A STUDY ON THE SUPPORT SYSTEM OF SHIP BASIC PLANNING BY USING MARINE LOGISTICS BIG DATA

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A STUDY ON THE SUPPORT SYSTEM OF SHIP BASIC PLANNING BY USING MARINE LOGISTICS BIG DATA

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SUMMARY

In last decade, a large amount of data is growing exponentially which forms as Big Data. In maritime industries, marine logistics Big Data i.e. port data, ship data, route data, international trade data, and data provided by AIS increased rapidly. If these data are effectively utilized, a great innovation might be achieved. The objective of this study is to develop a support system of ship basic planning which can examine the demand and the principal particulars of bulk carrier by utilizing the marine logistics Big Data. In order to realize this, the authors develop ship allocation model consists of three distinct models i.e. shipper model, shipowner model, and operator model that developed by using the marine logistics Big Data. In this paper, a bulk carrier which is operating between Australia and Japan is taken as an example. The details and the effectiveness of proposed method are discussed in the paper.

1. INTRODUCTION

Big Data is clearly more than a buzz word and a business benefit of utilizing Big Data is widely known. A study by MIT found that data-driven organizations perform 5% to 6% better per year [1]. Big Data is already playing a larger role in shaping the future of the maritime industry. By embracing analytics and turning data into actionable insights, marine logistics players have an opportunity to drive improved efficiency and quality [2]. Moreover, it is widely believed that Big Data can aid in improving forecasts, and Big Data can be effective for forecasting demand and planning process [3][4].

There are many potentials and highly useful values hidden in the huge volume of Big Data which is used in various fields [5]. In maritime industries, marine logistics Big Data i.e. port data, ship data, route data, international trade data, and data provided by AIS (Automatic Identification System) can be used in the present situation. These data has a potential to innovate the maritime industries.

By the way, the global marine logistics industry has changed significantly which is influenced by the global goods movement [7]. In this situation, it is important to develop the ships that meet the market requirements. Actually, research of ship demand prediction has been conducted [8]. However, the detailed prediction, on the route which the demand will increase, is difficult to be executed at the present time.

The objective of this study is to develop the support system of ship basic planning by using the marine logistics Big Data which can predict the demand of bulk carrier and examine the effective ship principal particulars for cargo transportation. As a marine logistics Big Data, we utilize the Marine Logistics Database (MLDB) which was developed in our previous study (see section 2). The bulk carriers which operate between Australia and Japan are taken as an example. The details and effectiveness of proposed model is discussed in the paper.

2. OVERVIEW OF PREVIOUS STUDY

2.1 OBJECTIVES OF THE MLDB

In the previous study, the authors developed the MLDB using AIS data and statistical data [6]. The MLDB consists of the latest information of marine logistics Big Data, i.e. operation information from AIS data, ship, port, route and international trading information as shown in Figure 1. The data is integrated to find the estimation of cargo type and cargo volume. The objectives of developing MLDB are shown in the followings;

- To manage the unstructured marine logistics Big Data into structured data.
- To insight the valuable information which is buried in marine logistic Big Data.
- To extract valuable information by developing MLDB.

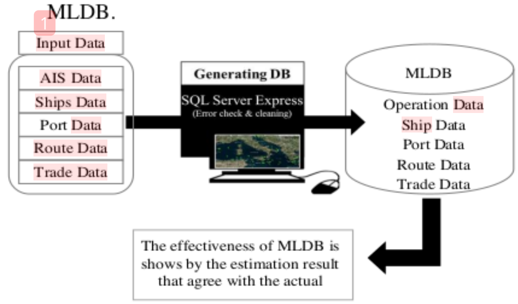

Figure1: Basic concept of previous study

2.2 INPUT DATA OF MLDB

Input data of the MLDB is described as follows:

- AIS Data [11]; e.g., indicated speed, draft, position, and time (arrival and departure date, arrival and departure port from MINT).
- Port Data [12]; e.g., port name, port number, longitude, latitude, port dimension, cargo handling.
- Ship Data [13]; e.g., ship name, DWT, IMO number, ship dimension, operator, shipbuilder, etc.

- Route Data [12] [14]; e.g., distance, route, via, etc.
- Trade Data [15]; e.g., commodity trade, a period of trade between country, code, trade value ($), trade quantity, reporter, and partner etc.

2.3 DATA STRUCTURE

In order to extract valuable information easily, the structure of the MLDB was defined and the unstructured data was changed into a relational database. For example, by integrating ship and port data with operation data, some information related to ships operational states can be analyzed (e.g., berthing, anchoring, or sailing).

2.4 ERROR CLEANING

In high-density shipping area where thousands of ships may transmit AIS messages, it is a challenge for the AIS system to efficiently collect, process, and download all the messages. It results that many messages are lost and sometimes error data collection occurred. The samples of errors from AIS data are shown as follows:

- The draft value (d) is zero (0).
- Unrealistic ships movements.
- Duplication information.
- Null information or blank space.

Therefore, in order to ensure the quality of the data, the duplicate and NULL data was deleted, and the draft data between arrival and departure were checked.

2.5 GENERATING CARGO INFORMATION

Cargo information on an operating ship is important for demand forecasting and basic planning. However, such information does not exist in AIS data. Therefore, we estimated the cargo type and volume of each operation as follows:

2.5 (a) Checking the reliability of the data

The confirmation of the reliability of data is required in order to get a good result during estimating cargo volume. In our study, the reliability of data is evaluated by checking the draft rate d_i (%) of the ship during the operation.

2.5 (b) Estimating the cargo type using port data

The port data has an information of the cargo type which is handled at the port. By using this data, cargo of each operation is estimated [6]. Estimation of cargo type is conducted by checking the combination of cargo from arrival port and departure port. By checking the combination of cargo from arrival port and departure port, cargo types of 75% operations are fixed.

2.5 (c) Estimating the cargo type using ship size

If two or more common cargo type exists by executing the estimation using port data, the cargo types are estimated by using ship size [6]. The threshold of each country is decided by using the operation data between the countries.

2.5 (d) Estimating the cargo volume

Ship data has information on deadweight and max draft of the target ship, while AIS data has information in the sailing draft. The cargo volume basically estimated by using the following equation:

$$V_i[ton] = DWT_i[ton] \times \frac{(d_i - 0{,}2)}{(1 - 0.2)} \tag{1}$$

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

2.6 CONFIRMATION OF THE CARGO ESTIMATION

In order to verify the result from proposed methods, the estimation result is evaluated and compared with the actual value of trade data. Target ships are bulk carriers between Japan and Austraria. The estimation results covered 90% of iron ore, 94% of coal and 97% of grain and others compared with the result from trade data.

2.7 EXTRACTING DATA FOR BASIC SHIP PLANNING USING MLDB

The structure of the relational database in MLDB allows a user to get some valuable knowledge. The operation information and another important information e.g. DWT (ton), LOA (m), B (m) d (m), design speed (knot) can be extracted easily. By identifying the extracted data from MLDB, the characteristics of the bulk carrier from Australia to Japan which is important for basic ship planning could be identified [6]. Moreover, the important information for predicting demand of ship in the future can be obtained.

3. BASIC CONCEPT OF THIS STUDY

3.1 BASIC PLANNING SUPPORT USING SHIP ALLOCATION MODEL

The core of this study is a ship allocation model which is developed by using the information from MLDB. Ship allocation model predicts the ship allocation when user inputs the trade volume, economical situation and so on. Therefore, when user inputs the future scenario e.g., the state of the world economy, fluctuation of fuel price, expansion of canal and port, the new ship allocation is generated and what types of ships are effectively used can be estimated based on the simulation. Moreover, by inputting the new ship in the simulation, we can estimate whether new ship will be used or not.

The objectives of the ship allocation model can be summarised as follows:

- To realize the actual ship allocation based on the inputting data (e.g., cargo trade between two ports or countries, fuel prices, etc.).
- If some conditions are changed, the allocation model estimates the new state. Therefore by inputting future scenario and new types of ship, we can forecast the ship demand and evaluate the new ship is effective or not.

3.2 CONFIGURATION OF SHIP ALLOCATION MODEL

The ship allocation model in this study consists of the following three models:

- The shipper model issues a request for cargo transportation between two or more ports.
- The operator model requests all shipowner models to estimate the cost, cargo volume, and transport time based on shipper requests. Then, based on the answer from the shipowner model, the operator model decides a ship for the allocation.
- The shipowner model performs estimations (cargo volume, costs and so on) in response to requests from the operator model.

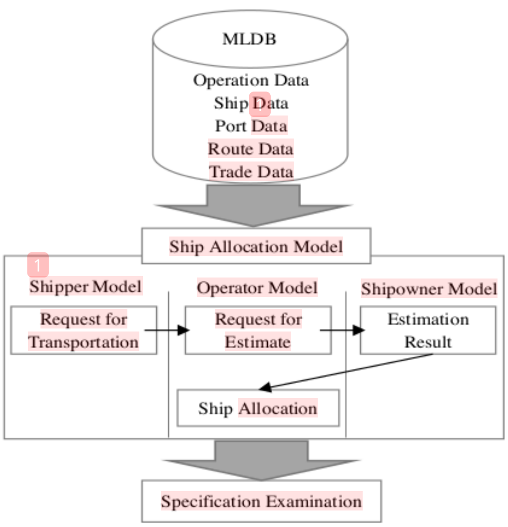

Figure 2: Basic concept of this study

3.3 REQUIREMENTS TO DEVELOP SHIP ALLOCATION MODEL

The ship allocation model should be developed by considering the followings requirements;

- To realize actual ship allocation conditions, three distinct models, the shipper model, shipowner model, and operator model should be developed.
- All data that is important for developing the three models should be extractable from the MLDB.
- The reproducibility of the allocation model should be evaluated and confirmed.

4. DEVELOPING THE SHIP ALLOCATION MODEL

The information extracted from the MLDB is used to develop the ship allocation model. In this study, cargo shipments of iron ore from Australia to Japan in 2014 are taken as an example. As shown in the previous section, the ship allocation model consists of three models: shipper model, shipowner model, and operator model. These models are detailed as follows:

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 is generated using cluster analysis. Cluster analysis is a method of defining the similarity in data, grouping similar things together, and classifying them into several groups (clusters). To generate the shipper model in this study, the following steps were taken:

4.1 (a) Extracting Operation Data from the MLDB

All data from 2014 that were important for defining shippers from Australia to Japan were extracted from the MLDB. The information from the MLDB includes operation data, port data, and ship data. By utilizing this data, we can easily analyze the number of port callings from Australia to Japan.

4.1 (b) Defining the Shipper using Cluster Analysis

To define a shipper between Australia and Japan, we must identify the number of port calling in 2014 using cluster analysis. The following steps were taken:

(1) Extracting the number of Port Callings
The number of port callings is extracted from MLDB. Extracted data are managed by using a matrix between the ports (P1…Pn) and ships (S1… Sn) as shown in Table 1(1).

(2) Measuring the Euclidean Distance
Data standardization is shown in Table 1(2) and performed by using the following equation.

$$z = \frac{X-\mu}{\sigma} \tag{2}$$

Where, X; the observation, μ; average number of calls at each port, and σ; standard deviation.

Then, the Euclidean distance is calculated using the standardized data by using the equation (3). The calculation of Euclidean distance is shown in Table 1(3).

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

Where; x_i; the number of calls after standardization of ship i at port x, and y_i; the number of calls after standardization of ship i at port y.

Table 1: Cluster analysis process

(1) Port Calling Calculation

Port \ Ship	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

Port \ Ship	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

In this study, to measure the distance between two clusters, the average linkage method has been applied. The equation is shown below;

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

Where;

C_n; cluster, and x_n; port, and $d(C_1, C_2)$: Euclidean distances between C_1 and C_2.

The goal of this method for this study is to group heterogeneous of the port into homogeneous clusters of the port. As shown in Figure 3, the ports are grouped into four Clusters (Shipper A - D).

The ports in Shipper A match with the JFE Steel locations, and the ports in Shipper B and Shipper C match the Nippon Steel Sumikin locations. That is, the clusters match actual conditions.

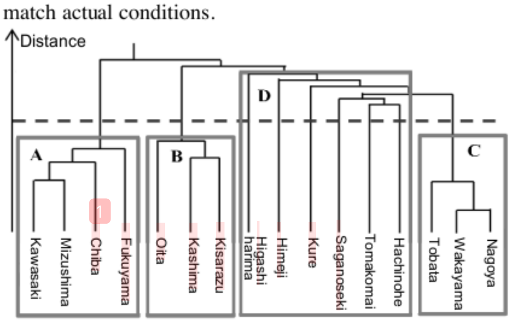

Figure 3: Defined clusters using dendrogram

4.2 SHIPOWNER MODEL

The shipowner model estimates draft rate, average speed in loading and ballast conditions, and days in port due to loading and ballast conditions in response to cargo transportation request from an operator. In this study, the shipowner model is defined using data extracted from the MLDB. To perform these estimations, we employ deep learning. In this study, the estimations are executed based on the followings steps;

4.2 (a) Training Data

In this study, all of the ship data (from the world to Japan, 2014-2015) which is extracted from MLDB is used for training data.

4.2 (b) Generating Learning Model

To predict the following items as mentioned in the previous explanation, the input layer and output layer are set as the followings;

- Input Layer; DWT (ton), length (m), breadth (m), depth (m), draft (m), service speed (knot), horsepower (HP), years of built, new construction of new shipbuilding price index, etc.
- Output Layer; the expected output to be obtained from this generation e.g., draft rate, average voyage speed, and arrival time at the port for loading and unloading condition.

4.2 (c) Calculating the Shipment Time, Amount of Cargo, and Cost

Shipment days are calculated by considering the route distance, navigation speed, and number of days in port. The cargo transport volume and shipment cost are calculated based on the method of Kigure et al. [16] and Aoyama et al. [17] by using the generated data shown in above.

The average error by using the deep learning analysis shows that the draft rate error is 3.4%, the service speed error is 0.2 knots, and the error of staying time in port is 0.9 days. These errors are smaller than the response surface methodology.

4.3 OPERATOR MODEL

The operator model selects the best ship regularly based on the estimation results from shipowner models. The procedure to determine the ship allocation is as follows:

4.3 (a) Calculating the Total Cost and Cargo Volume

As shown in Table 2(1), shipowner are bidding for all shipment requests. The cost per unit transports volume is calculated by considering the total operation cost ($) and the total amount of transportation volume (t).

4.3 (b) Calculating the Standard Deviation

The deviation values of some ships are calculated for each route as shown in Table 2(2). The deviation value is an index for judging which ship is good to what kind cargo transportation of a certain route.

4.3 (c) Ship Assignment

Ship with the highest standard deviation value is assigned to a shipment of the selected route. For example, as shown in Table 2(3), Ship B is assigned to route A2.

4.3 (d) Recalculating the Amount of Cargo Shipment Request

When the shipment is assigned to the selected route as shown in step 4.3 (c) the amount of cargo shipment is updated and the process is repeated from steps 4.3 (a) – 4.3 (c) until all of the cargo successfully transported.

Table 2: Ships allocation process

(1) Calculation of 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) Calculation of standard deviation

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	2.0×10^6	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) Ship assignment

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	$\mathbf{0.6\times10^6}$	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

4.4 CONFIRMATION OF PROPOSED MODEL

To evaluate the effectiveness of the proposed model, we simulate the ship allocation between Australia and Japan. The result of the simulation was compared with the actual result as shown in Figure 4.

As shown in Figure 4, the result of ship allocation (shows by the number of the operations) from the simulation for all Shippers i.e., Shipper A, Shipper B, Shipper C, and Shipper D generally agrees with the actual result. From this point of view, it can be concluded that the effectiveness of the developed model in this research is confirmed.

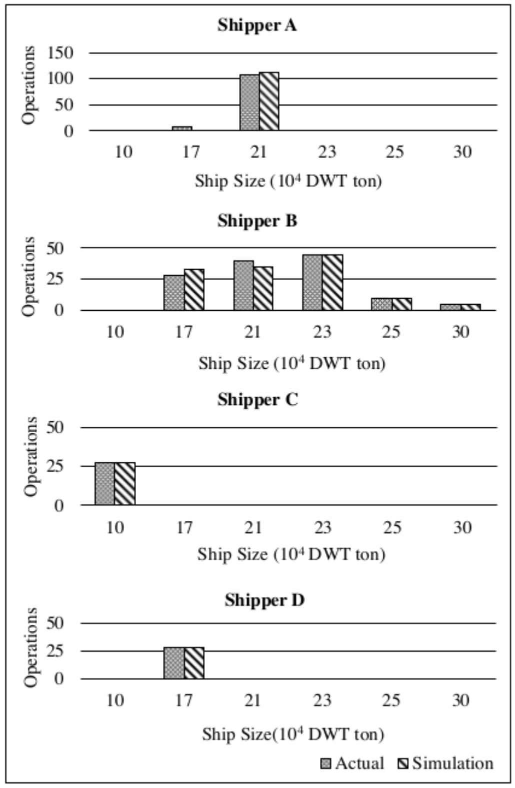

Figure 4: Comparison of the actual and simulation result

5. CASE STUDIES

We conducted a simulation aimed to examine the ship supply-demand balance and examine the influence of ship size and performance to the ship allocation as described below:

5.1 EXAMINATION OF SHIP SUPPLY-DEMAND BALANCE

We define ship supply-demand balance to examine the present condition of ship supply-demand operating between Australia and Japan in 2014, where the cargo types transported was iron ore. Firstly, we carry out a ship simulation when there is no restriction considered, it means there is no limited number of cargo shipment by ship for one-year operation. Secondly, we define supply and demand. In the case using restriction (using the actual number and ship types which are used in 2014 between Australia and Japan), the simulation result is defined as supply. In the case without using restriction, the simulation result is defined as demand.

As shown in Figure 5, we conducted ship supply-demand estimates. Without restriction, the allocation of ships in the 210,000, 250,000, and 300,000 DWT ton clusters increased. However, ship allocation in the 170,000 and 230,000 DWT ton clusters decreased. Therefore, 170,000 and 230,000 DWT ton ships are not very competitive for shipments from Australia to Japan. Meanwhile, there is an insufficient supply of 210,000, 250,000, and 300,000 DWT ton ships. Hence, these ships are competitive for shipments from Australia to Japan and are expected to be in demand in the future.

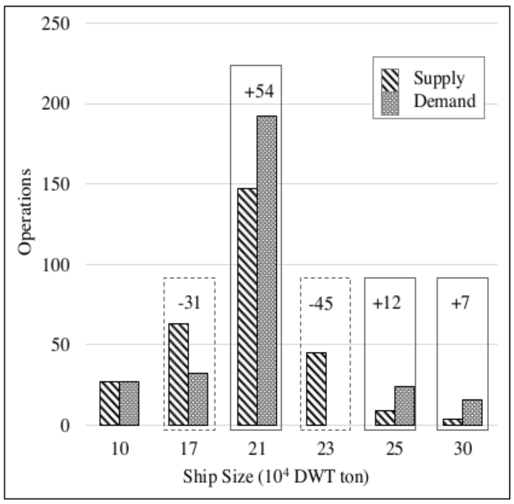

Figure 5: Supply-Demand Balance of Ships

5.2 EXAMINATION OF SHIP ALLOCATION BY THE SHIP SIZE

To examine the influence of ship size for the ship allocation and examine which size is the most competitive and could be operated on multiple routes, the ship allocation simulation is conducted. The simulation is conducted by considering the result from the previous section. Based on the discussion in the section 5.1, ships in the 210,000, 250,000, and 300,000 DWT ton clusters are expected to be in demand. Therefore, we simulate the ship allocation by changing the size of new ships.

As shown in Figure 6, Ship A (300,000 DWT ton) is in demand on a single route. In contrast, Ship B (250,000 DWT ton), and Ship C (210,000 DWT ton) can be expected to be in demand on multiple routes. In other words, the Ship B (250,000 DWT ton), and Ship C (210,000 DWT ton) is more competitive than Ship A (300,000 DWT ton).

However, when the fuel efficiency improves by 10%, Ship C (210,000 DWT ton) is more competitive than Ship B (250,000 DWT ton). As shown in Figure 7, the number of allocated ship and routes for Ship C (210,000 DWT ton) is increased rapidly (5 additional ships and 3 additional routes).

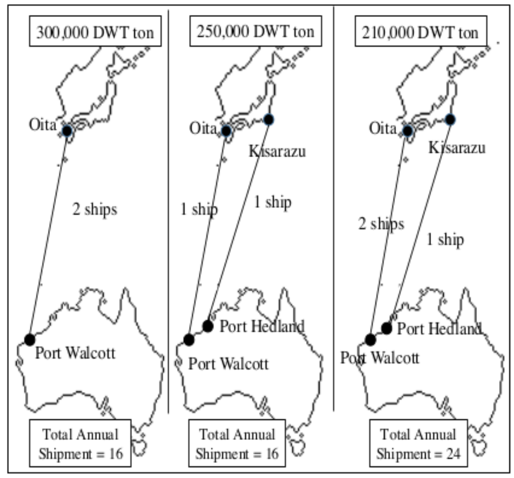

Figure 6: Ship allocation in various ship sizes

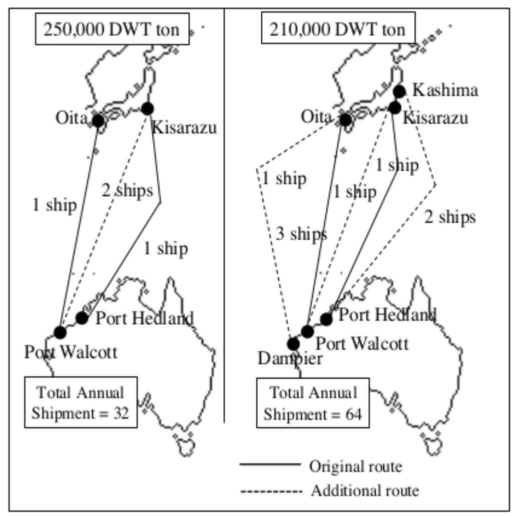

Figure 7: Ship allocation result when the fuel efficiency improved by 10%

5.3 EXAMINATION OF SHIP ALLOCATION BY THE PERFORMANCE

To examine the impact of the performance (fuel efficiency) on ship demand, we simulate by improving fuel efficiency by 5%, 10%, and 15%. A ship with no fuel efficiency change is defined as S_0. Ships with fuel efficiency improves of 5%, 10%, and 15% are denoted by S_1, S_2, and S_3, respectively. Since ships in the 210,000 DWT ton cluster are the most competitive, these ships are simulated. Furthermore, to evaluate these ships effectiveness, the simulation result (replacement using this ship) is compared with the actual ship allocation.

By using the proposed methods, the simulation result of ship allocation in cluster 210,000 DWT ton that is simulated by modifying the fuel efficiency which defined as S_0, S_1, S_2, and S_3 shows as follows;

- S_0, the number of operation is 40 within 3 routes.
- S_1, the number of operation is 47 within 4 routes.
- S_2, the number of operation is 61 within 5 routes.
- S_3, the number of operation is 128 within 10 routes.

Furthermore, the simulation result of replacement from the ship in cluster 210,000 DWT ton which simulated with various fuel efficiency is compared with the actual condition.

As shown in Figure 8, when fuel efficiency improves by 10%, ships in the 170,000 and 230,000 DWT ton clusters show minor demand on that route. Moreover, ships in the 210,000 and 250,000 DWT ton clusters also do not need to be replaced by new ships, since the simulation result shows the same number of the operations compared with actual ship allocation.

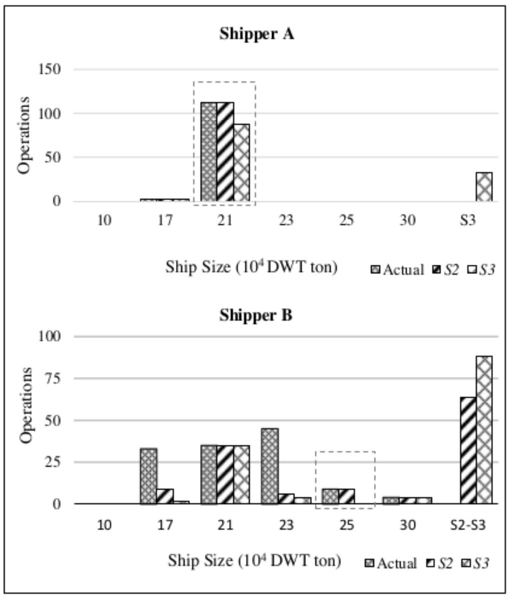

Figure 8: Differences of ship S_2 & S_3 for Shipper A and B

When efficiency improves by 15%, replacing ships in the 210,000 DWT ton cluster greatly improves the number of operations for Shipper A. However, when the efficiency improves by 15%, the ships in the 210,000 DWT ton cluster are the same as actual conditions for Shipper B. In contrast, the ship in the 250,000 DWT ton cluster shows that a replacement has occurred that greatly improves the number of operations.

In summary, using the proposed model, we can simulate ship supply and demand. Moreover, the ship allocation that influenced by ship size and ship performance can be simulated. In addition, we can obtain the impact of fuel efficiency on ship demand.

6. CONCLUSIONS

In this study, we have focused on developing a support system for basic ship planning using Marine Logistics Big Data, and have drawn the following conclusions:

- By utilizing the data extracted from MLDB, the ships allocation models which composed of three distinct models; shipper model, shipowner model, and operator model was successfully developed.
- By inputting the future scenario into the simulation, we can examine future ship supply-demand balance, the influence of ship size and fuel efficiency of ship allocation.

7. ACKNOWLEDGNMENT

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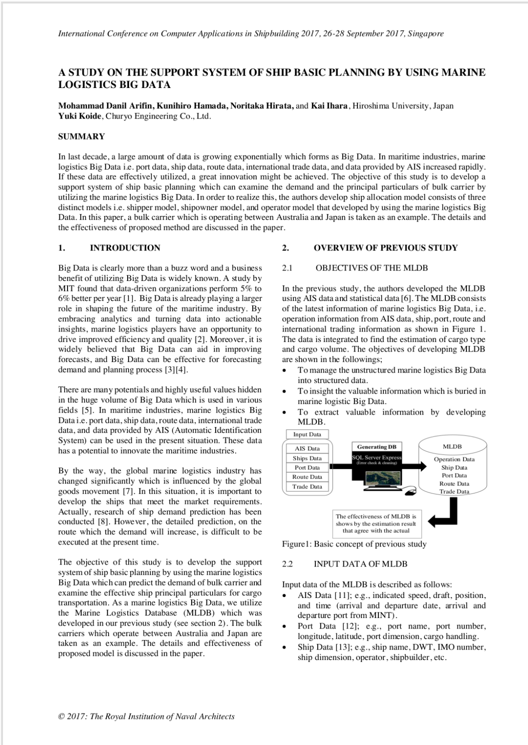

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A STUDY ON THE SUPPORT SYSTEM OF SHIP BASIC PLANNING BY USING MARINE LOGISTICS BIG DATA

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SUMMARY

In last decade, a large amount of data is growing exponentially which forms as Big Data. In maritime industries, marine logistics Big Data i.e. port data, ship data, route data, international trade data, and data provided by AIS increased rapidly. If these data are effectively utilized, a great innovation might be achieved. The objective of this study is to develop a support system of ship basic planning which can examine the demand and the principal particulars of bulk carrier by utilizing the marine logistics Big Data. In order to realize this, the authors develop ship allocation model consists of three distinct models i.e. shipper model, shipowner model, and operator model that developed by using the marine logistics Big Data. In this paper, a bulk carrier which is operating between Australia and Japan is taken as an example. The details and the effectiveness of proposed method are discussed in the paper.

1. INTRODUCTION

Big Data is clearly more than a buzz word and a business benefit of utilizing Big Data is widely known. A study by MIT found that data-driven organizations perform 5% to 6% better per year [1]. Big Data is already playing a larger role in shaping the future of the maritime industry. By embracing analytics and turning data into actionable insights, marine logistics players have an opportunity to drive improved efficiency and quality [2]. Moreover, it is widely believed that Big Data can aid in improving forecasts, and Big Data can be effective for forecasting demand and planning process [3][4].

There are many potentials and highly useful values hidden in the huge volume of Big Data which is used in various fields [5]. In maritime industries, marine logistics Big Data i.e. port data, ship data, route data, international trade data, and data provided by AIS (Automatic Identification System) can be used in the present situation. These data has a potential to innovate the maritime industries.

By the way, the global marine logistics industry has changed significantly which is influenced by the global goods movement [7]. In this situation, it is important to develop the ships that meet the market requirements. Actually, research of ship demand prediction has been conducted [8]. However, the detailed prediction, on the route which the demand will increase, is difficult to be executed at the present time.

The objective of this study is to develop the support system of ship basic planning by using the marine logistics Big Data which can predict the demand of bulk carrier and examine the effective ship principal particulars for cargo transportation. As a marine logistics Big Data, we utilize the Marine Logistics Database (MLDB) which was developed in our previous study (see section 2). The bulk carriers which operate between Australia and Japan are taken as an example. The details and effectiveness of proposed model is discussed in the paper.

2. OVERVIEW OF PREVIOUS STUDY

2.1 OBJECTIVES OF THE MLDB

In the previous study, the authors developed the MLDB using AIS data and statistical data [6]. The MLDB consists of the latest information of marine logistics Big Data, i.e. operation information from AIS data, ship, port, route and international trading information as shown in Figure 1. The data is integrated to find the estimation of cargo type and cargo volume. The objectives of developing MLDB are shown in the followings;

- To manage the unstructured marine logistics Big Data into structured data.
- To insight the valuable information which is buried in marine logistic Big Data.
- To extract valuable information by developing MLDB.

Figure1: Basic concept of previous study

2.2 INPUT DATA OF MLDB

Input data of the MLDB is described as follows:

- AIS Data [11]; e.g., indicated speed, draft, position, and time (arrival and departure date, arrival and departure port from MINT).
- Port Data [12]; e.g., port name, port number, longitude, latitude, port dimension, cargo handling.
- Ship Data [13]; e.g., ship name, DWT, IMO number, ship dimension, operator, shipbuilder, etc.