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Development of Ship Allocation Models using Marine Logistics Data and its Application to Bulk Carrier Demand Forecasting and Basic Planning Support

by Mohammad Danil Arifin

Development of Ship Allocation Models using Marine Logistics Data and its Application to Bulk Carrier Demand Forecasting and Basic Planning Support

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Summary

In recent years, the global marine logistics industry has changed significantly because of the influence of the global movement of goods; this situation has increased the importance of developing ships that meet market requirements. One such change is the exponential growth in the amount of available data, and attention paid to big data analysis in a variety of fields. It is now possible to obtain vast amounts of marine logistics data, e.g., port, ship, route, international trade, and automatic identification system data. If these data are effectively utilized, great innovation can be achieved in the marine logistics industry.

In this study, we develop a ship allocation model that can predict the demand for bulk carriers and examine the effective principal particulars of ships for cargo transportation. To realize these goals, we develop three distinct models—shipper, shipowner, and operator models—using statistical, hierarchical, and deep learning analysis methods. Moreover, we examine the principal particulars of ships that are expected to be in demand to demonstrate the effectiveness of our proposed model.

1. Introduction

Big data can typically be thought of as datasets that are large, complex, and generated at high speeds. The most highlighted characteristics of big data are its high volume, velocity, and/or variety. Big data provides information that can make maritime operation efficient[1]. Moreover, it is widely believed that big data in the maritime industry can aid in improving forecasts[2,3].

There is significant potential and high value hidden in the huge volumes of data that are widely used in various fields, including the marine logistics industry. The global marine logistics industry has changed significantly because of influence from the global movement of goods. Hence, it is important to develop ships that meet specific needs and market requirements.

Simultaneously, marine logistics data can be acquired more easily than ever before (e.g., port, ship, route, trade, and Automatic Identification System (AIS) data). If these data are effectively utilized, great innovation might be achieved.

Many studies have applied big data to the maritime industry. For construction applications, Hiekata et al.[4] proposed a high-accuracy block component measurement method that uses point cloud data from a 3D laser scanner. Aoyama et al.[5] proposed new methods of extracting and utilizing monitoring data by introducing two additional monitoring technologies and considering the reliability of each for advanced shipbuilding construction management.

In the operations field, Perera et al.[6] analyzed large ship performance datasets to propose a model for evaluating ship performance under various seagoing conditions. Ando et al.[7] and Yoshida et al.[8] proposed a data collection platform called the Ship Information Management System and utilized the data collected for many purposes (e.g., energy efficiency determinations, ship performance monitoring, and engine monitoring).

Note that many of these studies have employed big data to improve ship construction, operation, and performance; few have examined the use of big data for ship demand prediction[9]. However, detailed predictions of the routes on which demand will increase are currently difficult to execute. Therefore, the objective of this study is to develop a support system for basic ship planning by predicting the demand for new ships. To realize the objective, we focus on the following two points:

- Ship allocation model: By inputting the present condition of trade, the number of ships, fuel prices, allowable ships, etc., we can implement actual ship allocation using our model.

- Simulations using the ship allocation model: By inputting the new ship principal particulars, we can predict the demand for a new ship using the ship allocation model. Therefore, by executing simulations, we can examine effective ship principal particulars.

The ship allocation model and simulations using the ship allocation model are developed using information extracted from the Marine Logistics Database (MLDB), which we developed in a previous study (see Section 2). The details and effectiveness of the proposed model are discussed in this paper. We consider bulk carriers that operate between Australia and Japan as an example.

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2.　Overview of Previous Study

2. 1 Marine Logistics Database

In a previous study, the authors developed the MLDB using AIS and statistical data[10]. The MLDB consists of the latest marine logistics data, i.e., operation information from AIS, ship, port, route and international trading information, as shown in Fig. 1. The data are managed, integrated, and structured to derive valuable insights from information buried in marine logistics data.
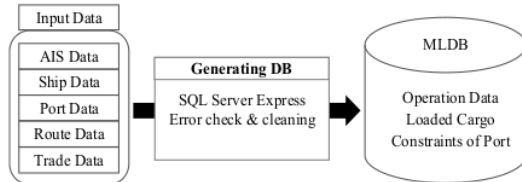

Fig. 1 Basic concept of previous study

2. 2 MLDB Input Data

To develop the MLDB, we employed the following data as input.

- AIS data: indicated speed, indicated draft, ship position, timing arrival and departure dates, and arrival and departure port collected from the Market Intelligence Network [11].
- Port data: port name, longitude, latitude, port dimension, and cargo handling collected from Sea-web Port[12].
- Ship data: ship name, deadweight, International Maritime Organization number, classification, ship dimension, operator, shipbuilder, ship status, and build year collected from Sea-web Ship[13].
- Route data: departure port, arrival port, route choices, and distances collected from Sea-web Port and IHS-Fairplay[12),14].
- Trade data: commodity trade, the period of trade between countries, commodity code, trade value, trade quantity, reporter, and partner collected from UN Comtrade[15].

2. 3 Data Structure

To more easily extract valuable information, we defined a structure for the MLDB and modified unstructured data into a relational database. For example, by integrating ship and port data with operation data, some information related to a ship's operational state can be analyzed (e.g., berthing, anchoring, or sailing). A detailed explanation of the data structure can be found in the earlier study.

2. 4 Error Cleaning

To ensure and the reliability and quality of the data used to construct the MLDB, the following error cleaning methods were performed.

- Keeping the first data recorded in AIS based on the arrival date and time, and deleting duplicate data points.
- Deleting unrealistic voyage data by checking the average voyage speed, which is calculated by considering the navigation days and distance between two ports. If the average voyage speed exceeds the service speed, it is defined as an error and the data are deleted.
- Deleting inappropriate zero values, such as 0-m drafts, null data, and unavailable data.

2. 5　Generating Cargo Information

Cargo information on an operating ship are important for demand forecasting and understanding the ship's use. However, such information does not exist in AIS data. Therefore, we estimated the cargo type and volume of each operation. In the case of a bulk carrier, the cargo type is selected from three types: iron ore, coal, and grain and minor bulk (MB). The estimation methods used in the previous study are described as follows.

2. 5. 1 Checking data reliability

Confirmation of data's reliability is required to for a good cargo volume estimation. In our study, data reliability were evaluated by checking the draft rate d_i by using Eq. (1)

$$d_i = \frac{d_{sail(i)}}{d_{\max(i)}}, \tag{1}$$

where $d_{sail(i)}$ (m) is the sailing draft and $d_{max(i)}$ (m) is the maximum draft of the ship.

2. 5. 2 Estimating cargo type using port data

By identifying the cargo type from port data, the cargo of each operation could be estimated. As shown in Table 1, cargo type estimation was conducted by checking the combination of cargo from the arrival and departure ports. In the case of operation from Port A to Port D, the only common cargo is coal. Therefore, the cargo type was estimated to be coal. In contrast, in the case of operation from Port B to Port D, there are two common cargos: coal and iron ore. In this case, cargo type was defined as multi-cargo and decided using the ship size.

Table 1 Checking cargo type combinations using a matrix

	Port D (Coal, Iron Ore)	Port E (Coal, Iron Ore, Grain & MB)	Port F (Coal, Iron Ore)
Port A (Coal, Grain & MB)	Coal	Coal, Grain & MB	Coal
Port B (Coal, Iron Ore)	Coal, Iron Ore	Coal, Iron Ore	Coal, Iron Ore
Port C (Iron Ore, Grain & MB)	Iron Ore	Iron Ore, Grain & MB	Iron Ore

2. 5. 3 Estimating cargo type using ship size

If two or more common cargo types exist in port data, the cargo types were estimated using ship size. Since ship size and cargo type are closely related, the remaining operation could be estimated.

2. 5. 4 Estimating cargo volume

Ship data has information on the deadweight and maximum draft of the target ship, while AIS data has information about the sailing draft. The cargo volume was basically estimated using Eq. (2).

$$V_i[ton] = DWT_i \times \frac{(d_i - 0.2)}{(1 - 0.2)} \tag{2}$$

where V_i (ton) is cargo volume, DWT_i is deadweight, and d_i is the draft rate.

Operation conditions of ships were defined as loading, ballast, and unknown. In the unknown condition, cargo volume was estimated by considering the average draft of ships of the same size operating on the same route.

2. 6 Confirmation of Cargo Estimation

To verify the cargo estimation in Section 2.5, we compared our results with actual trade value from UN Comtrade data, using bulk carriers operating from Australia to Japan in 2014 as an example. The estimation result covered about 94% of coal cargo, 90% of iron ore cargo, 97% of grain and MB cargo, and 94% of all cargo, validating our cargo estimation method.

2. 7 Extracting Data for a Ship Allocation Model Using the MLDB

The following information can be extracted from the MLDB to develop a ship allocation model and execute simulations:

- Ship information: deadweight (DWT), length overall (LOA), breadth (B), depth (D), draft (d), service speed (knot), horse power (HP), ship operator, shipbuilder etc.
- Port information: port constraints (e.g. maximum DWT, maximum draft (m), maximum length (m), maximum breadth (m)), cargo handling, position of port, country etc.
- Operation information: departure and arrival times, arrival and departure ports, cargo type, cargo volume, operator etc.
- Trade information: trade article and volume between ports and countries.
- Others: new construction of shipbuilding price index, fuel price.

3.   Basic Concept of this Study

The basic concept of this study is shown in Fig. 2, which highlights the two important steps for realizing the objectives laid out in Section 1: first, developing a ship allocation model, and second, carrying out simulations using the ship allocation model.

The data for developing the ship allocation model and conducting simulations is extracted from the MLDB. An overview of these concepts is given in this section.

3. 1 Development of the Ship Allocation Model
3. 1. 1 Overview of the ship allocation model

A ship allocation model can reproduce actual ship allocation. Input and output data of the ship allocation model are shown in Table 2.

Table 2 Input and output of ship allocation ship

Input	Trade conditions: fuel price, trade volume between the ports.
	Allowable ships specifications: DWT, LOA (m), B (m), D (m), d (m), service speed (knot), horsepower
	Constraints of the canal and ports: Max DWT, max LOA (m), max B (m), and max D (m) etc.
	Number of allowable ships
Output	Ship allocation of all ships

3. 1. 2 Configurations of the ship allocation model

To realize actual ship allocation conditions, we develop three distinct models—the shipper, shipowner, and operator models.

- The shipper model issues a request for cargo transportation between two or more ports. The shipper model is defined using cluster analysis.
- The shipowner model estimates the shipment days, amount of cargo, and operating cost in response the cargo transportation requests. The shipowner model is defined using deep learning analysis.
- The operator model requests all shipowner models to estimate shipment costs, cargo volume, and transport time based on shipper requests; then, based on the answer from the shipowner model, the operator model decides on a ship for cargo transport.

A detailed explanation of ship allocation is shown in Section 4, and the confirmation of the proposed models is shown in Section 5.
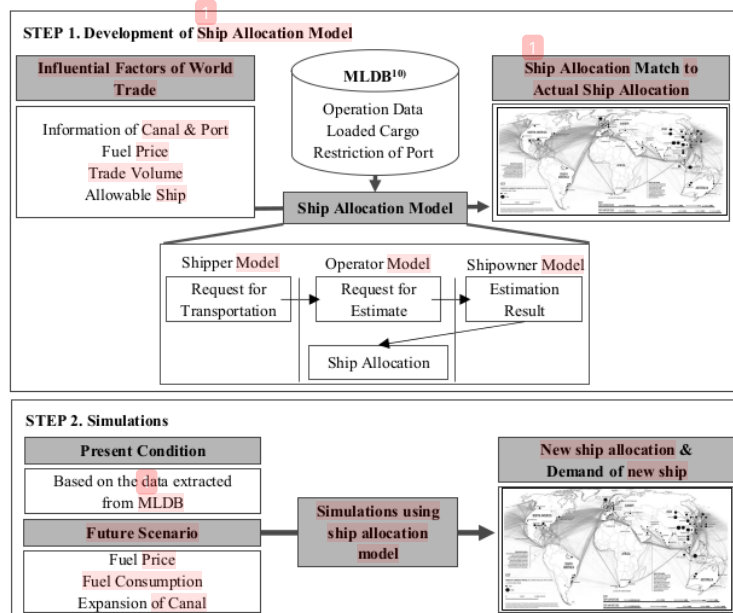

Fig. 2 Basic concept of ship allocation

3. 2 Simulations Using the Ship Allocation Model

In the ship allocation model, a competitive ship is allocated to a prioritized route. Moreover, following data can be set freely in executing the simulation:

- Future scenario (fuel price, trade volume between ports)
- New ship specifications
- Number of ships (freely selectable by the operator)
- Constraints of ports and canals

With these characteristics, we can execute the following simulations:

(1) Examination of the supply–demand balance of various ships

In our system, supply is defined as a ship allocation only using existing ships, and demand is defined as a ship allocation in which all the ships can be used freely for cargo transportation. Therefore, by changing the number of ships that can be used in the simulation, we can estimate the supply–demand balance.

(2) Examination of effective ship specifications

As discussed in the previous section, we can change the specifications freely. Then, by changing ship specifications and simulating ship allocation, we can understand the demand for various kind of ships. Therefore, by executing this simulation, we can examine effective ship specifications and the kinds of ships that are attractive for operation on the intended routes.

(3) Influence of economic situations on demand

In our system, port constraints can be changed. Moreover, fuel price and trade volume between the ports can be freely changed. By forecasting such a future situation using a ship allocation model, we can understand logistics and demand results. Moreover, we can understand the kinds of ships that will operate effectively on intended routes in the future.

In this paper, we take bulk carriers that operate between Australia and Japan as an example. Detailed simulations are shown in Section 6.

4.　Development of the Ship Allocation Model

As discussed in Section 3, the ship allocation model is composed of shipper, shipowner, and operator models. The data extracted from the MLDB were used to develop these models. Details of these three models are discussed in this section.

4. 1 Shipper Model

The shipper model issues a request for cargo transportation between two or more ports from Australia to Japan. Herein, the shipper model was generated using cluster analysis, which is a method of defining similarities in data, grouping similar items, and classifying them into clusters. Using hierarchical cluster analysis, we clustered shippers between Japan and Australia. We generated the shipper model using the following steps:

4. 1. 1 Extracting operation data from the MLDB

Operation data from 2014 from Australia to Japan were extracted from the MLDB. The information extracted from the MLDB included operation, port (origin and destination), and ship (name, principal particulars, etc.) data. By utilizing these data, we easily analyzed the number of port callings from Australia to Japan.

4. 1. 2 Define the shipper using cluster analysis

To define a shipper between Australia and Japan, we identified the number of port callings in 2014 using cluster analysis. The clustering process can be described as follows:

(1) Calculate the number of port callings

The number of port callings was calculated by identifying data extracted from the MLDB. By using a matrix between the ports (P1, P2, …, Pn) and ships (S1, S2, …, Sn). As shown in Table 3(1), the number of port callings could be calculated.

(2) Measure the Euclidean distance

Euclidean distance is a measure of the true straight-line distance between two points in Euclidean space. In hierarchical clustering, in which the distance measure is Euclidean, data must first be normalized or standardized to prevent the covariant with the highest variance from driving the clustering.

The data consist of many calling ships whose weights and numbers of calls differ. Therefore, it was necessary to standardize the differences in each property. Data standardization was performed as shown in Table 3(2) for each port. Then, the Euclidean distance was calculated using Eq. (3), the result of which is shown in Table 3(3).

$$d(x,y) = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + \cdots + (x_n - y_n)^2} \quad (3)$$

where x_i and y_i are the number of calls after standardizing ship i at ports x and y, respectively.

Table 3 Cluster analysis process

(1) Port Calling Calculation

Ship / Port	S1	S2	S3	S4	S5	S6
P1	0	0	1	0	2	0
P2	0	0	1	0	3	2
P3	0	0	0	1	0	0
P4	5	1	0	0	0	0
P5	2	0	0	0	0	0

(2) Standardization

Ship / Port	S1	S2	S3	S4	S5	S6
P1	-0.7	-0.7	0.65	-0.7	1.96	-0.7
P2	-0.9	-0.9	0	-0.9	1.73	0.87
P3	-0.4	-0.4	-0.4	2.24	-0.4	-0.4
P4	2.19	0	-0.5	-0.5	-0.5	-0.5
P5	2.24	-0.4	-0.4	-0.4	-0.4	-0.4

(3) Calculation of Euclidean distances

Port / Port	P1	P2	P3	P4	P5
P1		1.71	3.94	4.04	3.94
P2	1.71		4.08	4.21	4.08
P3	3.94	4.08		3.87	3.79
P4	4.04	4.21	3.87		0.49
P5	3.94	4.08	3.79	0.49	

(3) Clustering using hierarchical cluster analysis

First, before any clustering was performed, it was necessary to populate a proximity matrix with the distance between each point using a distance function. Then, the matrix was updated to display the distance between each cluster. In this study, to measure the distance between two clusters, we applied the average linkage method, which is commonly used and represents a natural compromise between linkage measures to provide a more accurate evaluation of the distance between clusters[16]. The distance between two clusters is calculated using Eq. (4).

$$d(C_1, C_2) = \frac{1}{|C_1||C_2|} \sum_{x_1 \in C_1} \sum_{x_2 \in C_2} d(x_1, x_2), \qquad (4)$$

where C_n is a cluster, x_n is a port, and $d(C_1, C_2)$ is the distance between cluster C_1 and C_2.

The goal of this method was to group heterogeneous port data into homogeneous clusters. By doing so, we could identify groups without previous knowledge of group membership or even the number of possible groups. Thus, shippers operating between Australia and Japan could easily be defined. Hierarchical cluster analysis is best illustrated using a dendrogram (a visual display of the clustering process). As shown in Fig. 3, the ports were grouped into four clusters (Shippers A–D), defined as follows:

- Shipper A (Kawasaki, Mizushima, Chiba, and Fukuyama)
- Shipper B (Oita, Kashima, and Kisarazu)
- Shipper C (Nagoya, Wakayama, and Tobata)
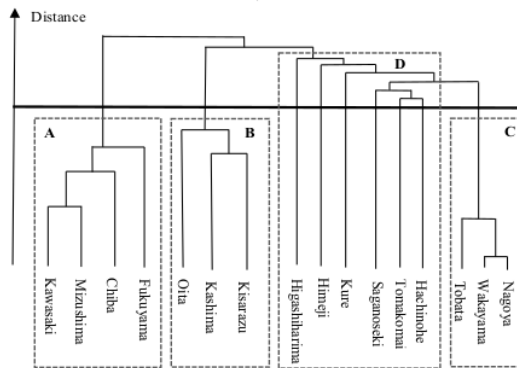- Shipper D (Higashi-Harima, Himeji, Kure, Saganoseki, Tomakomai, and Hachinohe)

Fig. 3 Dendrogram of cluster results

As shown in Fig. 3, the destination ports (Japan) can be identified clearly. However, to identify the origin ports (Australia), we checked the operation of each cluster and then selected its origin port of each cluster. As a result, the shippers from Australia to Japan were generated as in Table 4.

Table 4 Shippers from Australia to Japan

Shipper	Origin Port	Destination Port
A	Dampier	Chiba
	Parker Point	Fukuyama
	Port Hedland	Mizushima
	Port Walcott	Kawasaki
	Esperance	
B	Dampier	Kashima
	Parker Point	Kisarazu
	Port Hedland	Oita
	Port Walcott	
	Esperance	
C	Port Walcott	Nagoya
		Tobata
		Wakayama
D	Port Hedland	Higashi-Harima
	Port Walcott	Kure
		Himeji

4. 2 Shipowner Model

The shipowner model can be used to estimate shipment days, cargo amounts, and shipment cost in response to a transportation request from an operator. To realize this model, we generated the draft rate, average speed in loading and ballast conditions, and time in port due to loading and ballast conditions using deep learning on data extracted from the MLDB.

4. 2. 1 Estimation using deep learning

Deep learning is an expressive machine learning technique that has recently attracted considerable attention. Machine learning is a mechanism for inputting training data into a learning machine, generating a learning model, and processing data using the learned model. The key benefit of deep learning is the analysis of massive amounts of unsupervised data, making it a valuable tool in big data analytics[17].

As shown in Fig. 4, the first layer of a neural network used for deep learning is the input layer. Each node in this layer takes an input and passes its output as input to each node in the next (hidden) layer, which have no connection to the outside and are only activated by nodes in the previous layer.
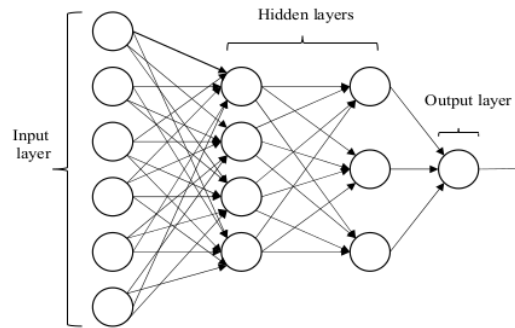
Fig. 4 Structure of a deep learning neural network

In this study, draft rate, average voyage speed, and time in port were predicted using the following steps:

(1) Collect training data

Usually, neural networks are trained to perform single-step prediction, in which the predictor uses some available input and outputs observations to estimate a variable of interest for the timestep immediately following the latest observation[18)19]. In this study, all shipping data were extracted from the MLDB. Around 75% of ship operation data from Australia to Japan in 2014 were used for training data and the remaining 25% were used for evaluation.

(2) Generate learning model

To generate a learning model, the input layer, output layer, and hyperparameters were set as follows:

- The input layer for the deep learning analysis in this model takes information including ship DWT, length, breadth, depth, draft, service speed, horsepower, year built, distance between routes, operator, shipyard, maximum draft, arrival limit, departure limit, new construction of shipbuilding price index, and loading and unloading ports.
- The output layer outputs the expected result, i.e., draft rate during navigation (loading and unloading), average voyage speed (at loading and ballasting), and time in port (at loading and ballasting).

- Hyperparameters must be set as priors to optimize the model by minimizing the cost function of learning from the dataset. The hyperparameters used to generate the deep learning models are shown in Table 5.

Table 5 Deep learning hyperparameters

Nodes in Hidden Layer	20
Hidden Layers	40
Activating Function	Max Out Function
Drop Out Rate	0.01
L_1 Regularization	0.001
L_2 Regularization	0.001

4. 2. 2 Calculating the shipment time, cargo amount, and cost

We next used deep learning estimation results to calculate the number of shipment days, amount of cargo, and shipment cost. Shipment days were calculated by considering the route distance, navigation speed, and time in port. The cargo transport volume was calculated based on the method developed by Kigure et al.[20] and the shipment cost was calculated using the method from Aoyama et al.[21] using the generated data.

4. 3 Operator Model

The operator model collects estimation results from the shipowner model. The procedure to determine ship allocation is as follows:

(1) Calculate the total cost and cargo volume

As shown in Table 6(1), shipowners bid for all shipment requests (Ships A–D) based on each selected route (Routes A–B) from Shippers A and B. The cost per unit transport volume was calculated by considering the total operation cost and total transportation volume t.

Table 6 Ship allocation process

(1)	Calculate the total cost and cargo volume					
Shipper	Route	Cargo Volume (t)	Ship A ($/t)	Ship B ($/t)	Ship C ($/t)	Ship D ($/t)
A	A1	3.5×10^6	14.8	14.1	16.9	19.9
	A2	2.0×10^6	14.7	13.9	16.4	19.4
B	B1	4.7×10^6	13.6	13	15.1	18.3
	B2	6.0×10^6	13.1	12.6	14.5	18.2
(2)	Calculate the standard deviation and ship assignment					
Shipper	Route	Cargo Volume (t)	**Deviation Value**			
			Ship A	Ship B	Ship C	Ship D
A	A1	3.5×10^6	57.2	60.31	47.9	34.59
	A2	$\mathbf{2.0 \times 10^6}$	56.64	**60.43**	45.58	34.35
B	B1	4.7×10^6	56.81	59.74	49.51	33.92
	B2	6.0×10^6	56.84	59.12	50.45	33.58
(3)	Recalculate the amount of cargo shipment request					
Shipper	Route	Cargo Volume (t)	Ship A ($/t)	Ship B ($/t)	Ship C ($/t)	Ship D ($/t)
A	A1	3.5×10^6	14.8	—	16.9	19.9
	A2	$\mathbf{0.6 \times 10^6}$	14.7	—	16.4	19.4
B	B1	4.7×10^6	13.6	—	15.1	18.3
	B2	6.0×10^6	13.1	—	14.5	18.2

(2) Calculate the standard deviation

Based on the cost per unit transport volume from the previous step, the standard deviations of some ships were calculated for each route. The deviation value is an index for judging which ship is good for transporting a given cargo type on a certain route. Table 6(2) shows a sample calculation of deviation values.

(3) Ship assignment

Ship assignment decides which kind of ship to charter regularly by considering standard deviation values. Ships with the highest standard deviation values are assigned to a shipment on the selected route. For example, as shown in Table 6(2), Ship B is assigned to Route A2.

(4) Recalculate the amount of cargo shipment requests

When a shipment is assigned to a selected route, as shown in Step 3, the remaining cargo shipment is calculated by subtracting the amount of cargo shipment requested by the shipper. Therefore, after assignment, the amount of cargo to ship is updated and Steps (1–3) are repeated until all cargo is successfully transported.

5.　Evaluation of the Proposed Model

5. 1 Confirmation of the Shipper Model

As shown in Fig. 3, ports were grouped into 4 clusters. We confirmed the cluster analysis result based on the following points:

5. 1. 1 Comparison with actual locations

In this study, the result of cluster analysis was compared with actual conditions. The ports in Cluster A match JFE Steel Company locations. Moreover, ports in Clusters B and C match Nippon Steel Sumikin Company locations. This shipper is divided into two clusters because the port constraints in Cluster B and C are quite different, as shown in Table 9. Ports of Cluster D match other companies (i.e., KOBELCO (Kobe Steel Kakogawa Works), Nisshin Steel, etc.).

5. 1. 2 Comparison with ship operation

Based on the result in Table 4, most ships operating from Australia to Japan loaded cargo from two or more ports in Australia, and unloaded at two or more ports in Japan. Here, we compare the results of cluster analysis with actual operation.

Some typical operations are shown in Table 7, where the gray represents ports in Australia, and the white represents ports in Japan.

Table 7 Characteristics of actual ship operation

Ship A		Ship C	
Origin	Destination	Origin	Destination
Port Walcott	Fukuyama	Port Walcott	Kisarazu
Fukuyama	Mizushima	Kisarazu	Port Walcott
Mizushima	Port Hedland	Port Walcott	Kashima
Port Hedland	Mizushima	Kashima	Port Walcott
Mizushima	Port Hedland	Port Walcott	Oita
Port Hedland	Chiba	Oita	Port Walcott
Chiba	Mizushima	Port Walcott	Kisarazu
Mizushima	Port Hedland	Kisarazu	Port Walcott
Port Hedland	Chiba	Port Walcott	Kashima
Chiba	Fukuyama	Kashima	Port Walcott

In the case of Ship A, cargo was loaded at Port Walcott–Port Hedland, then unloaded at Mizushima, Chiba, and Fukuyama, which matches the operation of Shipper A. In contrast, in the case of Ship C, cargo was loaded at Port Walcott, then unloaded at Kisarazu, Kashima, and Oita, matching Shipper B.

As discussed in this section, cluster analysis matched actual location and ship operation conditions.

5. 2 Confirmation of the Shipowner model

In the shipowner model, we estimated the draft rate, average service speed, and time in port using deep learning analysis. To confirm the effectiveness of the shipowner model, we compared the standard deviation of the estimation result of deep learning analysis with that of response surface method.

(1) Comparison using response surface method

To confirm the draft rate, we used the response surface method; like a deep learning analysis method, the following input and output were set:

- Input: ship DWT, length, breadth, depth, draft, service speed, horsepower, year built, distance between routes, operator, shipyard, maximum draft, arrival limit, departure limit, new construction shipbuilding price index, and constraints of loading and unloading ports (e.g. Max DWT, max LOA (m), max B (m), and max D (m))
- Output: draft rate during navigation (loading and unloading), etc.

As shown in Table 8, the average draft rate error using the response surface method is 5.9%, higher than the result using deep learning analysis.

(2) Threshold of the estimation

The draft rate, average service speed and time in port are different even when the same ship operates on the same route. In this paper, the standard deviation of such a case is set as the threshold of the estimation. The threshold is also known in Table 8. These are calculated by using the actual data of bulk carriers which operate between Australia and Japan from 2013 to 2015. As shown in Table 8, estimation result using deep learning is better than the threshold although that of the response surface method is worse.

Table 8 Average estimate errors

Method	Draft Rate	Average Service Speed	Time in Port
Deep learning	3.4%	0.2 knots	0.9 days
Response surface	5.9%	-	-
Threshold	3.5%	0.9 knots	1.2 days

5. 3 Confirmation of the Ship Allocation Model
5. 3. 1 Problem definition

To evaluate the reproducibility of the proposed model, we simulated ship allocation. Trade condition (i.e. trade volume, trade routes, and fuel price), allowable ship specification, number of ships, and port constraints were set as inputs.   Then, the result of the allocation model was compared with actual ship allocation. Moreover, all information for simulating ship allocation was extracted from the MLDB. Operation from Australia to Japan in 2014 was taken as an example.

5. 3. 2 Simulation results

Fig. 5 showed the ship allocation for each shipper using the proposed model. As explained in the previous section, there are four Shippers (A–D). The vertical axis shows the number of operations (shipments). The horizontal axis shows ship size (in 10^3 DWT). Using cluster analysis, the ships are grouped into six clusters: 100, 170, 210, 230, 250 and 300 (10^3 DWT). The actual and simulation results are shown together to validate the proposed model.

5. 3. 3 Discussions

As shown in Fig. 5, the simulation results generally agree with actual conditions. In this section, we evaluate the allocation process:
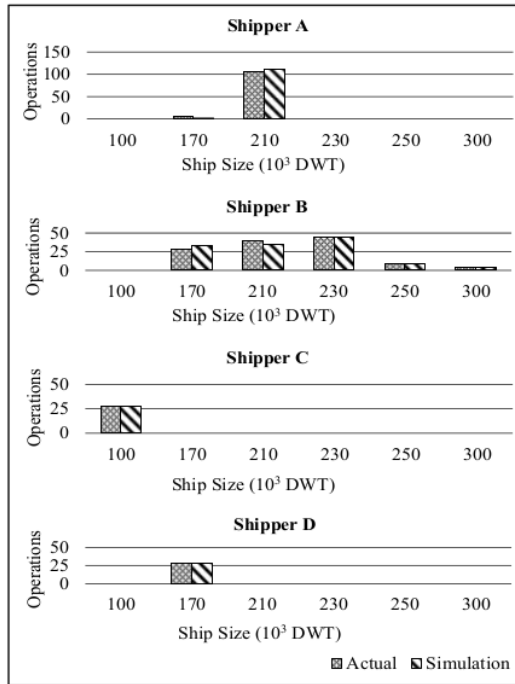

Fig. 5 Comparison of actual and simulation results

(1) Port constraints

In the MLDB, port constraints were generated in two steps:
Step 1: Extract the constraints from port information. First, port constraints were obtained from port information. However, some constraints were unavailable or did not match actual conditions.
Step 2: Modification using operating data. Port constraints in Step 1 were compared with actual operations. When the two did not match or when some constraints were not available, we modified the port constraints using operating ship specifications.

Some port constraints are shown in Table 9, in which white represents data from Step 1 and gray represents data modified based on actual operation (Step 2).

(2) Ship specifications

By examining the actual operation extracted from the MLDB, we identified typical ship specifications for each ship size, which are shown in Table 10.

Table 9 Port constraints

Shipper	Port Name	DWT	L (m)	B (m)	d (m)
A	Fukuyama	220,000	300	50	18
A	Chiba	220,000	300	50	18
A	Mizushima	260,000	340	50	18
A	Kawasaki	220,000	340	50	18
B	Kashima	300,000	340	60	19
B	Kisarazu	300,000	330	60	19
B	Oita	400,000	450	60	25
C	Nagoya	110,000	300	43	16
C	Tobata	160,000	327	43	16
C	Wakayama	160,000	300	43	14
D	Higashi-Harima	180,000	330	47	17
D	Kure	276,000	360	45	18
D	Himeji	257,000	335	47	16

Table 10 Typical ship specifications

DWT	L (m)	B (m)	D (m)	d(m)	HP
106,507	255	43	19	13	16,680
177,855	292	45	25	18	22,920
210,036	300	50	25	18	21,808
229,013	320	54	24	18	30,499
250,813	330	57	25	18	29,789
297,736	325	55	29	21	30,808

(3) Allocation process

Ship allocation was started from Shipper C, because its port constraints were most severe. Hence, B ≤ 43 m and d ≤ 14 m became active constraints and ships with 100,000 DWT (B ≤ 43 m) were selected. Next, ships for Shipper D were allocated where B (m) should be less than 45 m. After that, ships for Shipper A were allocated because its port constraints were more severe than those of Shipper B. Finally, the remaining ships were allocated to Shipper B.

Based on Fig. 5, we see that the simulation results for all shippers generally agreed with the actual results. Moreover, as shown in Fig. 5, Shipper A mostly used 210,000 DWT ships for their operation. Shipper B used various kinds of ships (170,000–300,000 DWT).

Since the simulation of ship allocation matched actual ship allocation, and the ship specifications agreed with port constraints, we confirmed the effectiveness and reproducibility of the proposed models.

6. Case Studies

Based on the discussion in Section 3.2, we execute the following simulations in this section:
- Examination of supply–demand balance
- Examination of effective ship size
- Influence of fuel efficiency on demand

6. 1 Examination of Ship Supply–Demand Balance
6. 1. 1 Problem definition
We examine the supply–demand balance of bulk carriers that operated between Australia and Japan in 2014 carrying iron ore.

In contrast with the simulation conducted in Section 5.3, we carried out ship simulation without constraints, meaning that there was no limit to the number of ships per year of operation. The operator shipped cargo shipment with freely selectable ships. In this restricted example (using the actual number and ship types used in 2014 between Australia and Japan), the simulation result is defined as supply. In the unrestricted case, the simulation result is defined as demand.

6. 1. 2 Simulation results
Figure 6 shows the difference in ship allocation results using constraints (supply) and without constraints (demand). These results were compared to evaluate ship supply–demand balance and determine the kind of ship likely to be in demand in the future. The vertical axis is the number of operations (shipments). The horizontal axis is the size of the ships (in 10^3 DWT).

6. 1. 3 Discussions
As shown in Fig. 6, without constraints, the allocation of 210,000, 250,000 and 300,000 DWT ships increased. However, the allocation of 170,000 and 230,000 DWT ships decreased. Therefore, 170,000 and 230,000 DWT ships were not very competitive for shipments between Australia and Japan. Meanwhile, there was an insufficient supply of 210,000, 250,000 and 300,000 DWT ships. Hence, these ships are competitive for shipments from Australia to Japan and are expected to be in demand in the future. This result can be understood from the port constraints shown in Table 9.
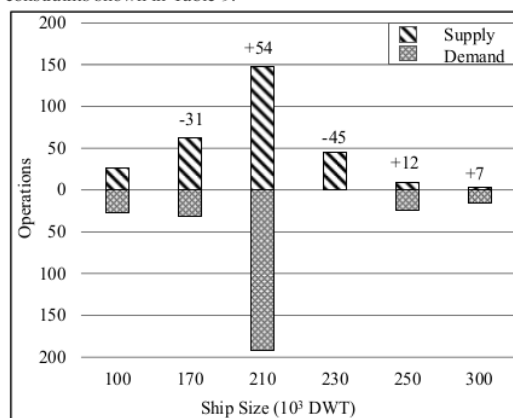

Fig. 6 Supply–demand balance of ships

6. 2 Examination of Ship Allocation by Ship Size
6. 2. 1 Problem definition
Based on the discussion in the previous section, 210,000, 250,000 and 300,000 DWT ships are expected to be in demand. Thus, it is necessary to examine the influence of ship size on allocation and examine the distribution of ships (210,000, 250,000 and 300,000 DWT) for which increased demand is expected on the selected route (Australia to Japan). In this simulation, we accounted for the depreciation value of a new ship and ignored the depreciation value of existing ships. The useful life of a ship was set to 15 years[22], and depreciation value was calculated based on reference[23].

6. 2. 2 Simulation results
The principal particulars of 210,000, 250,000 and 300,000 DWT ships are shown in Table 10. Using the proposed method, we

examined the principal particulars of the ships. Moreover, by conducting this simulation we could identify the number of routes and ships that could be allocated for the selected route.

As shown in Fig. 7, 300,000 DWT ships were in demand on a single route. In contrast, 250,000 DWT and 210,000 DWT ships can be expected to be in demand on multiple routes.
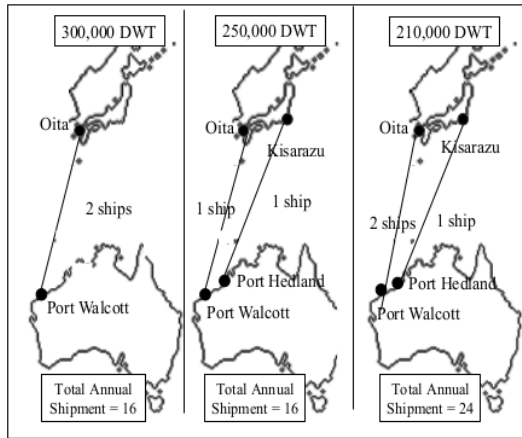

Fig. 7 Ship distribution by size

6. 2. 3 Additional Simulations

From the simulation result shown in Fig. 7, 250,000 DWT and 210,000 DWT ships are in demand. To clarify which is preferred, we executed an additional simulation in which the fuel efficiency of 250,000 DWT and 210,000 DWT ships increased by 10%. The results are shown in Fig. 8.
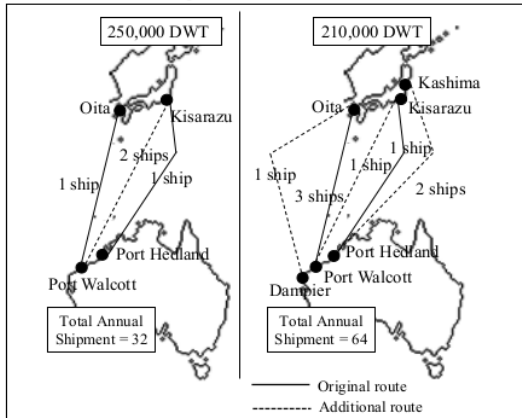

Fig. 8 Ship distribution when fuel efficiency increases by 10%

In Fig. 8, the number of allocated ships and routes for 210,000 DWT ships increased rapidly (five additional ships and three additional routes). However, only two additional ships and one additional route were called for in the 250,000 DWT ship simulation. Therefore, 210,000 DWT ships have the highest potential in iron ore transportation between Australia and Japan.

This result is affected by the port constraints shown in Tables 9 and 11. Ship of 210,000 DWT can enter all main ports in Australia and Japan and 250,000 DWT ships cannot enter some key ports.

Table 11 Port constraints in Australia

Port Name	DWT	L (m)	B (m)	d (m)
Port Hedland	260,000	330	55	19.2
Dampier	250,000	340	55	19.5
Port Walcott	340,000	335	60	19.5
Parker Point	220,000	300	50	18.5
Esperance	220,000	300	50	18

6. 3 Influence of Fuel Efficiency on Demand

6. 3. 1 Problem definition

To examine the influence of fuel efficiency on ship demand and to draw future development targets, we simulated increasing fuel efficiency by 5%, 10%, and 15%. A ship with no fuel efficiency change is defined as S_0. Ships with fuel efficiency increases of 5%, 10%, and 15% are denoted by S_1, S_2, and S_3, respectively. The 210,000 DWT ships were simulated as they were the most competitive. As in the simulation in Section 6.2, we considered depreciation values. To evaluate ship effectiveness, we compared the simulation result (ship replacement) with actual ship allocation.

6. 3. 2 Simulation results

Table 12 shows the simulation result of ship allocation on the intended route (Australia to Japan) after modifying the fuel efficiency of S_0, S_1, S_2, and S_3. The table shows the number of allocated routes, operations, and ships.

Table 12 Replacement 210,000 DWT ships

	Number of Allocated Routes	Number of Operations	Number of Ships
S_0	3	40	5
S_1	4	47	6
S_2	5	64	8
S_3	10	122	16

As shown in Table 12, the number of operations and ships for S_2 and S_3 increased greatly. However, only a small increase occurred for S_0 and S_1. Therefore, we focused on ships S_2 and S_3.

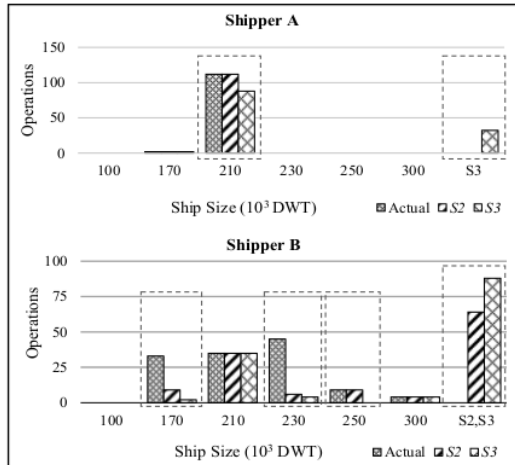The simulation result of increasing fuel efficiency by 10% and 15% is shown in Fig. 9.

Fig. 9 Comparison of simulation result by increasing fuel efficiency 10% (S_2) and 15% (S_3) with actual ship allocation

The vertical axis shows an operation number. The horizontal axis shows the ship size. In Fig. 9, the simulation results of ships S_2 and S_3 are compared with actual ship allocation.

6. 3. 3 Discussions

As shown in Fig. 9, when fuel efficiency increases by 10% (S_2), the replacement by 210,000 DWT ships of 170,000, 210,000, 230,000 and 250,000 DWT ships has not occurred for Shipper A, since the simulation result shows the same number of operations compared with actual ship allocation. Hence, Shipper A will not buy a new ship. However, in contrast, Shipper B will buy a new ship because operation number increased by 64.

By improving fuel efficiency by 15%, Shippers A and B might each buy a new ship, as significant replacement occurred for both shippers. For Shipper A, the number of the operation increased by 32, and for Shipper B, the number of the operation increased by 90. Moreover, as shown in Table 12, the total of the operation number is increased from 64 to 122, and the number of ships from 8 to 16.

In summary, using the proposed model, we simulated ship supply and demand. Moreover, the principal particulars of the ships expected to be in demand were identified. In addition, we obtained the impact of fuel efficiency on ship demand.

7.　Conclusions

In this study, we have focused on developing a ship allocation model using marine logistics data and its application to demand forecasting and basic planning support of bulk carriers, and have drawn the following conclusions:

- A ship allocation model composed of distinct shipper, shipowner, and operator models was developed. This model was effective in estimating ship supply and demand, the influence of ship size and fuel efficiency on ship allocation, and the principal particulars of ships for which demand is expected to increase.

- By using the proposed model, we confirmed the reproducibility of the ship allocation model. The supply–demand balance, effective ship specifications, and influence of ship efficiency on demand could be realized using the ship allocation model proposed in this study.

- The ship with the most competitive demand on the selected route (Australia to Japan) for iron ore was the 210,000 DWT ship. In the future, we plan to automate the ship allocation model to simulate worldwide ship allocation for various cargos, ship sizes, and ship types.

Acknowledgement

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Development of Ship Allocation Models using Marine Logistics Data and its Application to Bulk Carrier Demand Forecasting and Basic Planning Support

FINAL GRADE

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GENERAL COMMENTS

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