment cargo to/from port m via hub port [USD/TEU]	γ	Coefficient for slot utilization
pc_r^e	Port charge of vessel type e within service r [USD/times]	λ, μ, ρ	Coefficients for scenarios (cargo demand, bunker price, and value of time)
hc_r	Handling charge within service r [USD/TEU]	θ_m	Deviation parameter in port m
BP	Bunker price [USD/ton]	$\hat{\xi}_m, \check{\xi}_m$	Cost required to tranship in port m [USD/TEU]
$\hat{x}_k^{n,m}, \check{x}_k^{n,m}$	A binary variable, which takes 1 if the port k is the same as port m and otherwise 0.		
y_r^e	A binary variable which takes 1 if service r is served by vessel type e and otherwise 0		
$\hat{z}_r^{n,m}, \check{z}_r^{n,m}$	A binary variable which takes 1 if service r includes port n and port m and otherwise 0		

Appendix B. Share of direct cargo for the 54 simulated combinations

Cargo demand	Low																	
Bunker price	Half						Base						Double					
Vessel size	Base			Expansion			Base			Expansion			Base			Expansion		
Value of time	Half	Base	Double	Half	Base	Double	Half	Base	Double	Half	Base	Double	Half	Base	Double	Half	Base	Double
China-1 [%]	72.5	75.7	48.6	67.3	74.2	64.1	69.1	71.8	44.3	47.1	71.6	45.4	44.3	69.3	19.3	0	68.3	0
China-2 [%]	44.0	45.0	82.7	0	30.9	0	67.3	73.8	45.9	75.3	0	0	35.9	0	0	0	0	30.1

Cargo demand	Base																	
Bunker price	Half						Base						Double					
Vessel size	Base			Expansion			Base			Expansion			Base			Expansion		
Value of time	Half	Base	Double	Half	Base	Double	Half	Base	Double	Half	Base	Double	Half	Base	Double	Half	Base	Double
China-1 [%]	72.9	74.3	63.8	75.9	70.5	63.8	70.4	74.6	71.8	76.1	48.5	76.7	70.9	75.5	74.9	76.1	64.3	51.8
China-2 [%]	58.9	64.6	72.1	51.9	69.2	50.9	77.7	64.6	65.0	54.1	66.1	47.9	67.8	74.6	77.7	54.1	75.1	19.8

Cargo demand	High																	
Bunker price	Half						Base						Double					
Vessel size	Base			Expansion			Base			Expansion			Base			Expansion		
Value of time	Half	Base	Double	Half	Base	Double	Half	Base	Double	Half	Base	Double	Half	Base	Double	Half	Base	Double
China-1 [%]	76.7	79.0	77.4	73.5	69.3	72.5	80.8	75.9	71.6	78.2	74.9	69.4	79.4	77.1	77.9	46.9	76.0	79.6
China-2 [%]	85.4	78.1	79.1	85.2	82.7	54.8	77.8	74.3	76.8	49.7	66.9	71.0	74.0	74.8	63.6	43.9	58.9	36.1

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