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Application of Internet of Things (IoT) and Big Data in the Maritime Industries: Ship Allocation Model

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***Abstract*— The Internet of Things (IoT) and Big Data (BD) are growing significantly. IoT is defined as a gateway of technology to digital transformation. To work effectively, BD, Artificial intelligence (AI), and blockchain all rely on those data. Once the physical framework information is changed into computerized digital data, an opportunity opens up to improve vessel operations. Research shows that much of the hidden information can help improve vessel operations by leveraging BD and IoT. Therefore, other sectors of the value chain players such as consignees, shipyards, shippers, manufacturers, and classification societies are also interested in maritime BD. In recent years, the world's ship logistics industry has undergone major changes due to the global shipping cargo movement. The availability of numerous BD is also growing exponentially. This will make it possible to utilize many BDs and IoT in the shipping industry. Successful utilization of these BDs and IoT will bring about major innovations in the shipping industry. In this study, we reviewed several applications of BD and IoT in the maritime domain and developed a ship allocation model using maritime BD and IoT-extracted data. As a result, ship allocation establishment is discussed, and the ship allocation result is evaluated.**

Keywords—*Big Data (BD), Internet of Things (IoT), Ship Allocation Model*

I. INTRODUCTION

The IoT may be an arrangement of physical objects that consolidate the computing control essential to gather, processing, and transmitting information. IoT is the association point between the physical and advanced universes [1].

In a maritime context, this gets interestingly good. The IoT is transforming the maritime industry. Smart connected vessels gain the advantages of the IoT in several ways, from driving down costs by decreasing fuel consumption to scaling maintenance time. As a gateway technology of digital transformation, AI, BD, and blockchain all rely on data to function efficiently and effectively. Once the physical framework information is changed into computerized digital data, an opportunity opens to improve vessel operations. From ship tracking and maintenance to crew safety and well-being, wherever there is a physical operation, IoT can digitize and enhance it [2].

About each industry is making endeavors to get a handle on and explore the potential of IoT innovation. The shipping industry as of now employments a few of these innovations and seem advantage incredibly from IoT [3]. The maritime industry has broad systems networks and requires speedy decision-making. Ships require communication between all related objects (ships, operators, ports, etc.) [4]. Obsequious or satellite communication, a moderate and costly shape of communication, is commonly utilized in shipping transport. IoT develops at a time when the fast advancement of different advances requires the integration of sensor innovation, computer handling innovation, data, and communication innovation (ICT), and electronic control innovation. There are three major IoT application domains in maritime industries: smart ships, smart ports, and smart transportation [5]. Other application domains can be seen in **Figure 1**.

BD is more than just a word and the commerce esteem of utilizing BD is well known. Data-driven organizations have been shown to improve performance significantly per year [6]. BD is as of now playing a more noteworthy part in forming the long run of the shipping industry. By analyzing the information, dispatch coordination partners can seize openings to make strides in effectiveness, efficiency, and quality [7]. In addition, it is well known that BD helps improve forecasting and that BD helps the demand forecasting and planning process [8] [9].

A common definition of BD is big volume, big speed, and a big assortment of data resources that require modern shapes of preparation to upgrade decision-making, knowledge, and handle optimization [10][11]. The properties of BD are characterized as three Vs (Volume, Velocity, and Variety) as appeared in **Figure 2**. It can be advanced explained as follows:

- Data volume characterizes the sum of information, and numerous components can contribute to information volume development. It can be hundreds of tera/petabytes of data being produced all over [12].
- Data rate is characterized as the quick era of information. Their collection, handling, and examination require quick components. This speed highlights BD's real-time processing control for undertaking needs [13].
- Diversity of information characterized as BD information sorts counting organized and unstructured information such as content, sound, video, sensor information, posts, and log records [13].

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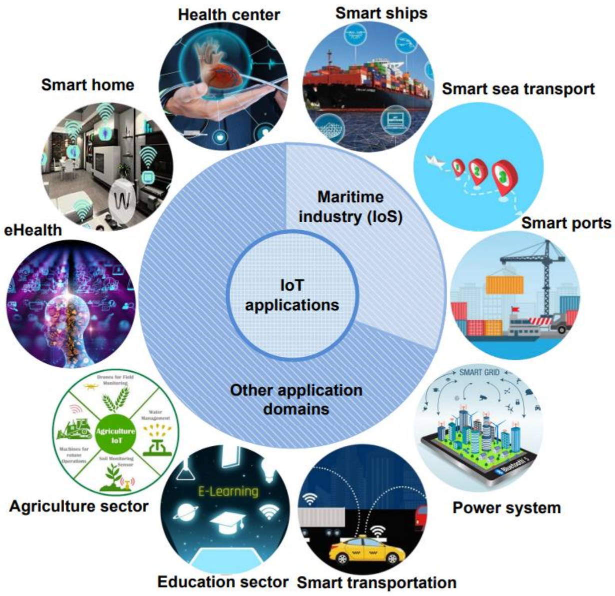


Figure 1 Major IoT application domains

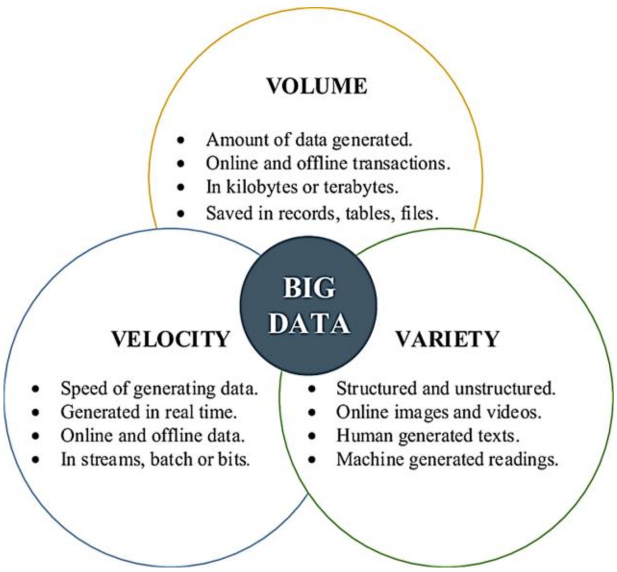


Figure 2 The 3Vs of Big Data

The gigantic sum of information broadly shared in different areas, including the maritime field, stows away awesome potential and esteem. The global movement of goods has profoundly changed the world's transportation logistics. Therefore, it is important to create ships with determinations that meet the market requirement or demanded request. At the same time, maritime logistics BDs such as port, vessel, and AIS data are recorded more efficiently. The effective use of this data can lead to great innovation. BDs are often redundant, so the database should be extended and cleaned up.

Considering the available data on maritime BD and IoT, the purpose of this study is to review the application of IoT and BD in the maritime industries and give an example by establishing a ship allocation model utilizing the information extricated from the already created database [8].

A. Review of BD and IoT

IoT may be a worldwide arrangement of interconnected objects, interestingly addressable based on standard communication protocols, that empowers individuals and things to put through with anybody, anyplace, anytime, and with anything. Ideally, it empowers the network over any path or network and anyway. Based on IoT, diverse devices, tools, and objects communicate data or information to each other to form educated choices. and sharing allows us to think, hear, feel, sense, and work.

IoT changes these devices or objects from customary to brilliantly by leveraging basic advances in technology such as sensor systems, communication innovations, omnipresent and omnipresent computing, web conventions, and implanted computing. As shown in

Figure 1, smart devices and their properties lead to different domains and specific applications. Overall, the IoT is anticipated to open up critical applications in several domains i.e. smart home sectors, the power system sector, the transportation sector, the education sector, the maritime industry sector, and numerous other regions that progress the worldwide economy and lifestyle. Key applications of IoT in the maritime industry include real-time route planning and tracking, cargo tracking, storage capacity optimization, and e-navigation [14] [15].

Another application of BD and IoT for maritime applications is the Ship Information Management System "SIMS". SIMS was jointly established by Monohakobi Technology Institute (MTI) and NYK [16]. The use of SIMS onboard enables the timely exchange of detailed data between crew on board and operations personnel onshore. This information incorporates exact hourly operation on working conditions and consumption of fuel. This empowers the ideal assessment of operational statuses such as vessel speed and consumption of fuel, as well as information such as climate conditions, to attain more effective operation and assignment of the ship.

Until 2015, the SIMS is installed on more than 140 vessels, including the following ships: container, bulk carriers, car vessels, tankers, and LNG. Recently, research was conducted to make the BD obtained from this system available for wider use. The illustration of the SIMS overview is shown in **Figure 3-4** [16].

TABLE 1.
INSTALLATION RECORDS OF SIMS ONBOARD [16]

Vessel Type	SIMS 1 Installed	SIMS 1 Installed	Total
Bulk	5	48	53
Tanker	0	8	8
Car Vessels	6	32	38
Container	19	27	46
LNG	1	2	3
Total	31	117	148

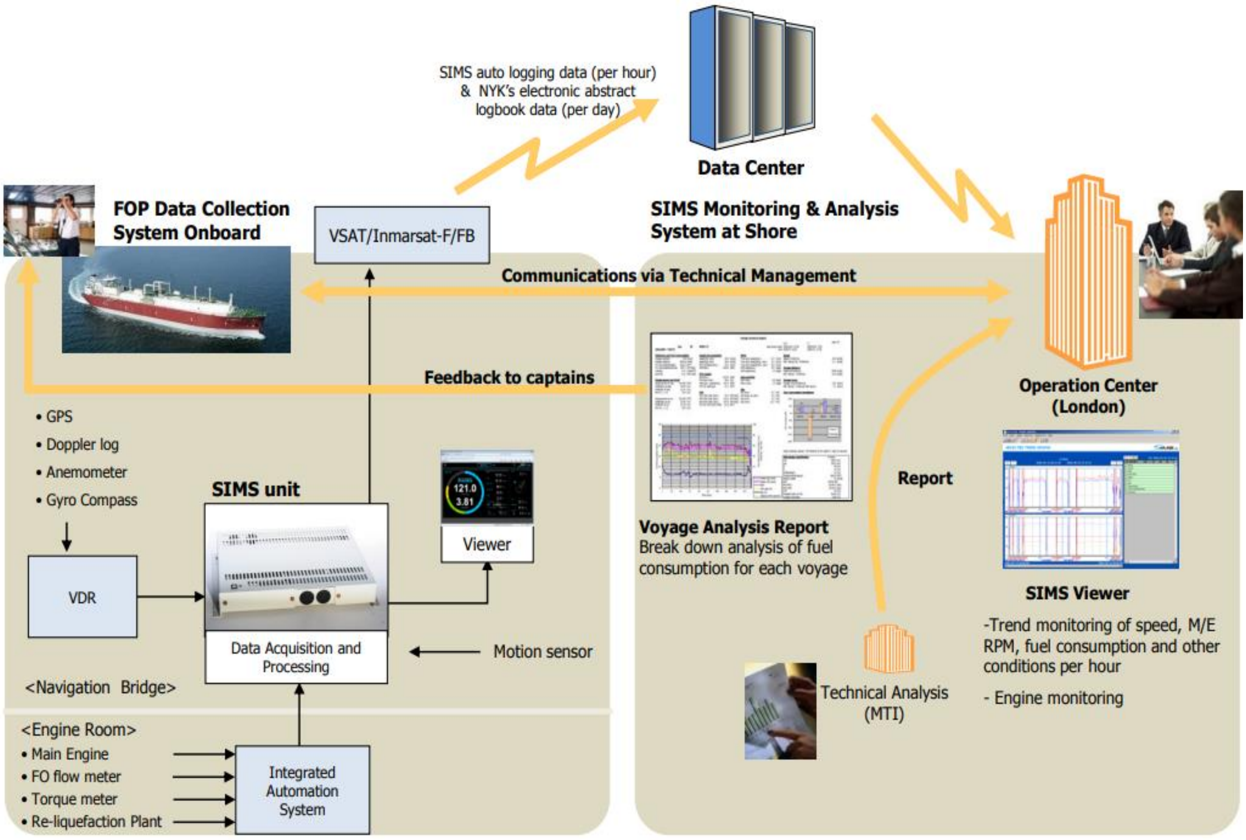


Figure 3. Illustration of SIMS [16]

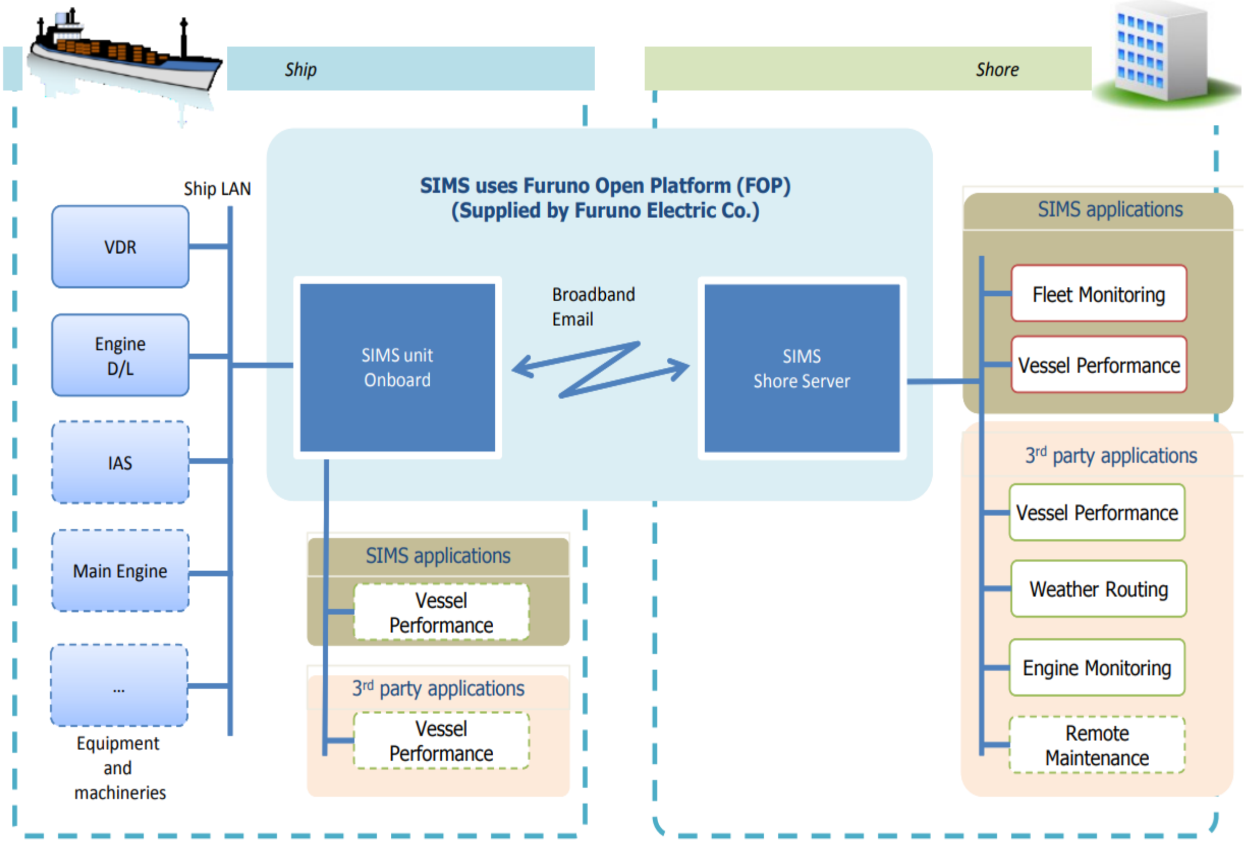


Figure 4. SIMS as an open platform [16]

An example of BD and IoT data in maritime industries i.e., voyage information: automatic data collection (IoT), and noon report; machinery information: manual report information, and trouble or maintenance information; AIS data: satellite AIS or shore AIS (IoT); weather and climate: forecasting data, information of wave measurement (IoT); and trading information data: cargo transport data [16] [17].

B. *Review of Marine Logistic DB*

Marine Logistics DB was developed by integrating maritime BD and IoT data: port, ship, route, AIS, and trade data into an integrated database [18-20]. It was built as a foundation for the ship allocation model. This section describes the basic concept of database defined as MLDB, allocation model, and simulation as shown in **Figure 5**.

II. METHOD

A. *Data Extraction of MLDB*

MLDB is a relational database that arranged the data on AIS ship's operations, ships, ports, routes, and trading data. All data is systematically integrated to provide useful insights for identifying compelling ship specifications. The MLDB structure is shown in **Figure 6**. All necessary data to develop a ship allocation model: port arrivals data, ship operations, and cargo transport data extracted from MLDB. The MLDB was constructed based on the following BD:

- AIS data: AIS data includes ship names International Maritime Organization (IMO) numbers, travel time stamps, sailing speed, vessel draft, and the coordinates position of latitude/ longitude [14] [21].
- Ship operational data includes vessel name, IMO number, Specified Draft, Departure/Arrival Date, and Departure/Arrival Port,
- Ship data: includes ships name, number of IMO, principal dimensions, operator, shipyard, age, and status.
- Port data: Port data includes port name, a measure of the dimension, longitude and latitude coordinates, and types of cargo handled the information.
- Route data. Route data is collected from departure and arrival port information in AIS. The route data includes the distance between these port data.

B. *Development of Ship Allocation Model*

To develop a ship allocation model at least three distinct models are required: (1) shipper; (2) shipowner; and (3) operator model. The methods of three distinct models are described as follows:

- The shipper model is defined to demonstrate the characteristics of each sort of cargo from two or more ports such as iron ore, and coal. This demonstration gives a practical way to reflect worldwide cargo request shipping. (See **Figure 7**).
- The shipowner model uses the date of the voyage, the volume of cargo, and operating costs associated with the demand for freight transport from the shipper model. (See **Figure 8**).

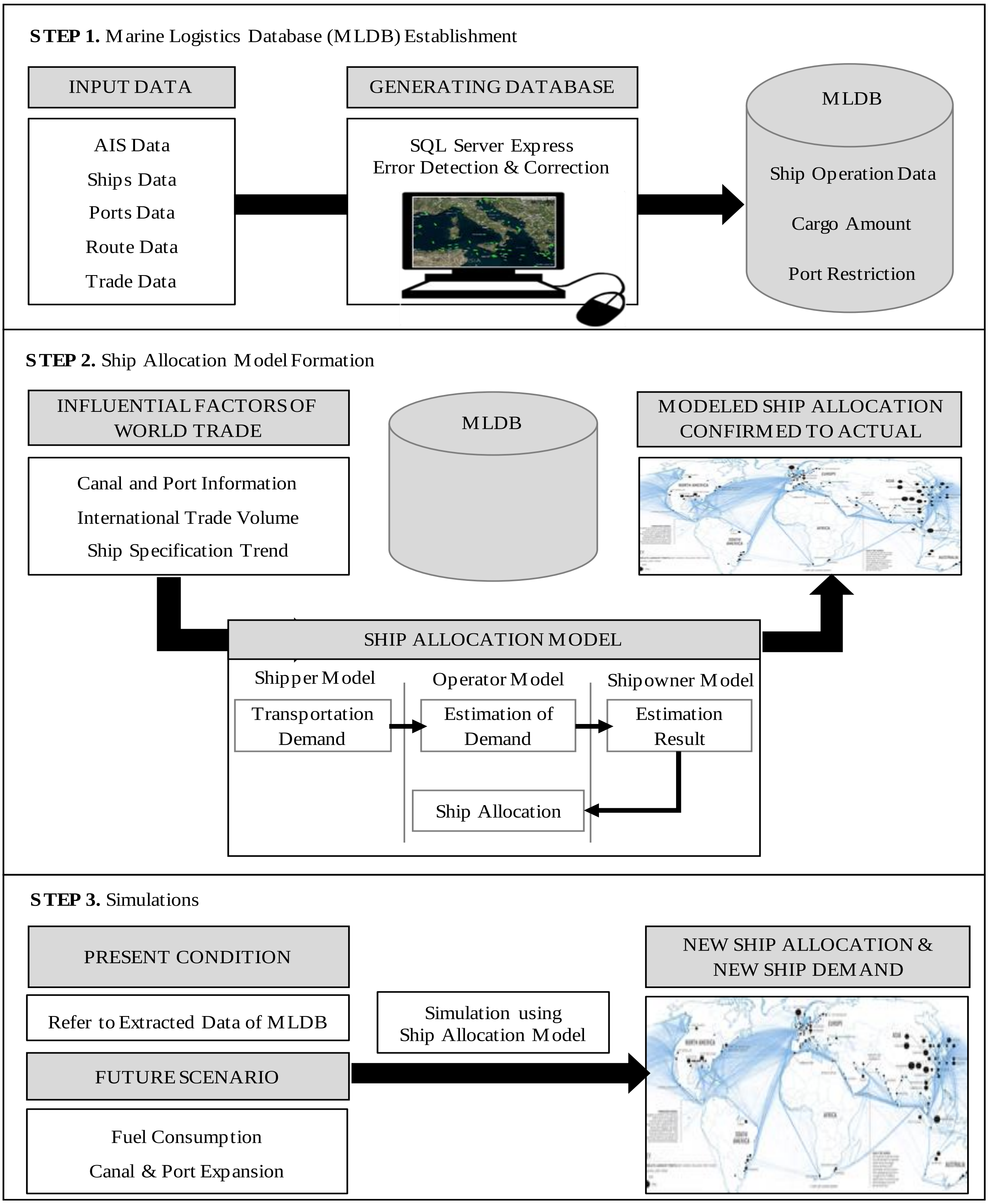


Figure 5. Basic Concept of MLDB [18]

- The operator model is defined for each ship. This model was developed to identify the most capable ships meeting freight transportation demand based on estimates of shipowner model results. (See **Figure 9**).

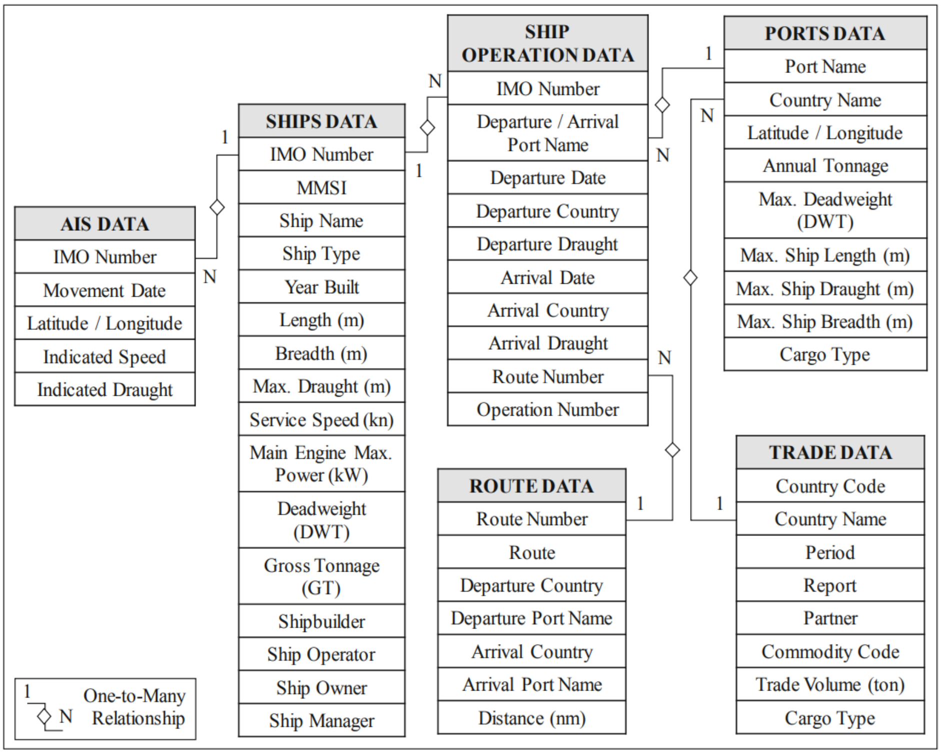


Figure 6. Construction of database [14] [18]

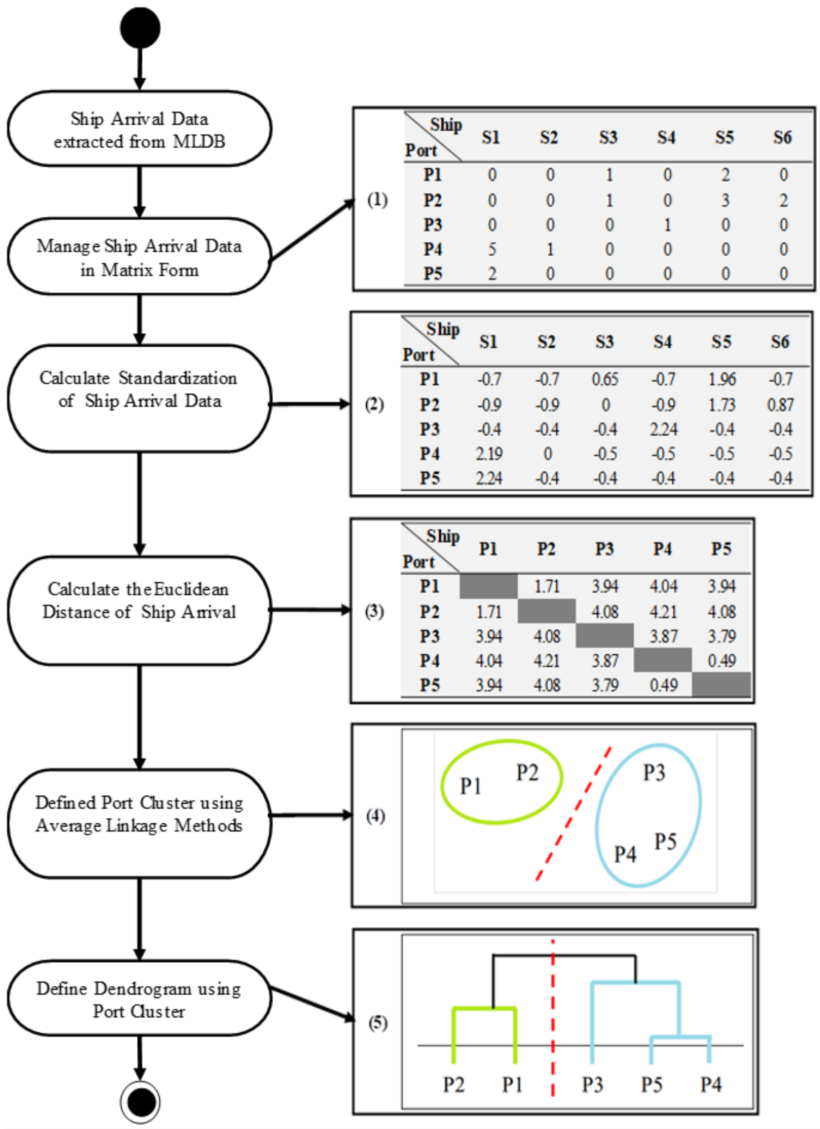


Figure 7. Shipper Model

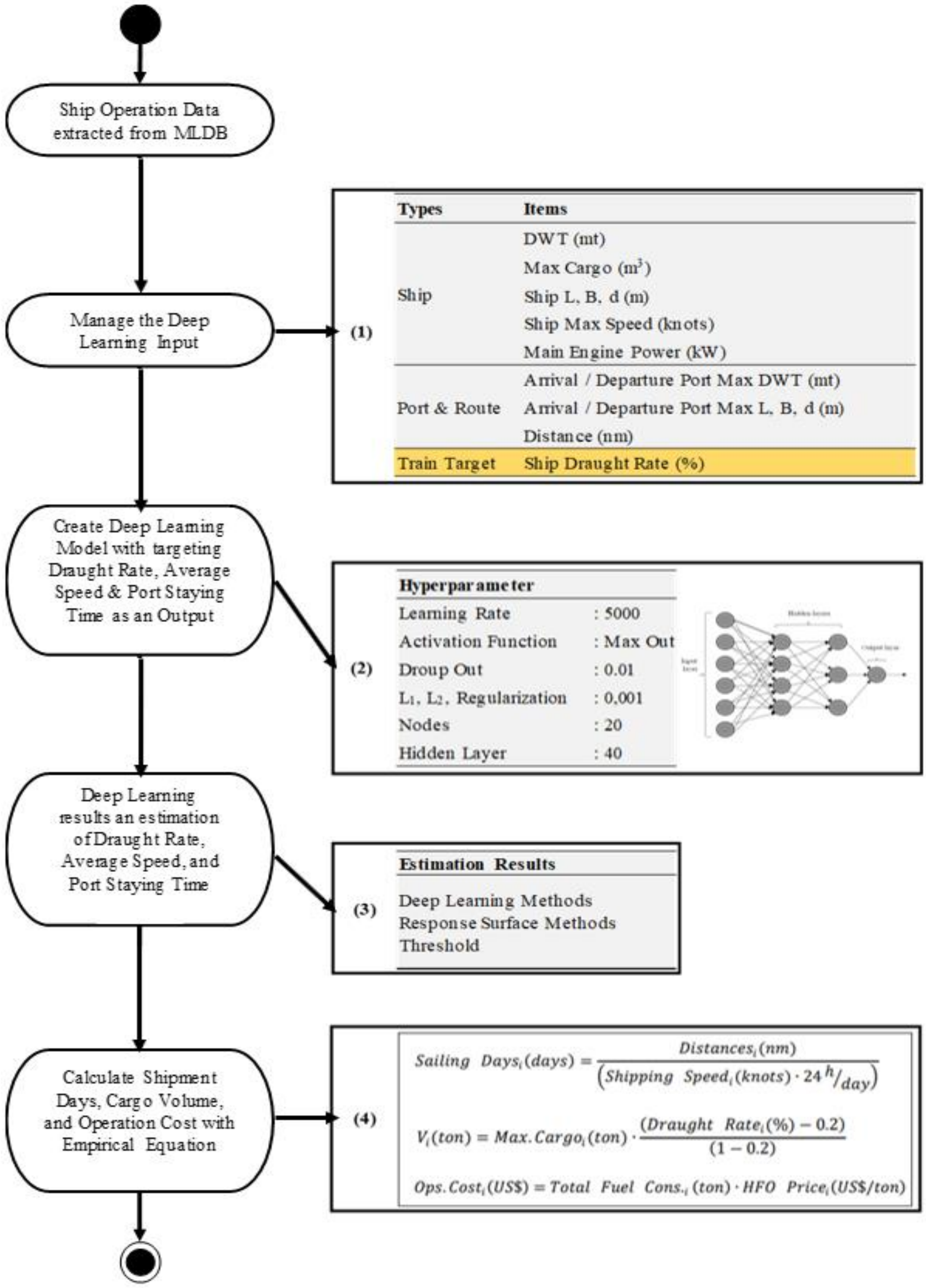
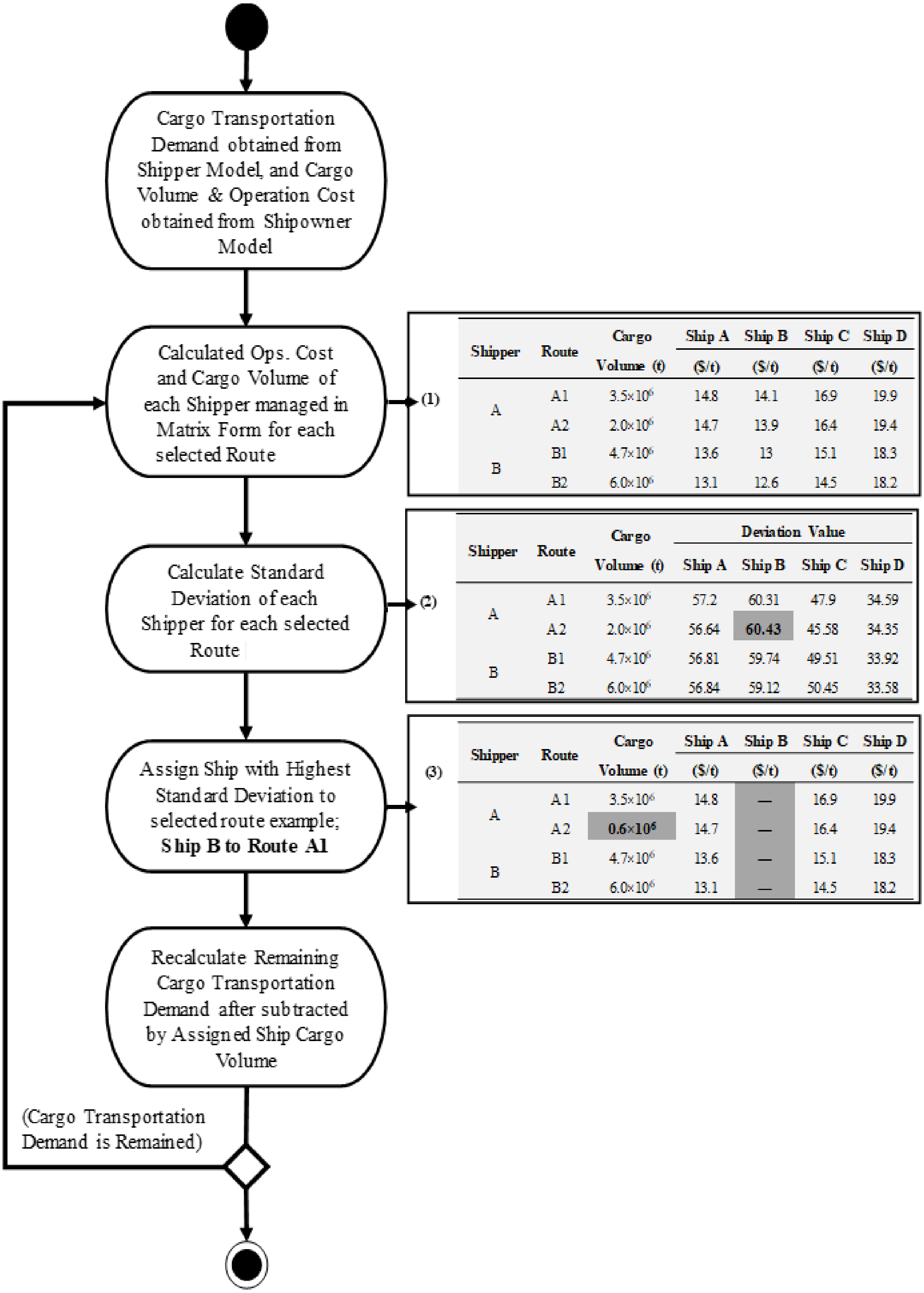


Figure 8. Shipowner Model



(1)

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)

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)

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	**0.6×10^6**	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

Figure 9. Operator Model

III. DISCUSSION

A. Shipper model result

The shipper model shown in this study is characterized in terms of exporters and consignees. As a result of shippers operating between Australia and Japan, the ports were assembled into 4 clusters (A-D) based on the consignee's perspective shown in **Figure 10**. However, the shipper cluster results are based on the shipper view and the ports are grouped into 3 clusters (A-C) shown in **Figure 11**.

By using the shipper model, the correlation of the amount of cargo, port sizes, and clusters easily can be identified as shown in **Figure 12-13**. Moreover, the characteristics of shippers based on port restriction and the relation between shippers can be clearly defined as shown in **Figure 14-15**.

Overall, the characteristics of the shippers between Australia and Japan are described as follows:

- JFE Steel (Japan Future Enterprise) features a close relationship with BHP Billiton because it handles the foremost cargo reaching 51%, and Rio Tinto follows in second place with 49% coverage.
- NSSMT (Nippon Steel & Sumitomo Metal Terminal) contains an exceptionally solid relationship with Rio Tinto, reaching 78% coverage.

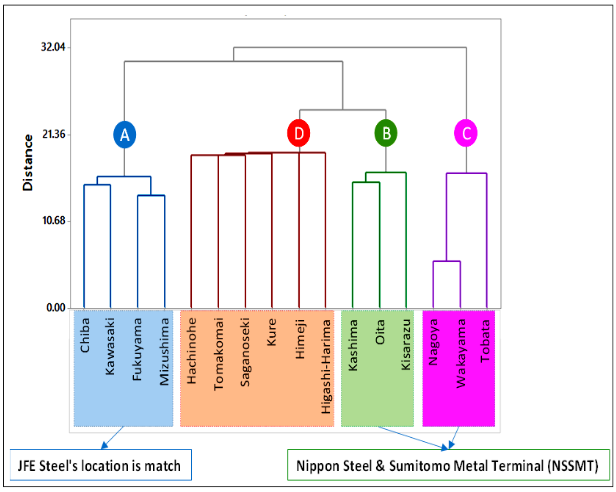


Figure 10. Cluster-based on the consignee's perspective

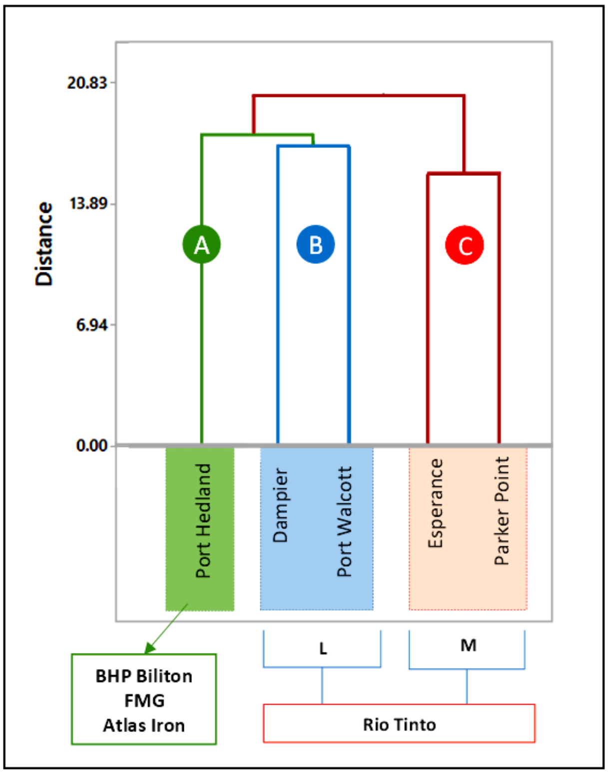


Figure 11. Cluster-based on the shipper's perspective

B. Shipowner model result

To affirm the adequacy of the shipowner model, the standard deviation of the estimation result of the deep learning (DL) examination is compared with the response surface (RS) examination and the threshold (Th) of the estimation results. Based on **Table 2**, the estimation result by DL is better than the Th, but the estimation result by the RS method is worse.

TABLE 2.
COMPARISON RESULTS

Methods	Draft Rate	Average Service Speed	Port Staying Time
DL	3.4%	0.2 knots	0.9 days
Th	3.5%	0.9 knots	days
RS	5.9%	-	-

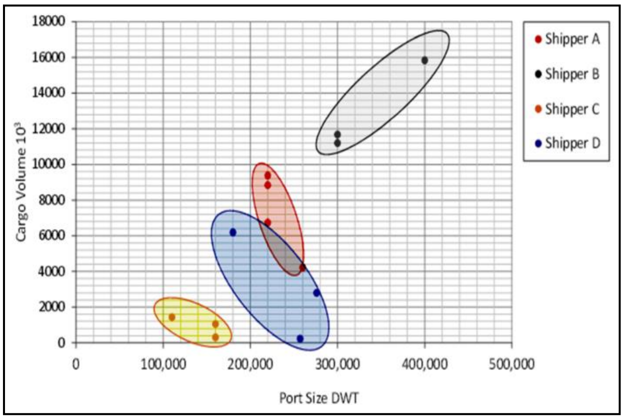


Figure 12. Correlation based on the consignees.

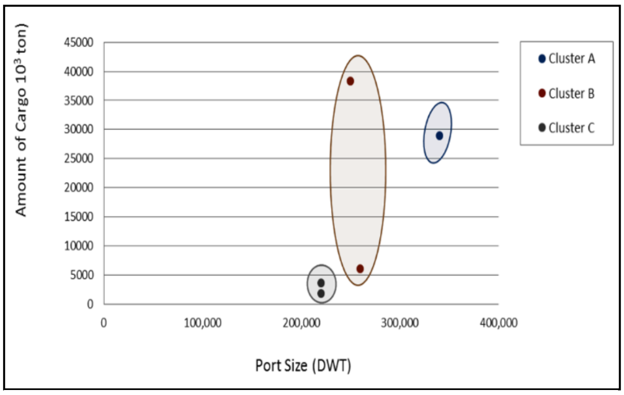


Figure 13. Correlation based on the shippers.

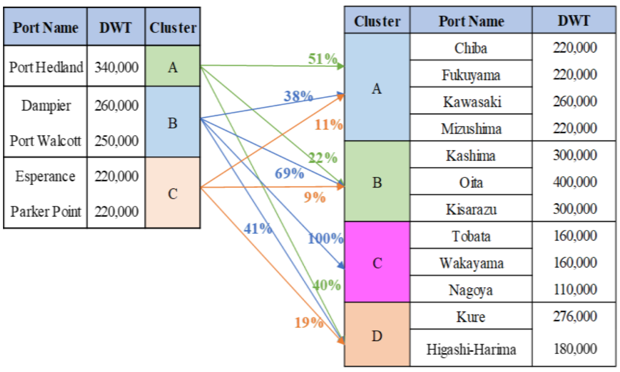


Figure 14. Characteristic based on port restriction.

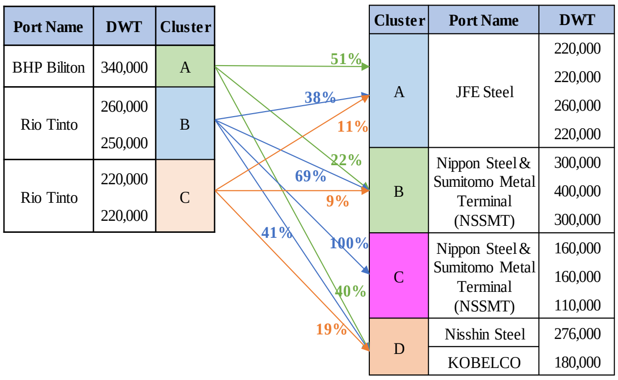


Figure 15. Characteristics based on the relation between ports.

C. Ship allocation model result

The proposed methods evaluate the foremost specific properties of ships. Furthermore, by generating this simulation, it can recognize the routes number and ships that can be assigned to the chosen route as appeared in **Figure 16**.

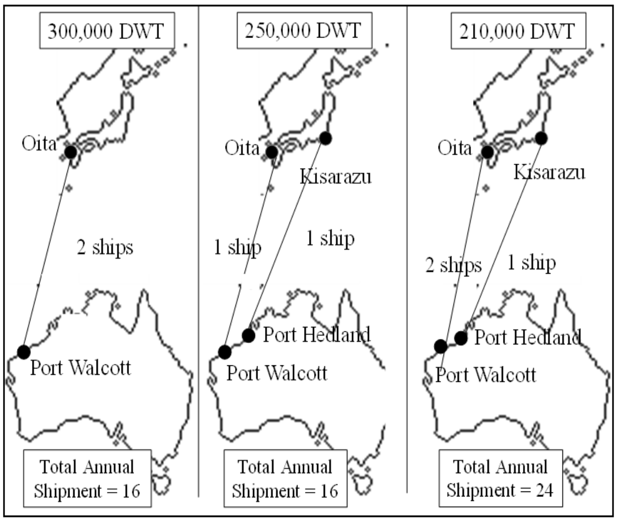


Figure 16. Ship distribution simulation

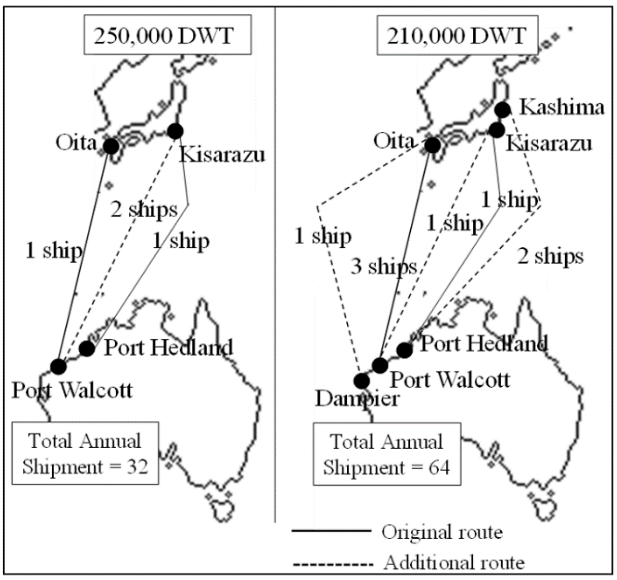


Figure 17. Ship distribution simulation

As shown in **Figure 16**, one route is required 300,000 DWT vessels. On the other hand, 250,000 DWT and 210,000 DWT vessels may be in request on multiple routes. However, by expanding fuel effectiveness to 10%, the 210,000 DWT vessel has the most noteworthy potential for iron ore transport between Australia and Japan as appeared in **Figure 17**.

IV. CONCLUSION

In this research, a ship allocation has developed a system using maritime BD and IoT data. The shipping model consists of three specific models: the shipper model, the shipowner model, and the operator model. The shipper demonstrate makes clusters of trade and consequence ports whose cargo request is transported within the chosen year. The request forecasted by the operator model is at that point utilized as a cargo request. After the request, the owner will provide the cost and capacity of the route operated by the owner's vessel. After the charter agreement between the operator and the shipowner, the operator selects the tenders submitted based on economic considerations and makes the quota of ships. The reproducibility of the ship allocation model was confirmed using the proposed model. Demand-supply balance, effective vessel specifications, and the impact of vessel efficiency on demand can be realized in the vessel allocation model proposed in this study. The vessel with the foremost competitive request or demand on the selected route for iron ore (Australia to Japan) was the 210,000 DWT vessel. In the future, the automatic ship allocation model needs to be simulated based on the global ship allocations for different cargoes, ship sizes, and ship types.

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