공학석사 학위논문

A Study on the Method for the Estimation of Energy Efficiency Operational Indicator of a Ship Based on Technologies of Big Data and Deep Learning

빅데이터와 딥러닝 기술을 기반으로 한 선박 에너지 효율 운항 지표 예측 방법에 대한 연구

2018년 2월

서울대학교 대학원
조선해양공학과
김 성 훈

Contents

Figures

Tables

Abstract

A Study on the Method for the Estimation of Energy Efficiency Operational Indicator of a Ship Based on Technologies of Big Data and Deep Learning

Seong-Hoon Kim

Department of Naval Architecture and Ocean Engineering

The Graduate School

Seoul National University

In shipyards, EEOI estimation is required to compare the efficiency of ships and to check the time-varying efficiency of the ships. However, since it is difficult to obtain operating data required for EEOI estimation, it is necessary to estimate EEOI using public data such as Automatic Identification System (AIS) data, ship and engine data, and weather data.

In this study, a method for EEOI estimation using public data was proposed. In the proposed method, total resistance and propeller efficiencies are estimated using the Holtrop-Mennen method, additional resistance is estimated following the International Organization for Standardization (ISO)15016:2015, and engine power is estimated using

the modified Direct Power Method (DPM) and Holtrop-Mennen method.

Since the public data have a large capacity, big data technologies such as Hadoop and Spark were applied. The public data was stored to Hadoop, and the data was processed using Spark. Moreover, to reduce the computation time for EEOI estimation, a surrogate model constructed using deep learning was also applied.

To evaluate the effectiveness of the proposed method, it is applied to estimate EEOI of the example ship. The result shows that the method can estimate EEOI effectively and accurately.

Keywords: Automatic Identification System (AIS), Big data, Deep learning, Energy Efficiency Operational Indicator (EEOI), Hadoop, Spark, Surrogate model

Student number: 2016-21130

1. Introduction

1.1. Regulations on energy efficiency of ships

In 1973, as interest in the marine environmental protection increases globally, the International Maritime Organization (IMO) adopted the Prevention of Pollution from Ships (MARPOL) as requirements on pollution from chemicals, garbage, sewage, and other harmful substances. And, the MARPOL Annex VI was adopted in 1997 to deal with problems of main air pollutants contained in ship's exhaust gas. Moreover, the MARPOL Annex VI was amended to regulate ship efficiency in 2011 (IMO, 2011).

The MARPOL Annex VI includes the concept of Energy Efficiency Design Index (EEDI) and related regulations. EEDI is an index to show the efficiency of a designed ship. EEDI represents the amount of CO_2 generated by the ship while doing one tonne-mile of transport work, and it means efficient when the value of EEDI is small. The CO_2 emission is equal to the product of the engine power, Specific Fuel Oil Consumption (SFOC), and carbon factor. And, the transport work is equal to the product of the deadweight and speed of the ship. Therefore, EEDI can be represented as Equation 1.

$$EEDI = \frac{\text{Engine Power} \cdot \text{SFOC} \cdot \text{Carbon Factor}}{\text{Deadweight} \cdot \text{Speed}} \qquad \text{Equation 1}$$

According to the MARPOL Annex VI, EEDI shall be calculated for each new ship of 400 gross tonnage and above, and it shall be lower than required EEDI. The required EEDI also can be obtained from the MARPOL Annex VI.

The MARPOL Annex VI also includes the concept of Ship Energy Efficiency Management Plan (SEEMP) and related regulations. SEEMP is a management tool for improving the energy efficiency of a ship during its operation lifecycle. SEEMP has a continuous cycle of four steps as Figure 1; planning step, implementation step, monitoring step, and self-evaluation and improvement step. In the planning step, the current status of ship energy usage is checked, and target status is set. In the implementation step, a system for monitoring is established so that the energy efficiency measures can be evaluated. In the monitoring step, data related to the efficiency is collected and analyzed. In the self-evaluation and improvement step, the effectiveness of the implemented measures is evaluated, and improved measures are suggested.

Figure 1 Continuous cycle of SEEMP

According to the MARPOL Annex VI, SEEMP shall be kept on board for each ship of 400 gross tonnage and above. There is no specific reference for verifying SEEMP's content, but its existence on board must be verified (IMO, 2016).

1.2. Energy Efficiency Operational Indicator (EEOI)

In the monitoring step of SEEMP, Energy Efficiency Operational Indicator (EEOI) is applied as the primary monitoring tool for energy efficiency. EEOI, similar to EEDI, represents the amount of CO_2 exhausted by a ship while doing one tonne-mile of transport work, and it means efficient when the value of EEOI is small. However, EEOI represents the actual CO_2 emission during each voyage while EEDI is calculated for one design condition. For EEOI calculation, the actual CO_2 emission is calculated by multiplying the actual fuel consumption for each type of fuel with carbon factor of each fuel. And, the transport work is calculated by multiplying cargo mass and distance traveled of each voyage. Therefore, EEOI can be represented as Equation 2 (IMO, 2016).

$$EEOI = \frac{\sum_i \sum_j F_{ij} \cdot C_j^F}{\sum_i (m_{cargo,i} \cdot D_i)} \qquad \text{Equation 2}$$

In the Equation 2, i is the voyage number, j is the fuel type, F_{ij} is the mass of consumed fuel j at voyage i, C_j^F is the fuel mass to CO_2 mass conversion factor for fuel j, m_{cargo} is cargo carried (tonnes) or work done (number of TEU or passengers) or gross tonnes for

passenger ships, and *D* is the distance in nautical miles corresponding to the cargo carried or work done.

There are no specific requirements for EEOI. However, application of EEOI is recommended by IMO, and scope of use is expanded. EEOI changes during operation as the ship's performance changes. Therefore, EEOI enables ship owners and shipping companies to measure the efficiency of the ship in operation and to decide such as hull cleaning, decommissioning, and order for a new ship. Moreover, EEOI can be used to compare and track the efficiency of ships. In other words, it is possible to use EEOI for marketing and technical development for shipyards.

1.3. EEOI estimation for shipyards

EEOI represents the efficiency of a ship in operation. Therefore, comparing the EEOIs of two similar ships, it is possible to see which ship is more efficient in operation. By tracking the EEOI of a ship for years, it is possible to see how the efficiency of the ship changes over time. For shipyards, the information about EEOI can be used for marketing and technical development. If the EEOI of the ship is low and maintained, the information can be used to advertise. In the opposite case, it contributes to technology development for increasing efficiency of the ship.

Ship owners and shipping companies can use EEOI. However, shipyards hardly use EEOI because it is difficult to obtain the actual operating data such as actual Fuel Oil Consumption (FOC) after delivering ships. Therefore, to use EEOI for shipyards, it is necessary to estimate EEOI using public data only.

The public data available to shipyards includes ship dynamic data, ship static data, and environment data. The ship dynamic data contains position, speed, draft, and others which vary with time and condition. These data can be obtained from Auto Identification System (AIS) data. The ship static data covers principal dimensions, engine specification, and others which are unchanging over time and condition. These data can be obtained from shipyards, engine maker, and research companies. The environment data refers to information of wind, wave, current, etc.

To estimate EEOI using the public data, the values of each variable in the Equation 2, C_j^F, D, m_{cargo}, and F_{ij}, should be estimated one by one using the public data. First, the carbon factor, C_j^F, is fixed value according to fuel type. The values of C_j^F is as follows;

Table 1 Carbon factors for each fuel type (IMO, 2014)

Type of fuel	**Carbon factor**	
Diesel/Gas Oil	3.206	
Light Fuel Oil (LFO)	3.151	
Heavy Fuel Oil (HFO)	3.114	
Liquefied Petroleum Gas (LPG)	Propane	3.000
	Butane	3.030
Liquefied Natural Gas (LNG)	2.750	

The distance traveled by the ship, D can be estimated using real-time position from the ship dynamic data. The distance between two positions of a voyage can be the value of D. The actual cargo mass, m_{cargo} can be obtained using deadweight, design draft from the ship static data and actual draft from the ship dynamic data. The ratio of actual and design draft can be assumed to same with the ratio of actual and design cargo mass. Then, m_{cargo} can be calculated by multiplying the ratio of draft and deadweight as Equation 3.

$$m_{cargo} = \frac{T_{actual}}{T_{design}} \cdot m_{cargo,design} \qquad \text{Equation 3}$$

In the Equation 3, T_{actual} is the actual draft, T_{design} is the design draft, m_{cargo} is the actual cargo mass, and $m_{cargo,\ design}$ is the design cargo mass.

The FOC, F_{ij}, is equal to the product of the SFOC, operation hour, and actual engine power. The SFOC can be obtained from the ship static data. The operation hour can be calculated from the travel time in the ship dynamic data. However, the actual engine power cannot be obtained from the public data. Therefore, a method to estimate actual engine power is necessary, and it is proposed in this study. In the method, the Holtrop-Mennen method (Holtrop et al., 1982) is applied to estimate total resistance, propeller efficiencies, and actual engine power. And, the methods suggested by International Organization for Standardization (ISO)15016:2015 (ISO, 2015) are modified and applied to estimate additional resistance and actual engine power.

1.4. EEOI estimation using public data based on technologies of big data and deep learning

There are two problems to estimate EEOI using the public data. First, it is difficult to use traditional data processing system such as data warehouse and statistics packages because the volume of the public data is too large. The data size of the public data for one year is about 2 Terabyte (TB). Moreover, the accumulated data size for several years reaches dozens of TB. Therefore, using the traditional data processing system may occur errors or long computation time. Second, a lot of computation power is required to estimate EEOI. The EEOI estimation procedure including the proposed method uses various inputs and has many steps. Therefore, it causes a lot of computation time and requires high-performance computers.

In this study, technologies of big data and deep learning were applied to solve the problems. For the first problem, a big data platform was constructed and used for storing and processing the public data. Therefore, it was possible to handle the large size of data fast. For the second problem, a surrogate model was constructed using deep learning. The proposed method was substituted by the surrogate model. Therefore, it was possible to skip many steps of the EEOI estimation procedure and reduce processing time.

Figure 2 shows the overall procedure for EEOI estimation using the public data based on the technologies of big data and deep learning. The public data is used as input data, and EEOI is estimated following the proposed method. A surrogate model is constructed using the input data and the result of the EEOI estimation. Moreover, all procedure is performed based on big data technologies such as Hadoop and Spark. Each detail will be given later.

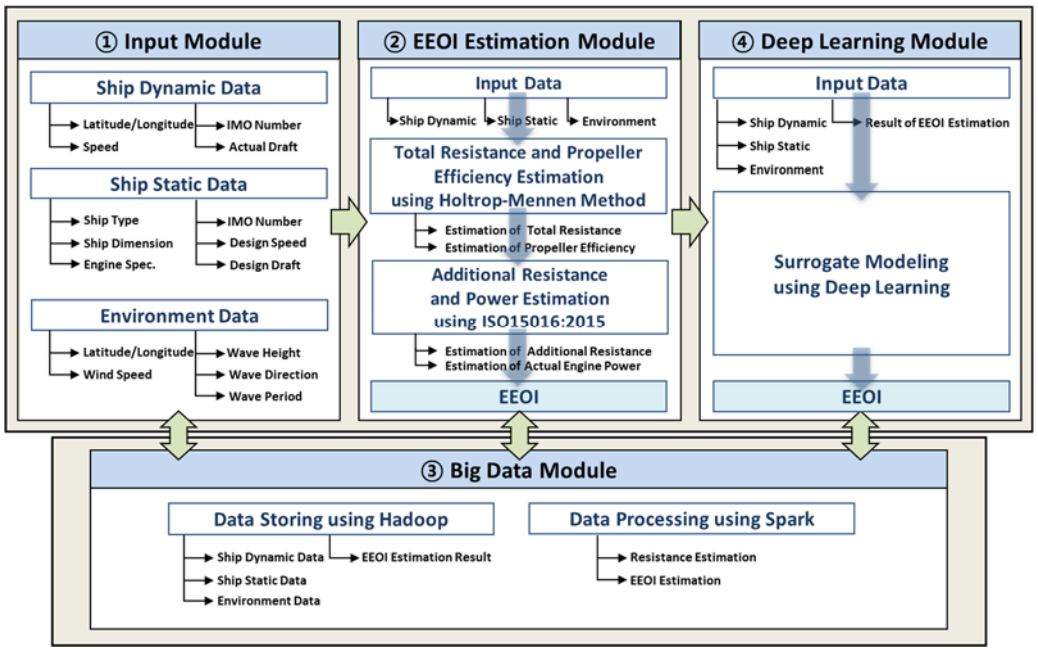

Figure 2 Overall procedure for EEOI estimation

1.5. Related works

As concerns and regulations on environmental protection increase, many studies related to EEOI has been done in the last few years. Even, some studies about EEOI estimation using public data also has been performed. Perez et al. (2009) estimated emission from ships. However, the emission was estimated using actual operating data, and AIS data was used only for calibration. Smith et al. (2013) suggested the method for EEOI estimation using public data. They considered loading condition, hull condition, and actual speed condition. And, the conditions were applied to the EEOI estimation as factors obtained from AIS data and ship specification. However, without taking actual marine environment into consideration, sea margin was assumed to be 15 percent. Chi et al. (2015) proposed an

AIS-based framework for real-time monitoring of ship efficiency. EEOI was estimated in real time based on position and speed from AIS data. However, actual engine power for EEOI estimation was simply assumed to have a cubic relationship with ship speed. Rakke (2016) estimated resistance and actual engine power using Holtrop-Mennen method with AIS data and ship specification. However, marine environment was not considered in the estimation. Wen et al. (2017) estimated EEOI using public data and applied it to green routing. For EEOI estimation, actual engine power is assumed to have a cubic relationship with ship speed, and ship speed was corrected considering wind speed.

As mentioned above, there are some researches about EEOI estimation using public data. Compared to the above studies, this study has several differences. First, EEOI was estimated without operating data, but only with public data. Second, marine environment such as wind, wave, and current, were considered. Third, to reduce computation time, the technologies of big data and deep learning were applied to EEOI estimation. The related studies mentioned above are summarized in Table 2 to be compared with this study.

Table 2 Summary of related studies and its characteristics

Related works	Objective of Research	Input Data	Environment Impact	Big Data	Deep Learning
Perez et al. (2009)	Estimating emission	AIS, actual operating data	Using operating data	X	X
Smith et al. (2013)	Estimating EEOI	AIS, ship and engine data	Assuming sea margin as 10~15%	X	X
Chi et al. (2015)	Real-time monitoring of vessel efficiency	AIS, actual operating data	Using operating data	X	X
Rakke (2016)	Estimating emission using Holtrop-Mennen method	AIS, world fleet, ship and engine data	Assuming sea margin as 15%	X	X
Wen et al. (2017)	Green routing to minimize EEOI	AIS, ship and engine, weather data	Speed correction using wind speed	X	X
This study	**Estimating EEOI based on big data and deep learning**	**AIS, ship and engine, weather data**	**Estimating additional resistance**	**O**	**O**

2. Input data for EEOI estimation

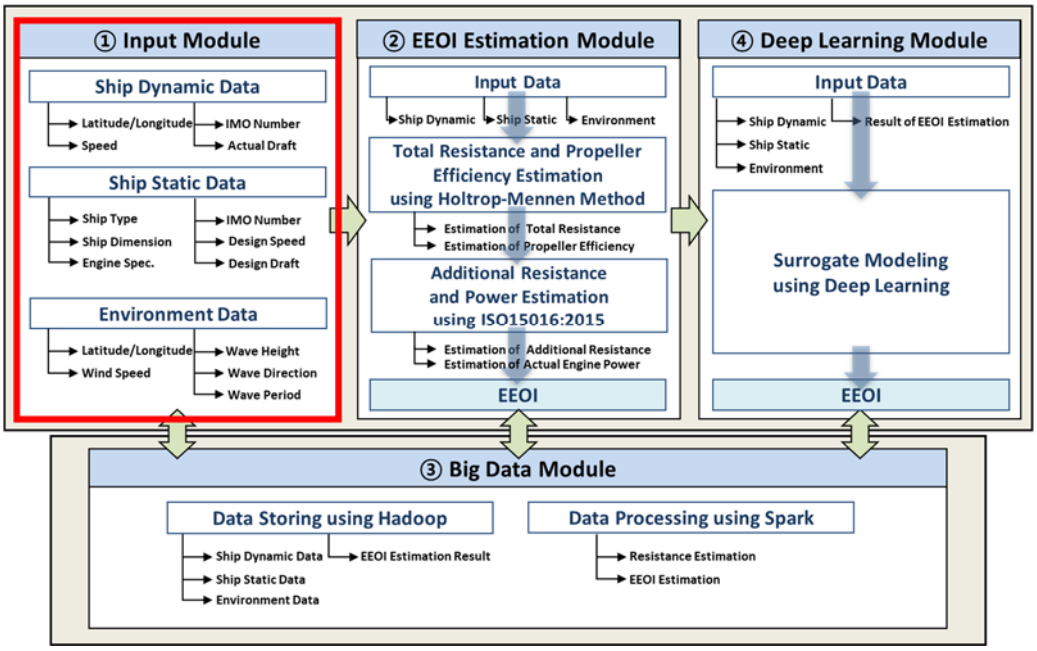

Figure 3 Input module for EEOI estimation

As shown in the Figure 3, the public data was used as input data for EEOI estimation. This chapter describes the input data for EEOI estimation; the ship dynamic data, ship static data, and environment data.

2.1. Ship dynamic data

The ship dynamic data refers the information that changes over time. A Ship travels at different speed and direction over time, and position of the ship changes in real time. Moreover, draft changes depending on loading condition. All these information is included in the ship dynamic data.

2.1.1. Auto Identification System (AIS) data

In the International Convention for the Safety of Life at Sea (SOLAS) Chapter V, regulations relating to AIS were adopted. Due to the regulations, all ship of 300 gross tonnage and upwards shall carry AIS capable of providing information about the ship to other and coastal authorities automatically (IMO, 2002).

The ship dynamic data is obtained from AIS data. AIS is a system that automatically transmits ship operational data. It provides complementary means in the event of a marine accident, and it is used for monitoring operation of ships. AIS sends 27 kinds of messages to satellites which are called Message 1 to 27. The information obtained from the messages is shown in Table 3. And, Figure 4 shows an example of location information for container ships larger than 65,000 gross tonnages, collected using AIS data.

Table 3 Classification of information transmitted/received from AIS base station (Park, 2015)

Contents	Information	Note
Static information	Name, IMO number	The data is input when change occurs.
	Ship type	
	Length, breadth, depth	
	Position of antennas	
Dynamic information	Location, speed, heading angle	The data is input automatically/manually according to ship's sailing status.
	Sailing status	
	Rate of turn, trim	
Voyage information	Draft	The data is input manually periodically before/during voyage.
	Cargo type	
	Destination, arrival time	
	Route planning	
Other information	Voyage/weather alert	.
	Short messages for safety	

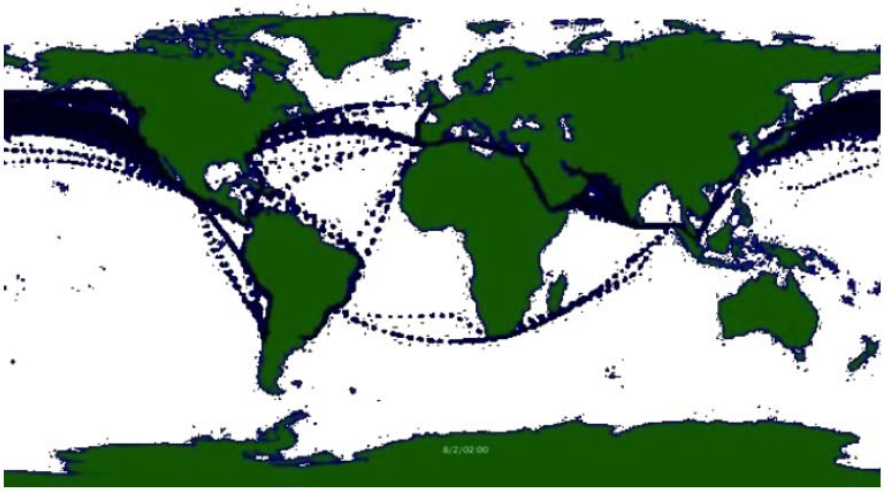

Figure 4 Coverage of container ships greater than 65,000 gross tonnages in August 2011. Black dots indicate messages received from vessel at the reported location (Smith, 2013)

In this study, the Message 1 and 5 were used for the EEOI estimation. The Message 1 includes Maritime Mobile Service Identity (MMSI), time, location, heading angle, speed over ground, etc. And, the Message 5 includes MMSI, International Maritime Organization (IMO) number, time, actual draft, etc.

2.2. Ship static data

The ship static data refers the information which are unchanging over time and condition. Basic information of a ship such as name, type, flag, class does not change once it is set. Principal dimensions which includes length, breadth, depth, deadweight, etc. also do not change after the ship is built. Moreover, engine specification is determined by the engine installed on the ship. All these information is included in the ship static data.

2.2.1. Ship and engine data

In this study, ship and engine data is defined as the ship static data for EEOI estimation. The ship and engine data includes basic ship information, principal dimensions, and engine specification. And, it is obtained from shipyards, engine maker, and research companies.

In this study, the ship and engine data were collected from several sources. And, principal dimensions such as length, breadth, depth, design draft, design speed, etc., and engine specification such as Nominal Maximum Continuous Rating (NMCR), Specific Fuel Oil Consumption (SFOC), etc. were used for the EEOI estimation. Figure 5 shows SFOC curves which is an example for the ship and engine data.

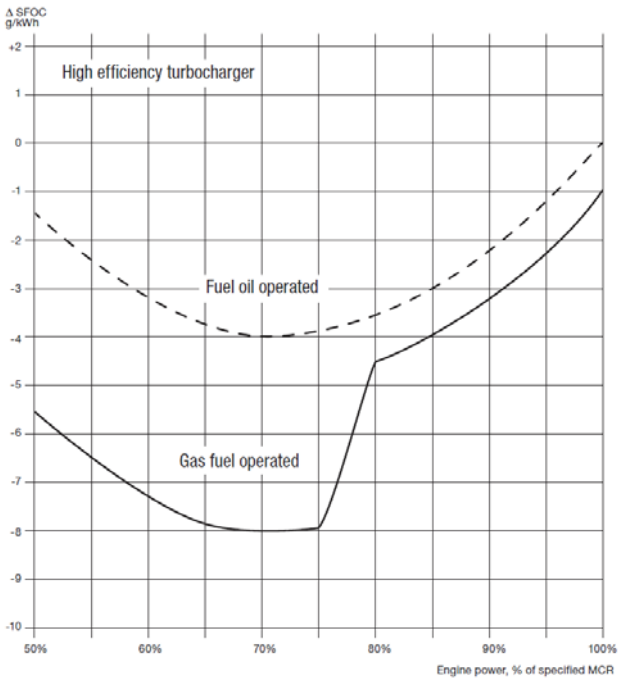

Figure 5 Example of part load SFOC curves for high efficiency turbochargers, valid for fuel oil and gas fuel operation, respectively (MAN B&W, 2014)

2.3. Environment data

To estimate actual engine power of a ship, additional resistance acting on the ship must be estimated. For the additional resistance estimation, the environment data of ship's location is required. The environment data includes sea state such as wave and current, and weather condition such as temperature and wind.

2.3.1. Weather data

In this study, weather data is defined as the environment data for EEOI estimation. The weather data includes information of wind, wave, current, etc. And, it is obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF) and National Oceanic and Atmospheric Administration (NOAA)

The ECMWF is an independent intergovernmental organization supported by 34 European countries which observes and forecasts weather. And, the NOAA is an American scientific agency which focuses on conditions of oceans and atmosphere. They store collected weather data and provide some of them to the public. Figure 6 shows an example of the weather data provided by ECMWF.

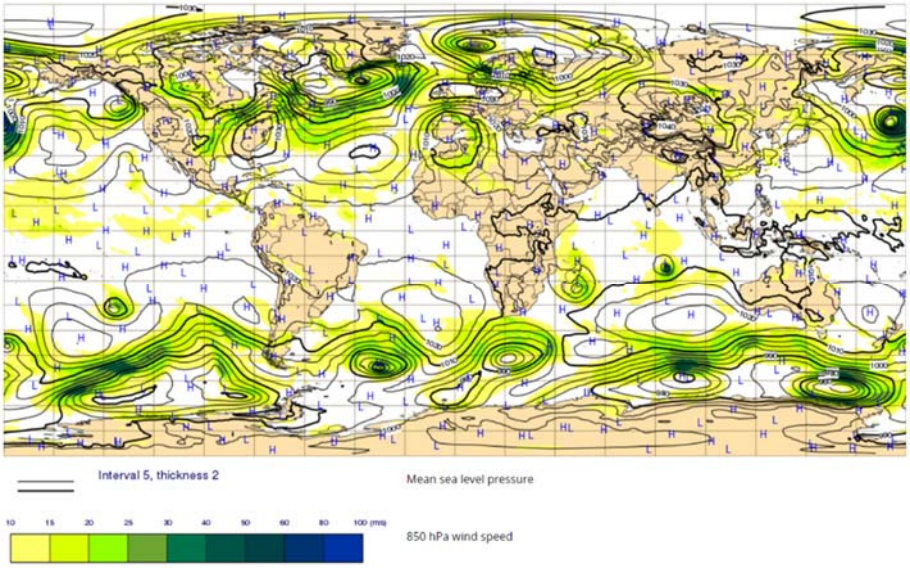

Figure 6 Mean sea level and wind speed at January. 7, 2017 provided by ECMWF

In this study, the weather data about wind, wave, and current was gathered from the ECMWF and NOAA. The weather data about wind includes wind speed and direction. The weather data about wave includes significant wave height, mean wave direction, and mean wave period. And, the weather data about current includes current speed and direction.

2.4. Format and size of input data

To apply the public data to EEOI estimation, it is important to check data type and size of the public data and determine appropriate data processing method. In this study, the AIS data and ship and engine data were pre-processed and used as data type of Comma-Separated Values (CSV). Moreover, size of the one-year data for 5,500 ships is almost 150

Gigabytes (GB). In case of the weather data, it is stored in the form of Network Common Data Form (NetCDF) which is generally used for environment data, and its size is almost 1.2 Terabytes (TB) for one year. Contents in detail, data type, and size of the public data mentioned above are summarized in Table 4.

Table 4 Contents, data type, and size of public data

	AIS data	**Ship and engine data**	**Weather data**
Contents	**Message 1** - Time - MMSI - Latitude / Longitude - Course over ground - Speed over ground - Heading angle **Message 5** - Time - MMSI - IMO number - Departure / Destination - Actual Draft	- IMO number - Ship type - Year built - Length / Beam / Depth - Design draft - Design speed - Specification for main engine - Specification for auxiliary engine - Cargo capacity	- Time - Latitude / Longitude - Wind speed - Wind direction - Significant wave height - Mean wave direction - Mean wave period - Current speed - Current direction
Data type	CSV	CSV	NetCDF
Size	150 GB (for 5,500 ships and 1 year)	20 Megabytes (MB) (for 5,500 ships)	1.2 TB (for 1 year)

2.5. Data mapping for EEOI estimation

All the information required for the EEOI estimation is included in the input data. However, the input data is not stored in a single file, and the scale of the time and location of each input data is not exactly same. Therefore, to use the input data for the EEOI estimation, it is required for mapping each input data. In this study, the input data is mapped based on the Message 1 in the AIS data.

2.5.1. Mapping between Message 1 and Message 5 of AIS data

In order to map the Message 1 and 5, it is necessary to find information of a specific ship in the AIS data. All ships have an MMSI, which is an identification number used for satellite communications. And, MMSI is included in the Message 1 and 5. Therefore, in this study, MMSI in the Message 1 was used to map information in the Message 1 and 5.

Additionally, it is also required to find information of the Message 1 and 5 at the same time. The time scales of the Message 1 and 5 are not constant because they are recorded when there is a change of the ship status. And, it is almost impossible to find information of the Message 1 and 5 at the exactly same time. Therefore, in this study, information of the Message 5 which is measured at the nearest time to information of the Message 1 was used. And, information of the Message 1 was not used if there is no information of Message 5 which has smaller time difference than one hour. It is due to the assumption that the draft in the Message 5 does not change drastically within a short hour.

2.5.2. Mapping between AIS data and ship and engine data

In order to map the AIS data and ship and engine data, it is necessary to find the information of a specific ship in the ship and engine data. All ships have an IMO number under regulation of SOLAS (IMO, 1996). And, the Message 5 of the AIS data and the ship and engine data include IMO numbers. Therefore, in this study, the IMO number of the Message 5 is used to retrieve ship information from the ship and engine data.

2.5.3. Mapping between AIS data and weather data

As shown in Figure 7, the weather data is observed at 0.25° intervals of latitude and longitude. And the time interval of observation is 6 hours.

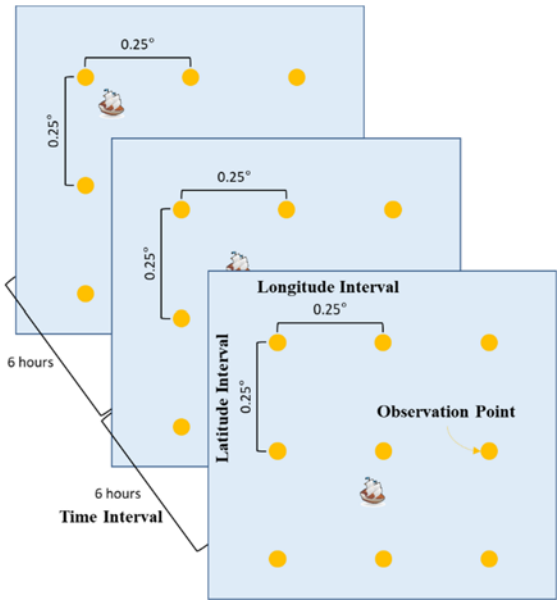

Figure 7 Observation intervals of weather data

Therefore, it is not possible to fully map the AIS data and weather data. In this study, the weather data which has the closest time and location with the AIS data was used. To map between the two data, latitude, longitude, and time information was taken from the Message 1 of the AIS data. Then, the values obtained were compared with the values in the weather data. And, information in the weather data with the nearest values was used for the EEOI estimation.

3. EEOI Estimation

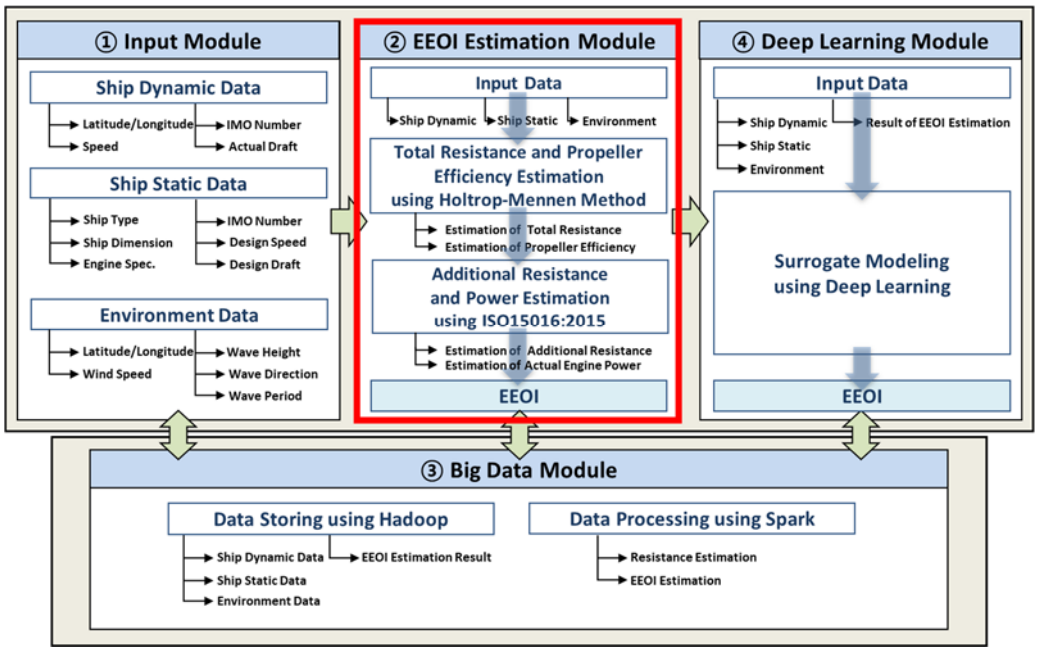

Figure 8 EEOI estimation module for EEOI estimation

As shown in the Figure 8, the proposed method was used for EEOI estimation. This chapter describes the proposed method for EEOI estimation and examines applicability. The proposed method includes speed correction for current, total resistance and propeller efficiency estimation, and additional resistance and actual engine power estimation. The proposed method was applied to data of a reference ship for verification.

3.1. Overall procedure for EEOI estimation

As mentioned, EEOI can be calculated using FOC, carbon factor, cargo mass, and distance. Since FOC is not provided to the public, the most important process is to estimate FOC for EEOI estimation. Moreover, actual engine power is a key factor for estimation because FOC can be calculated with actual engine power, SFOC, and operating hour. Actual engine power can be estimated from resistance acting on a ship and propeller efficiencies. In this study, the resistance was divided into total resistance due to shape and movement of the ship, and additional resistance due to environment condition.

For the EEOI estimation, the total resistance was estimated using the Holtrop-Mennen method. And, the additional resistance was obtained following the ISO15016:2015. Then, the actual engine power was estimated using the Holtrop-Mennen method and modified Direct Power Method (DPM) in the ISO15016:2015.

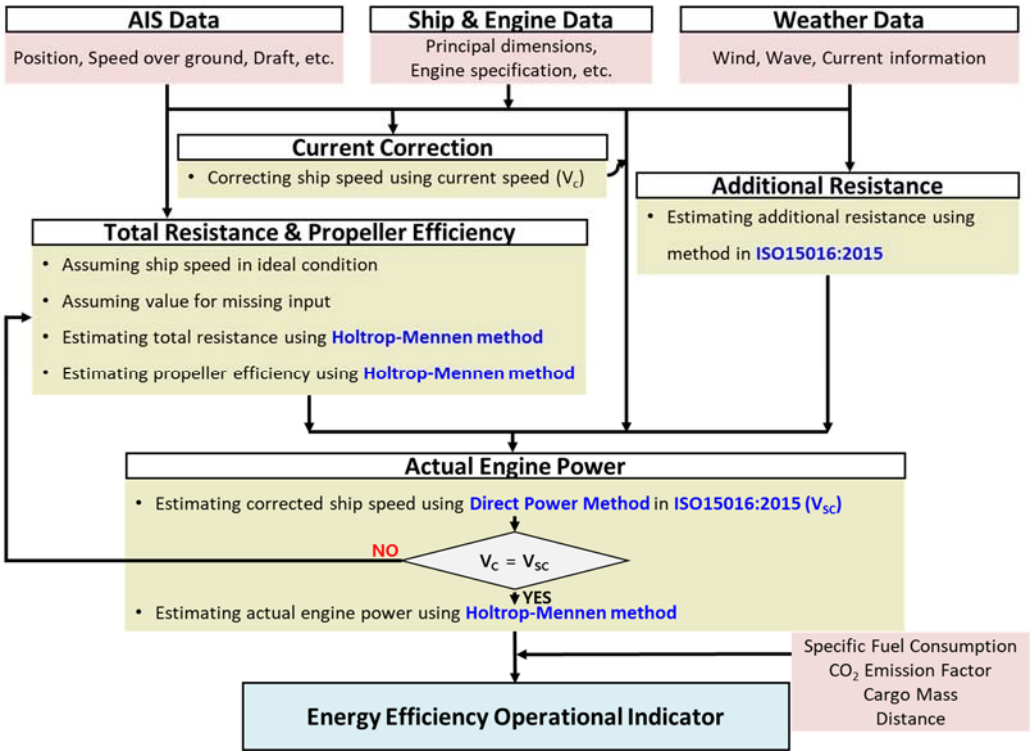

Figure 9 Overall procedure for EEOI estimation

The detailed procedure for EEOI estimation is shown in the Figure 9. The AIS, ship and engine, and weather data is used as input data. Current speed is removed directly from speed over ground. Using the input data and assumed ship speed in ideal condition, total resistance and propeller efficiencies are estimated. And, additional resistance is estimated following the ISO15016:2015. Then, the ship speed in ideal condition is corrected following and modifying the Direct Power Method (DPM) in the ISO15016:2015. In the DPM, the estimated total resistance, propeller efficiencies, and additional resistance are used, and speed changed by the weather condition is derived. The speed obtained by the DPM is compared to the ship speed corrected using the current speed. If they are different,

the ship speed in ideal condition is changed and total resistance and propeller efficiencies are estimated again. When they have same value, actual engine power is estimated using the assumed ship speed in ideal condition with the Holtrop-Mennen method. In other words, if the ship uses the estimated engine power, it travels at the assumed speed in ideal condition, and corrected speed using the DPM in actual environment condition. Lastly, after the actual engine power is estimated, EEOI is calculated using SFOC, CO_2 emission factor, cargo mass, and distance.

3.2. Current correction

The AIS data includes speed over ground. It is not possible to estimate actual engine power using speed over ground directly because a ship is affected by current. Therefore, speed over ground was corrected using current speed in this study. For the speed correction, speed over ground and heading angle in the AIS data and u and v components of current velocity in the weather data were used. In this study, u is velocity in the east direction and v is velocity in the north direction.

The corrected speed was calculated as sum of the velocities of the ship and current. The u and v components of the ship were obtained using the speed over ground and heading angle. Since the heading angle in the north direction is 0, the components were obtained by Equation 4 and Equation 5.

$$u_{ship} = \text{Ship Speed} \cdot \sin(\text{Heading Angle})$$ Equation 4

$$v_{ship} = \text{Ship Speed} \cdot \cos(\text{Heading Angle})$$ Equation 5

In the Equation 4 and Equation 5, u_{ship} and v_{ship} are the u component and v component of the ship velocity.

Then, the corrected speed of the ship was calculated by Equation 6

$$V_C = \sqrt{(u_{ship} - u_{current})^2 + (v_{ship} - v_{current})^2}$$ Equation 6

In the Equation 6, V_C is the speed corrected using the current speed, and $u_{current}$ and $v_{current}$ are the u component and v component of the current velocity.

3.3. Total resistance and propeller efficiency estimation

In this study, the total resistance and propeller efficiencies were estimated for the EEOI estimation. And, the Holtrop-Mennen method was used for the estimation. Almost of the inputs required to use the Holtrop-Mennen method were obtained from the AIS data and ship and engine data. And, the missing information was estimated using assumptions of other studies.

3.3.1. Total resistance and propeller efficiency estimation using Holtrop-Mennen method

The Holtrop-Mennen method provides formulas for estimating resistance and propeller efficiencies which are derived by regression analysis based on model test. In this method, total resistance of a ship is divided into six components; frictional resistance, appendage resistance, wave resistance, additional pressure resistance of bulbous bow near the water surface, additional pressure resistance due to immersed transom immersion, and model-ship correlation resistance. And, it can be expressed as Equation 7.

$$R_T = R_F(1+k_1) + R_{APP} + R_W + R_B + R_{TR} + R_A \qquad \text{Equation 7}$$

In the Equation 7, R_T is the total resistance, R_F is the frictional resistance, k_1 is the form factor of the hull, R_{APP} is the appendage resistance, R_W is the wave resistance, R_B is the additional pressure resistance of bulbous bow near the water surface, R_{TR} is the additional pressure resistance due to immersed transom immersion, and R_A is the model-ship correlation resistance.

And, formulas for each component are provided as Equation 8 to Equation 14.

$$R_F = 1/2\rho V^2 C_F S_{bh} \qquad \text{Equation 8}$$

In the Equation 8, ρ is the density of the sea, V is the ship speed, C_F is the coefficient of frictional resistance, and S_{bh} is the wetted surface area of the bare hull

$$\begin{aligned} 1 + k_1 = 0.93 + 0.487118 \cdot C_{14} \cdot (B/L)^{1.06806} \cdot (T/L)^{0.46106} \\ \times (L/L_R)^{0.121563} \cdot (L^3/\nabla)^{0.36486} \cdot (1 - C_P)^{-0.60247} \end{aligned} \qquad \text{Equation 9}$$

In the Equation 9, C_{14} is the prismatic coefficient based on the waterline length, B is the breadth of the ship, L is the waterline length, T is the draft of the ship, L_R is the length of run, ∇ is the displacement volume of the ship, and C_P is the prismatic coefficient of the ship.

$$R_{APP} = 1/2\rho V^2 S_{APP}(1+k_2)_{Eq} C_F$$ Equation 10

In the Equation 10, S_{APP} is the wetted area of the appendages, and k_2 is the appendage resistance factor.

$$R_W = \rho g \nabla C_1 C_2 C_5 \exp\{m_1 Fr^d + m_4 \cos(\lambda Fr^{-2})\}$$ Equation 11

In the Equation 11, g is the gravitational acceleration, Fr is the Froude number, and the other variables are coefficient for wave resistance.

$$R_B = 0.11 e^{(-3P_B^{-2})} \cdot Fr^3 A_{BT}^{1.5} \rho g / (1+Fr_i^2)$$ Equation 12

In the Equation 12, P_B is the measure for the emergence of the bow, A_{BT} is the cross-sectional area at the fore perpendicular, and Fr_i is the Froude number based on immersion of bulbous bow.

$$R_{TR} = 1/2\rho V^2 A_T C_6$$ Equation 13

In the Equation 13, A_T is the transom area under the waterline, and C_6 is the coefficient for additional pressure resistance of immersed transom immersion.

$$R_A = 1/2\rho V^2 S_{Total} C_A$$ Equation 14

In the Equation 14, S_{total} is the total wetted area of the ship, and C_A is the coefficient for model-ship correlation resistance.

Also, in the Holtrop-Mennen method, formulas for propeller efficiencies such as relative rotative efficiency and hull efficiency are provided as Equation 15 and Equation 16

$$\eta_R = 0.9922 - 0.05908 A_E / A_O + 0.07424(C_P - 0.0225 LCB)$$ Equation 15

In the Equation 15, η_R is the relative rotative efficiency, A_E/A_O is the propeller expanded area ratio, and *LCB* is the longitudinal center of buoyancy.

$$\eta_H = \frac{1-t}{1-w}, \qquad \text{Equation 16}$$

In the Equation 16, η_H is the hull efficiency, t is the thrust deduction fraction, and w is the wake fraction.

Moreover, the Holtrop-Mennen method provides detailed formulas for estimating each coefficient and variables in the formulas above. However, the detailed formulas are omitted in this study.

3.3.2. Input for total resistance and propeller efficiency estimation

In this study, the total resistance and propeller efficiencies were estimated using the AIS and ship and engine data with the Holtrop-Mennen method. For using the Holtrop-Mennen method, a lot of inputs are required. For example, ship principal dimensions such as length, breadth, depth, and design draft, engine specification such as Maximum Continuous Rating (MCR) and engine revolution per second at MCR, ship operational condition such as actual draft are used. Almost of the inputs can be obtained from the AIS and ship and engine data. However, there are some inputs that cannot be obtained from the data. Table 5 shows the inputs and data source.

Table 5 Input for total resistance and propeller efficiency estimation

Data Source	Input
Common information	g, ρ_{sea}, ρ_{air}, ν_{sea}
AIS data	T_{actual}
Ship and engine data	LBP, B, V_{design}, T_{design}, D, DWT, MCR, n_{MCR}
Missing information	LWL, C_B, C_M, C_{WP}, LCB, A_{BTt}, A_T

In the Table 5, ρ_{air} is the density of air, ν_{sea} is the kinematic viscosity of sea water, T_{actual} is the actual draft of the ship, LBP is the Length Between Perpendiculars, B is the breadth, T_{design} is the design draft, D is the depth of the ship, DWT is the deadweight, n_{MCR} is the engine revolution per second, LWL is the Load Waterline Length, C_B is the block coefficient, C_M is the midship section coefficient, C_{WP} is the water plane coefficient, and A_M is the midship section area.

In the Table 5, the common information and the missing information cannot be obtained from the AIS and ship and engine data. Therefore, in this study, the common information was assumed to have constant value. The gravitational acceleration, g, is 9.8 m/s^2, the density of the sea, ρ_{sea}, is 1.025 ton/m^3, the density of the air, ρ_{air}, is 0.0012 ton/m^3, and the kinematic viscosity, ν_{sea}, is 0.00000118 m^2/s.

Moreover, the missing information was estimated using AIS and ship and engine data, referring to related studies. The formulas used to estimate the missing information are explained below.

(1) *LWL*

The Load Waterline Length, *LWL*, was estimated using *LBP* in the ship and engine data following Equation 17 (Smith et al, 2013).

$$LWL = LBP / 0.97 \qquad \text{Equation 17}$$

(2) C_B, C_M, and C_{WP}

The block coefficient, C_B, was assumed to have a relationship with the Froude number as Equation 18 (Jensen, 1994).

$$C_B = -4.22 + 27.8 \cdot \sqrt{Fr} - 39.1 \cdot Fr + 46.6 \cdot Fr^3 \qquad \text{Equation 18}$$

The midship section coefficient, C_M, was assumed to be relevant to the block coefficient as Equation 19, (Benford, 1963)

$$C_M = 0.977 + 0.085 \cdot (C_B - 0.60) \qquad \text{Equation 19}$$

The water plane coefficient, C_{WP}, was also assumed to have a relationship with the block coefficient as Equation 20, (Schneekluth, 1987)

$$C_{WP} = (1.0 + 2.0 \cdot C_B) / 3.0 \qquad \text{Equation 20}$$

(3) A_{bt}, and A_t

The cross-sectional area at the fore perpendicular, A_{BT}, was assumed to 8 percent of the midship section area, A_M as Equation 21 (Charchalis, 2013).

$$A_{BT} = 0.08 \cdot A_M \qquad \text{Equation 21}$$

And, the transom area under the waterline, A_T, was also assumed to relevant to the midship section area as Equation 22 (Rakke, 2016).

$$A_T = 0.051 \cdot A_M \qquad \text{Equation 22}$$

3.3.3. Total resistance and propeller efficiency estimation for EEOI estimation

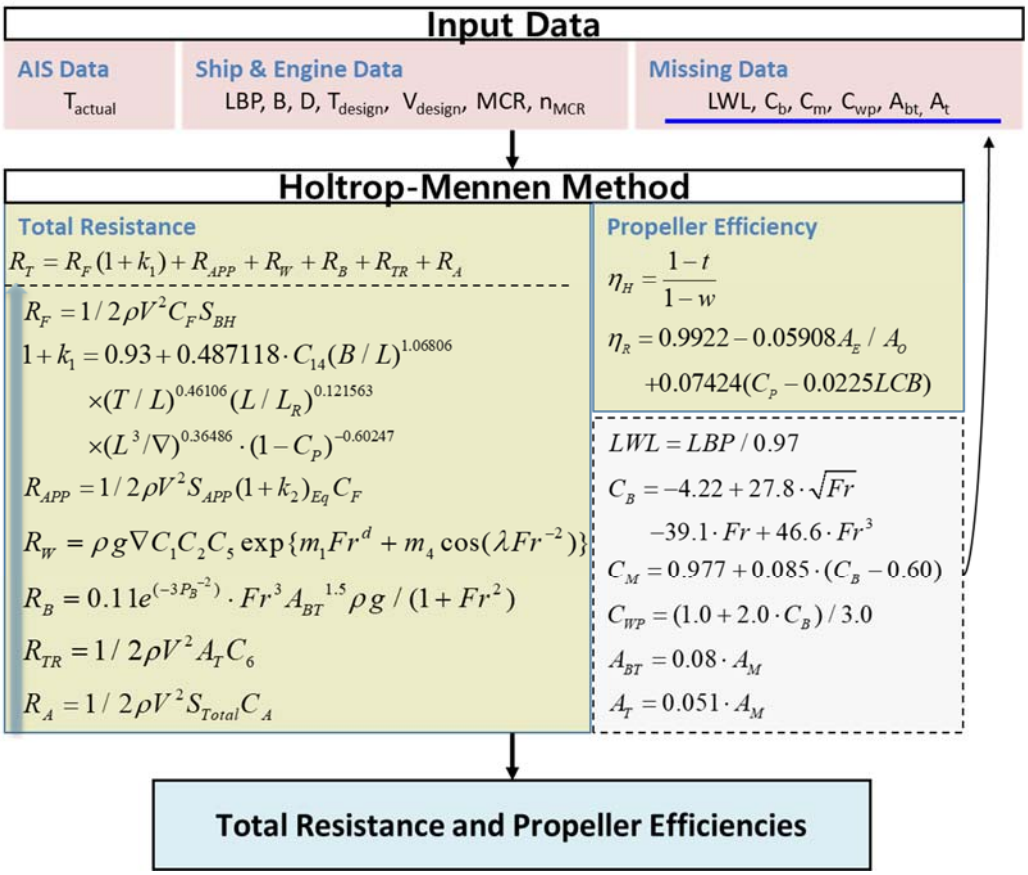

Figure 10 Procedure for total resistance and propeller efficiency estimation

Figure 10 shows the procedure for total resistance and propeller efficiency estimation which is described above. In this study, for the EEOI estimation, ship speed in ideal condition was assumed, and total resistance and propeller efficiencies were estimated

following the procedure. The estimated total resistance and propeller efficiencies were used in the DPM to be explained later.

3.4. Additional resistance estimation

In this study, additional resistance was estimated for the EEOI estimation. And, procedure for the estimation was performed following the ISO15016:2015. All inputs required for following the ISO10516:2015 were obtained from the AIS data, ship and engine data, and weather data. Moreover, the estimated information in the procedure for total resistance and propeller efficiency estimation was also used.

3.4.1. Additional resistance estimation following ISO15016

The ISO15016:2015 is a proposed international standard whose purpose is to estimate a ship performance within calm water. The ship performance can be estimated by excluding external effects caused by weather on measured performance in trial test. And, the ISO15016:2015 provides methods for estimating additional resistance to measure the effect of the weather.

In the ISO15016:2015, as Equation 23, additional resistance is divided into three components; resistance due to wind, resistance due to wave, and resistance due to water temperature and density.

$$\Delta R = R_{AA} + R_{AW} + R_{AS}$$ Equation 23

In the Equation 23, ΔR is the total increased amount of resistance, R_{AA} is the resistance increase due to relative wind, R_{AW} is the resistance increase due to wave, and R_{AS} is the resistance increase due to water temperature and density.

Method and formulas for calculating each resistance are explained below. However, the resistance due to water temperature and density is omitted because of its small value.

(1) Resistance due to wind

In the ISO15016:2015, the resistance due to wind is calculated by:

$$R_{AA} = 0.5 \cdot \rho_{air} \cdot C_{AA}(\psi_{WRref}) \cdot A_{XV} \cdot V_{WRef}{}^{2} - 0.5 \cdot \rho_{air} \cdot C_{AA}(0) \cdot A_{XV} \cdot V_{G}{}^{2}$$ Equation 24

In the Equation 24, C_{AA} is the wind resistance coefficient; $C_{AA}(0)$ means the wind resistance coefficient in head wind, ψ_{WRef} is the relative wind direction at the reference height, A_{XV} is the transverse projected area above the waterline including superstructures, V_{WRef} is the relative wind velocity at the reference height, and V_G is the measured ship's speed over ground.

In the ISO15016:2015, the data set of the wind resistance coefficient, C_{AA}, is provided. Figure 11 shows as an example for LNG carrier where $C_{AA} = -C_X$. Moreover, other inputs in the Equation 24 can be obtained from the public data.

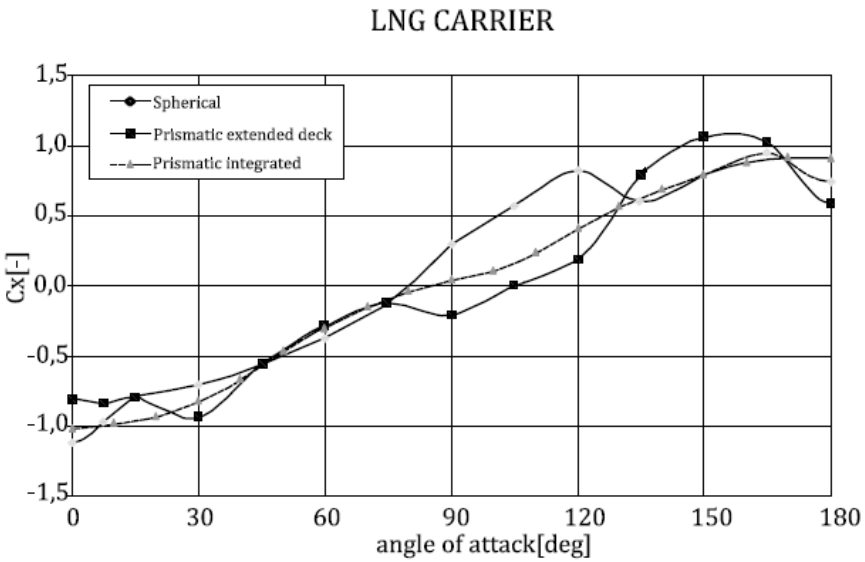

Figure 11 Wind resistance coefficient for

(2) Resistance due to wave

There are four methods for estimating resistance due to wave; STAWAVE-I, STAWAVE-II, theoretical method with simplified tank test with short waves, and seakeeping model tests. In this study, the resistance due to wind was estimated using the STAWAVE-I and STAWAVE-II. The STAWAVE-II was used basically, and the STAWAVE-I was used when restrictions of the STAWAVE-II were violated. The formulas and the restrictions are as follows;

① STAWAVE-II

In the STAWAVE-II, as Equation 25, the resistance due to wave is divided into two components; motion induced resistance and mean resistance due to wave reflection.

$$R_{AW} = R_{AWML} + R_{AWRL} \qquad \text{Equation 25}$$

In the Equation 25, R_{AWML} is the motion induced resistance, and R_{AWRL} is the mean resistance due to wave reflection. And, the formulas for each component are as follow;

$$R_{AWML} = 4\rho_{sea} g \zeta_A{}^2 \frac{B^2}{LBP} \overline{r_{aw}}(\omega) \qquad \text{Equation 26}$$

$$R_{AWRL} = \frac{1}{2} \rho_{sea} g \zeta_A{}^2 B \alpha_1(\omega) \qquad \text{Equation 27}$$

In the Equation 26 and Equation 27, ζ_A is the wave amplitude. $\overline{r_{aw}}(\omega)$ and $\alpha_1(\omega)$ are the function of ω which are explained in detail in the ISO15016:2015.

Moreover, the STAWAVE-II is applicable to the mean resistance increase in long crested irregular head waves as Equation 28.

$$R_{AWL} = 2\int_0^{\infty} \frac{R_{AW}(\omega;V_G)}{\zeta_A^{\ 2}} S_\eta(\omega) d\omega$$ Equation 28

In the Equation 28, R_{AWL}, is the mean resistance increase in long crested irregular waves, as substitute R_{AW}, and S_η is the frequency spectrum for wind waves modified Pierson-Moskowitz type.

The STAWAVE-II is available under following conditions;

$$75(m) < LBP$$ Equation 29

$$4.0 < \frac{LBP}{B} < 9.0$$ Equation 30

$$2.2 < \frac{B}{T} < 9.0$$ Equation 31

$$0.1 < Fr < 0.3$$ Equation 32

$$0.5 < C_b < 0.9$$ Equation 33

$$\text{wave direction} \leq \pm 45$$ Equation 34

In the Equation 34, wave direction is assumed to zero when wave comes from ahead to a ship. Moreover, wave direction has positive values on the starboard side of the ship and negative values on the port side.

In this study, the STAWAVE-II was used for estimating resistance due to wave basically, and the STAWAVE-I was used when the conditions of the Equation 29 to Equation 33 were violated. For the condition of the Equation 34, a factor calibrating the resistance due to wave was applied as Equation 35.

$$R_{AWL,corrected} = factor_{wave} \cdot R_{AWL}$$ Equation 35

In the Equation 35, $R_{AWL,corrected}$ is the resistance due to wind corrected by the factor, and $factor_{wave}$ is the factor for calibrating the resistance due to wind.

The factor was created using actual data from a container ship of 4,600 Twenty-foot Equivalent Unit (TEU). And, the factor is a function of wave direction as Equation 36.

$$factor_{wave} = 1.0148 - 0.0001 \cdot \text{wave direction} \qquad \text{Equation 36}$$

② STAWAVE-I

In the STAWAVE-I, the resistance due to wave is expressed as Equation 37.

$$R_{AWL} = \frac{1}{16} \rho_{sea} g H_{1/3}{}^{2} B \sqrt{\frac{B}{L_{BWL}}} \qquad \text{Equation 37}$$

In the Equation 37, $H_{1/3}$ is the significant wave height, and L_{BWL} is the distance of the bow to 95 % of maximum breadth on the waterline.

And, the STAWAVE-I is available under following conditions;

$$H_{1/3} \leq 2.25\sqrt{LBP/100} \qquad \text{Equation 38}$$

$$\text{Vertical acceleration at bow} < 0.05g \qquad \text{Equation 39}$$

$$\text{wave direction} \leq \pm 45 \qquad \text{Equation 40}$$

In this study, if the STAWAVE-I was to be used, the conditions of the Equation 38 and Equation 39 were checked. And, EEOI estimation was not performed when the conditions were violated. For the condition of the Equation 40, the factor in the Equation 36 also applied to the resistance due to wave.

3.4.2. Input for additional resistance estimation

In this study, the additional resistance estimated following ISO15016:2015 using the public data and the estimated information in the total resistance and propeller efficiency estimation. For following the ISO10516:2015, a lot of inputs are required. For example, ship principal dimension such as length, breadth, depth, and design draft, ship operational condition such as speed over ground and design draft, weather information such as wind speed and direction are used. Table 6 shows the inputs and data source.

Table 6 Input for additional resistance estimation

Data Source	Input
Common information	g, ρ_{sea}, ρ_{air}, v_{sea}
AIS data	V_G, T_{actual}
Ship and engine data	LBP, B, V_{design}, T_{design}, D, DWT
Weather data	u_{wind}, v_{wind}, $H_{1/3}$, *Wave direction*, T_{wave}
Estimated information	LWL, C_B, C_M

In the Table 6, u_{wind} is the wind velocity to the East, v_{wind} is the wind velocity to the North, and, T_{wave} is the mean wave period.

3.4.3. Additional resistance estimation for EEOI estimation

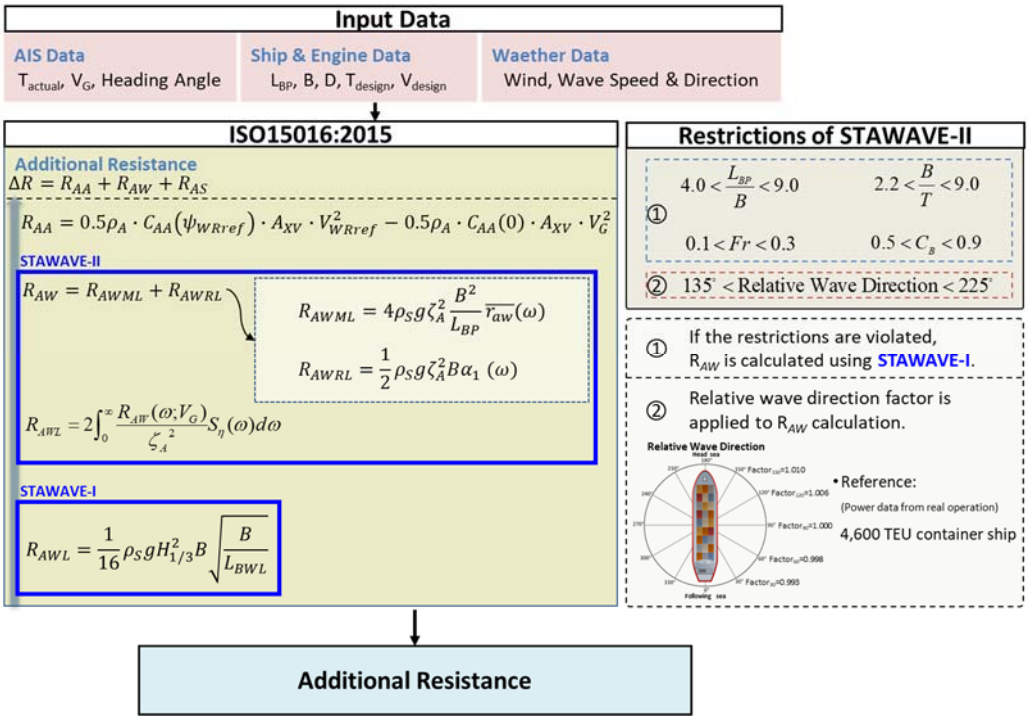

Figure 12 Procedure for additional resistance estimation

Figure 12 shows the procedure for additional resistance estimation which is described above. In this study, additional resistance was estimated following the procedure for the EEOI estimation. The estimated additional resistance was used in the DPM to be explained later.

3.5. Actual engine power estimation

In this study, actual engine power was estimated for EEOI estimation. The DPM was modified and applied to estimate speed changed by the weather, and the Holtrop-Mennen method was applied to estimate actual engine power. Almost of the inputs required for the engine power estimation were obtained from the AIS data, and ship and engine data. Moreover, the result of the total resistance, propeller efficiencies, and additional resistance estimation were also used.

3.5.1. Actual engine power estimation using modified DPM and Holtrop-Mennen method

In the ISO15016:2015, engine power in ideal condition is estimated using the DPM. The DPM estimates the engine power in ideal condition by removing the effects of environment condition from the measured engine power following procedure shown in Figure 13.

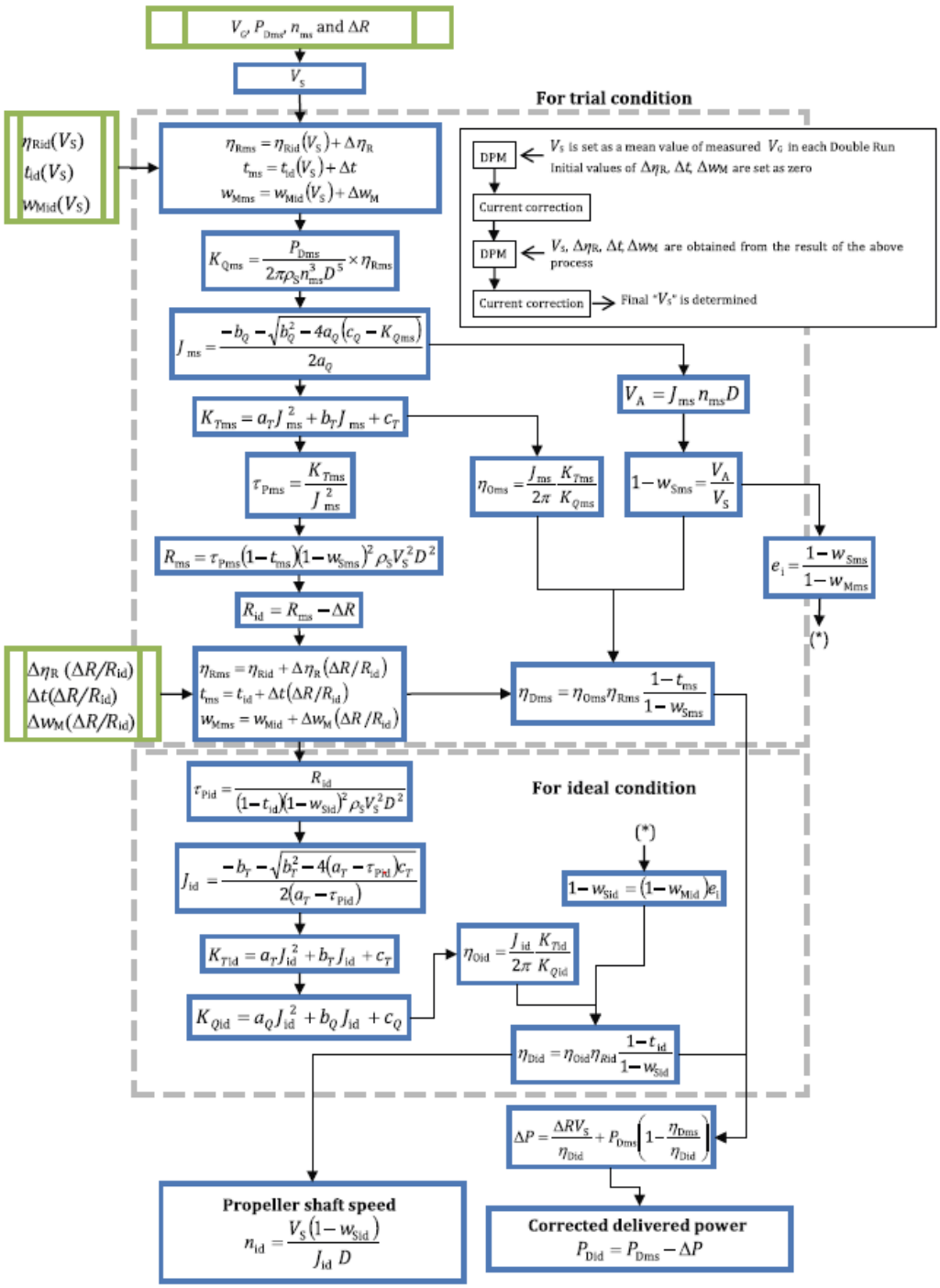

Figure 13 Flow chart of evaluation based on Direct Power Method (ISO, 2015)

In the Figure 13, η_O is the propeller efficiency in open water, η_D is the propulsive efficiency, P_D is the delivered power, K_T is the thrust coefficient, K_Q is the torque coefficient, n is the propeller revolution per second, V_A is the speed of advance, J is the propeller advance ratio, τ_P is the load factor, a_T, b_T, and c_T are the factors for the thrust coefficient curve, a_Q, b_Q, and c_Q are the factors for the thrust coefficient curve and '*id*' and '*ms*' subscripted below mean ideal condition and trial condition respectively.

However, in this study, there was no measured power data, and the purpose was to estimate actual engine power under the environment condition. Therefore, the procedure of the DPM was modified in reverse order and the Holtrop-Mennen method was applied to estimate actual engine power. In the estimation procedure, ship speed in ideal condition is assumed, and total resistance, propeller efficiencies, and additional resistance in ideal condition are used as inputs. Load factor is calculated by taking into consideration environment condition. Then, propeller advance ratio is calculated using the load factor. And, corrected ship speed is calculated using the propeller efficiencies. Lastly, actual engine power is calculated following the Holtrop-Mennen method when the corrected ship speed is equal to the ship speed corrected by current.

To explain the procedure in detail, the propeller advance ratio in ideal condition is first obtained using Equation 41.

$$J_0 = \frac{V_{id}(1-w)}{n \cdot D_P} \qquad \text{Equation 41}$$

In the Equation 41, V_{id} is the assumed ship speed in ideal condition, and J_0 is the propeller advance ratio in ideal condition.

Then, factors for the thrust and torque coefficient curve are obtained by fitting to quadratic equations as Equation 42 and Equation 43.

$$K_{T,0} = a_T J_0^{\ 2} + b_T J_0 + c_T \qquad \text{Equation 42}$$

$$K_{Q,0} = a_Q J_0^{\ 2} + b_Q J_0 + c_Q \qquad \text{Equation 43}$$

In the Equation 42 and Equation 43, $K_{T,0}$ is the torque coefficient for ideal condition, and $K_{Q,0}$ is the torque coefficient for ideal condition.

The load factor for operating condition considering weather is estimated using Equation 44.

$$\tau_{op} = \frac{R_T + \Delta R}{(1-t)(1-w)^2 \rho_{sea} V_{id}^{\ 2} D_P^{\ 2}} \qquad \text{Equation 44}$$

In the Equation 44, τ_{op} is the load factor for operating condition.

And, propeller advance coefficient for operating condition is calculated with the load factor and factors for the thrust and torque coefficient curve using Equation 45.

$$J_1 = \frac{-b_T - \sqrt{b_T{}^2 - 4(a_T - \tau_{op})c_T}}{2(a_T - \tau_{op})} \qquad \text{Equation 45}$$

Then, ship speed changed by the weather is calculated using Equation 46.

$$V_{SC} = \frac{nJ_1 D_P}{(1-w)} \qquad \text{Equation 46}$$

In the Equation 46, V_{SC} is the ship speed changed by the weather.

When the ship speed changed by the weather is equal to the ship speed corrected by current, the actual engine power is calculated using Equation 47.

$$P_D = \frac{R_T \cdot V_{id}}{\eta_D} \qquad \text{Equation 47}$$

In the Equation 47, P_D is the actual delivered engine power, and η_D is the propulsive efficiency in ideal condition. The propulsive efficiency, η_D ,can be calculated using Equation 48.

$$\eta_D = \eta_O \eta_R \eta_H \qquad \text{Equation 48}$$

In the Equation 48, η_O is the propeller efficiency in open water for ideal condition and can be calculated using Equation 49.

$$\eta_O = \frac{J_0}{2\pi} \frac{K_{T,0}}{K_{Q,0}} \qquad \text{Equation 49}$$

3.5.2. Input for actual engine power estimation

In this study, the actual engine power was estimated following the modified DPM and Holtrop-Mennen method using the public data and the estimated information in the total resistance, propeller efficiency estimation, and additional resistance estimation. For following the modified DPM and Holtrop-Mennen method, some inputs are required. For example, estimated value such as total resistance, propeller efficiencies, and additional resistance, and ship operational condition such as ship speed corrected by current are used. Table 7 shows the inputs and the data source.

Table 7 Input for engine power estimation

Data Source	Variable
Assumed information	V_{id}
Estimated information	V_C, R_T, ΔR , w, t, η_R , η_H
Missing information	n, $K_{T,0}$, $K_{Q,0}$

As shown in the Table 7, almost of the inputs can be obtained from the previous estimation procedures. However, some missing information cannot be obtained or estimated from the public data using the modified DPM and Holtrop-Mennen method. Therefore, in this study, the missing information was calculated based on several assumptions. The method used to estimate the missing variables are explained below.

(1) *n*

To find the propeller revolution per second at actual speed, the exact relation between the ship speed and propeller revolution per second is required. However, because of insufficient information, the propeller revolution per second was simply assumed to have linear relationship with the ship speed in this study. And, the coefficient for the relation was assumed to equal to ratio of revolution per second at MCR and design speed of ship. It can be expressed as Equation 50.

$$n = n_{MCR} \cdot \frac{V_C}{V_{Design}}$$ Equation 50

(2) $K_{T,0}$ and $K_{Q,0}$

The propeller thrust coefficient and torque coefficient depend on propeller type. In this study, the propeller was assumed to the Wageningen B-screw series. And, the coefficients were calculated using approximation formula as Equation 51 (Barnitsas et al., 1981).

$$K_{T,0} \text{ and } K_{Q,0} = \sum C_{s,t,u,v} (J_0)^s (P_i / D_P)^t (A_E / A_O)^u z^v$$ Equation 51

In the Equation 51, P_i is the propeller pitch which can be calculated following Equation 52, and z is the number of propeller blades which can be obtained from the public data. And $C_{s,t,u,v}$, s, t, u, and v can be obtained from Table 8.

$$P_i = \frac{V_C}{n}$$ Equation 52

Table 8 coefficients and terms of the K_T and K_Q polynomials for the Wageningen B-screw series for Reynolds number $= 2\times10^6$ (Barnitsas et al., 1981)

K_T					K_Q				
$C_{s,t,u,v}$	s	t	u	v	$C_{s,t,u,v}$	s	t	u	v
+0.00880496	0	0	0	0	+0.00379368	0	0	0	0
-0.204554	1	0	0	0	+0.00886523	2	0	0	0
+0.166351	0	1	0	0	-0.032241	1	1	0	0
+0.158114	0	2	0	0	+0.00344778	0	2	0	0
-0.147581	2	0	1	0	-0.0408811	0	1	1	0
-0.481497	1	1	1	0	-0.108009	1	1	1	0
+0.415437	0	2	1	0	-0.0885381	2	1	1	0
+0.0144043	0	0	0	1	+0.188561	0	2	1	0
-0.0530054	2	0	0	1	-0.00370871	1	0	0	1
+0.0143481	0		0	1	+0.00513696	0	1	0	1
0.0606826	1	1	0	1	0.0209449	1	1	0	1
-0.0125894	0	0	1	1	+0.00474319	2	1	0	1
+0.0109689	1	0	1	1	-0.00723408	2	0	1	1
-0.133698	0	3	0	0	+0.00438388	1	1	1	1
+0.00638407	0	6	0	0	-0.0269403	0	2	1	1
-0.00132718	2	6	0	0	+0.0558082	3	0	1	0
+0.0168496	3	0	1	0	+0.0161886	0	3	1	0
-0.0507214	0	0	2	0	+0.00318086	1	3	1	0
+0.0854559	2	0	2	0	+0.015896	0	0	2	0
-0.0504475	3	0	2	0	+0.0471729	1	0	2	0
+0.010465	1	6	2	0	+0.0196283	3	0	2	0
-0.00648272	2	6	2	0	-0.0502782	0	1	2	0
-0.00841728	0	3	0	1	-0.030055	3	1	2	0
+0.0168424	1	3	0	1	+0.0417122	2	2	2	0
-0.00102296	3	3	0	1	-0.0397722	0	3	2	0
-0.0317791	0	3	1	1	-0.00350024	0	6	2	3
+0.018604	1	0	2	1	-0.0106854	3	0	0	1
-0.00410798	0	2	2	1	+0.00110903	3	3	0	1
-0.000606848	0	0	0	2	-0.000313912	0	6	0	1
-0.00410798	1	0	0	2	+0.0035985	3	0	1	1
+0.0025983	2	0	0	2	-0.00142121	0	6	1	1
-0.000560528	3	0	0	2	-0.00383637	1	0	2	1
-0.00163652	1	2	0	2	+0.0126803	0	2	2	1
-0.000328787	1	6	0	2	-0.00318278	2	3	2	1
+0.000116502	2	6	0	2	+0.00334268	0	6	2	1
+0.000690904	0	0	1	2	-0.00183491	1	1	0	2
+0.00421749	0	3	1	2	+0.000112451	3	2	0	2
+0.0000565229	3	6	1	2	-0.0000297228	3	6	0	2
-0.00146564	0	3	2	2	+0.000269551	1	0	1	2
					+0.00083265	2	0	1	2
					+0.00155334	0	2	1	2
					+0.000302683	0	6	1	2
					-0.000425399	0	3	2	2
					+0.0000869243	3	3	2	2
					-0.0004659	0	6	2	2
					+0.0000553194	1	6	2	2

3.5.3. Actual engine power estimation for EEOI estimation

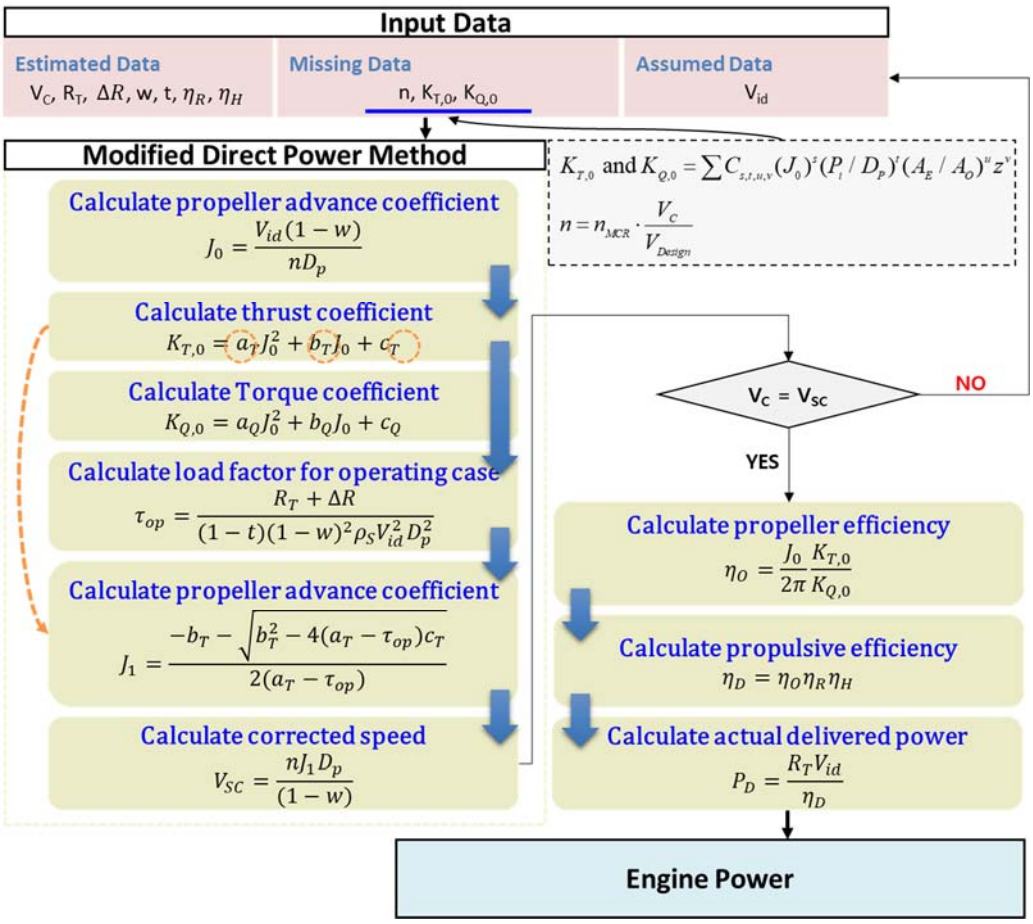

Figure 14 Procedure for actual engine power estimation

Figure 14 shows procedure for actual engine power estimation which is described above. In this study, ship speed in ideal condition was assumed, and the procedure was repeated until the ship speed corrected by current and the ship speed changed by environment condition were equal. Then, the actual engine power was estimated and it is used for the EEOI estimation.

3.6. EEOI estimation

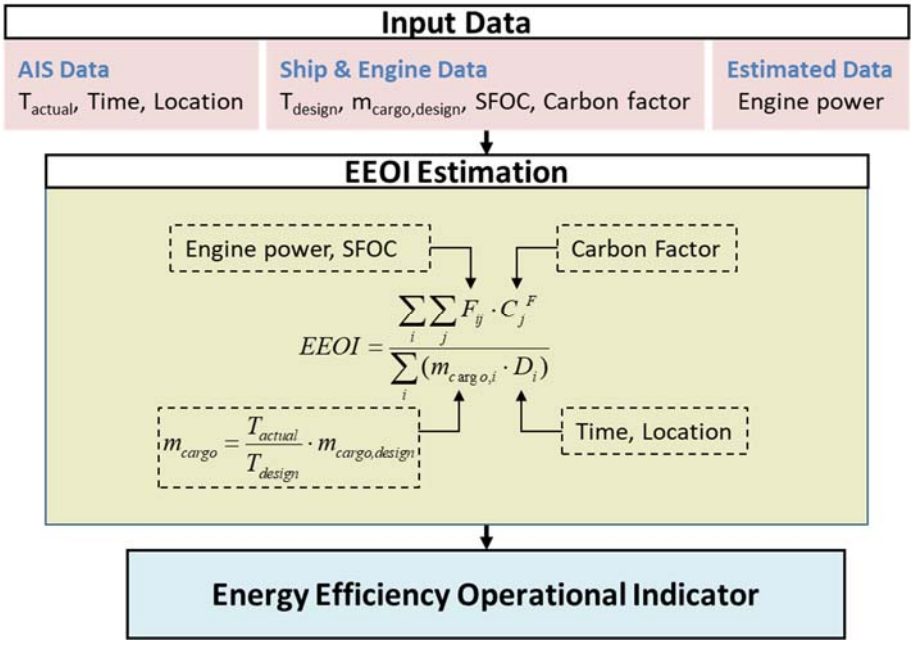

Figure 15 Procedure for Energy Efficiency Operational Indicator estimation

The Figure 15 shows procedure for EEOI estimation. In this study, the AIS data, ship and engine data, and the estimated information were used to calculate EEOI. FOC was calculated by product of estimated actual engine power and SFOC, cargo mass was estimated using design cargo mass and ratio of actual and design draft, and distance was estimated using time and location of the ship. Finally, EEOI was calculated using the FOC, carbon factor, cargo mass, and distance travelled.

3.7. Verification of proposed method

The procedure for EEOI estimation using the public data was applied to the reference ship data for verification. Table 9 shows some information about the reference ship data. It includes information about ship and engine specification. And, it also includes operating data such as actual engine power, ship speed, draft, and location from March, 2014 to January, 2015.

Table 9 Reference data for verification of proposed method

Category	Contents
Ship Type	Container ship
Ship size	13,100 TEU
Design speed	21.8 knot
Engine model	MAN B&W 10S90ME-C9.2
Period	March, 2014~ January, 2015

It is possible to calculate EEOI from the reference data. Therefore, in this study, EEOIs calculated using the reference data and EEOIs estimated using the public data with the proposed method were compared. Moreover, to confirm the accuracy of the proposed method, EEOIs were calculated using Equation 53 (Wen et al., 2017) with the public data, and it was also compared to the EEOIs estimated using the proposed method.

$$EEOI = \frac{P_{MCR} \cdot (\frac{V_C}{V_{design}})^3 \cdot T_m \cdot EF_m}{m_{cargo} \cdot D} \qquad \text{Equation 53}$$

In the Equation 53, T_m is the working time of the main engine, and EF_m is the CO_2 emission factors for the main engine. In this study, EF_m was set to 670 g/kWh for HFO (IMO, 2014).

Figure 16 to Figure 20 below shows the result of estimation.

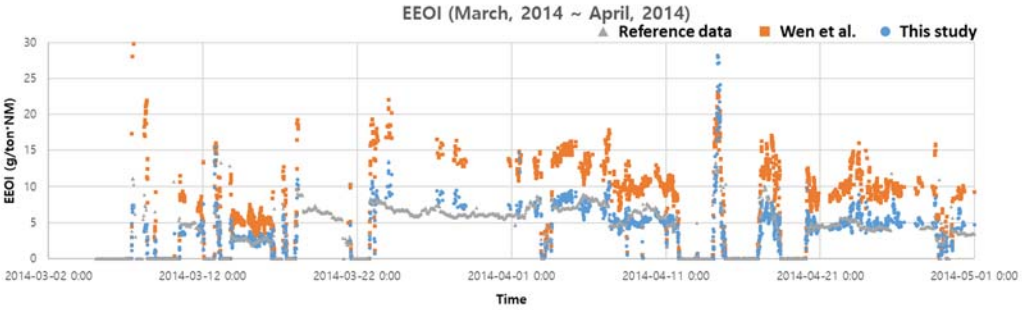

Figure 16 Result of EEOI estimation using data from March, 2014 to April, 2014

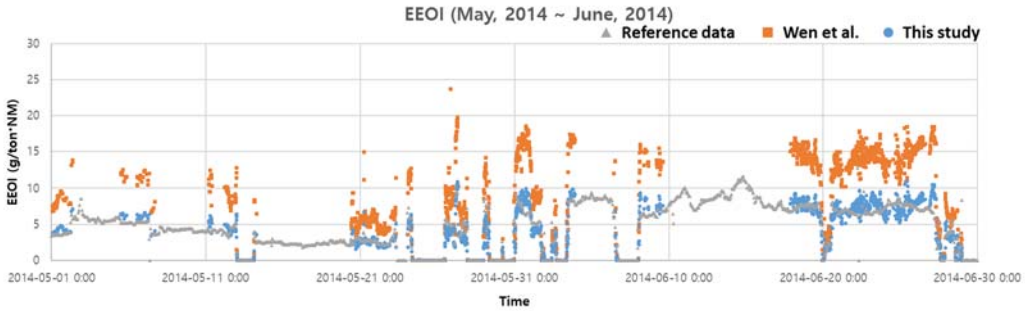

Figure 17 Result of EEOI estimation using data from May, 2014 to June, 2014

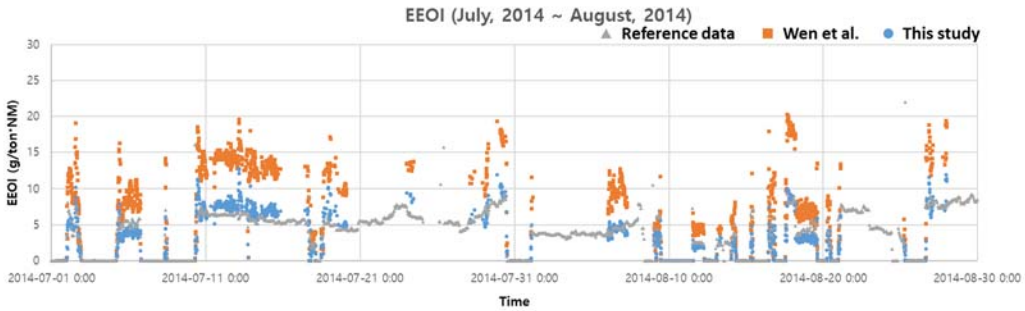

Figure 18 Result of EEOI estimation using data from July, 2014 to August, 2014

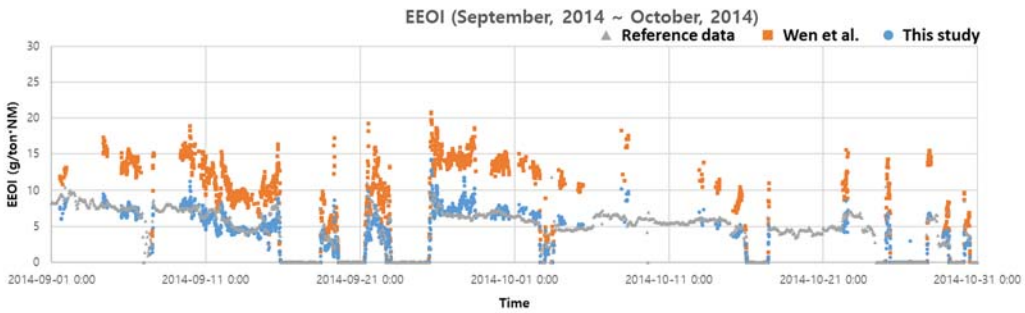

Figure 19 Result of EEOI estimation using data from September, 2014 to October, 2014

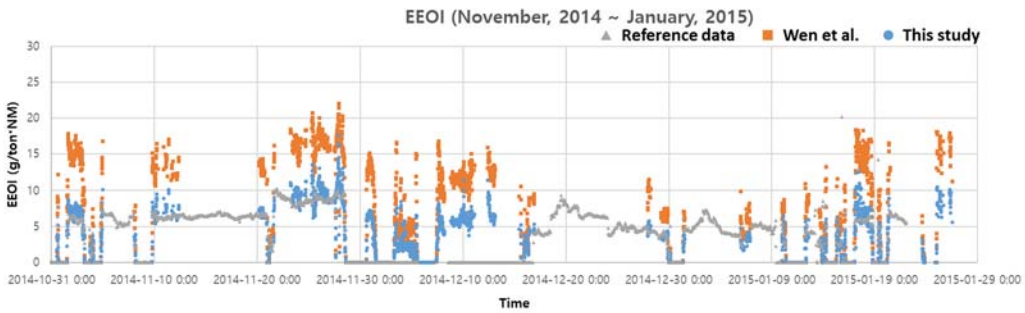

Figure 20 Result of EEOI estimation using data from November, 2014 to January, 2015

The result indicates that the EEOIs, obtained using the proposed method, have a similar tendency with the EEOIs calculated using the reference data. Moreover, compared to the EEOIs calculated using Equation 53, the EEOIs estimated using the proposed method has high accuracy. In the estimation result, there is no EEOI which is estimated using the public data in specific periods. This is usually caused by the lack of matched draft at the periods.

Additionally, for an exact comparison, average, Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) of EEOIs were obtained. Table 10 shows the result of the comparison.

Table 10 Verification result for EEOI estimation

	Average	RMSE	MSE
Reference	5.86	·	·
Wen et al. (2017)	10.42	6.08	2.31
This study	5.49	2.34	1.29

As in the Table 10, the result of EEOI estimation using the proposed method has similar average with the result of EEOI calculation using the reference data. Moreover, comparing RMSE and MAE, the proposed method has high accuracy than the related study's method which assumes actual engine power has cubic relation with ship speed.

3.8. Computation time for EEOI estimation

For shipyards, EEOI for different ships and for different periods should be estimated. And, because of the large amount of EEOIs to be estimated, the procedure for EEOI estimation should be fast. Therefore, computation time required for estimating EEOI by the proposed method was measured, and it was compared to computation time required for calculating EEOI using the reference data. Both calculations were made on the same computer and in the same environment. And, the reference data and the public data from March, 2014 to January, 2015 were used. Table 11 shows the result of comparison.

Table 11 Processing time for EEOI estimation

	Processing time
Reference	0.1 seconds
Proposed method	2,443 seconds

As in the Table 11, it only takes 0.1 seconds to calculate EEOI using reference data. However, it takes 2,443 seconds to estimate EEOI using the proposed method. In other words, it takes almost 7 seconds to estimate EEOI for one-day data using the proposed method. This time difference is due to the connection between the public data, and various calculation in the procedure of EEOI estimation.

As a result of the comparison, the proposed method is inappropriate to use in shipyards. Therefore, in this study, the technologies of big data and deep learning were applied to the proposed method to reduce computation time and increase applicability.

4. Big data technologies for EEOI estimation

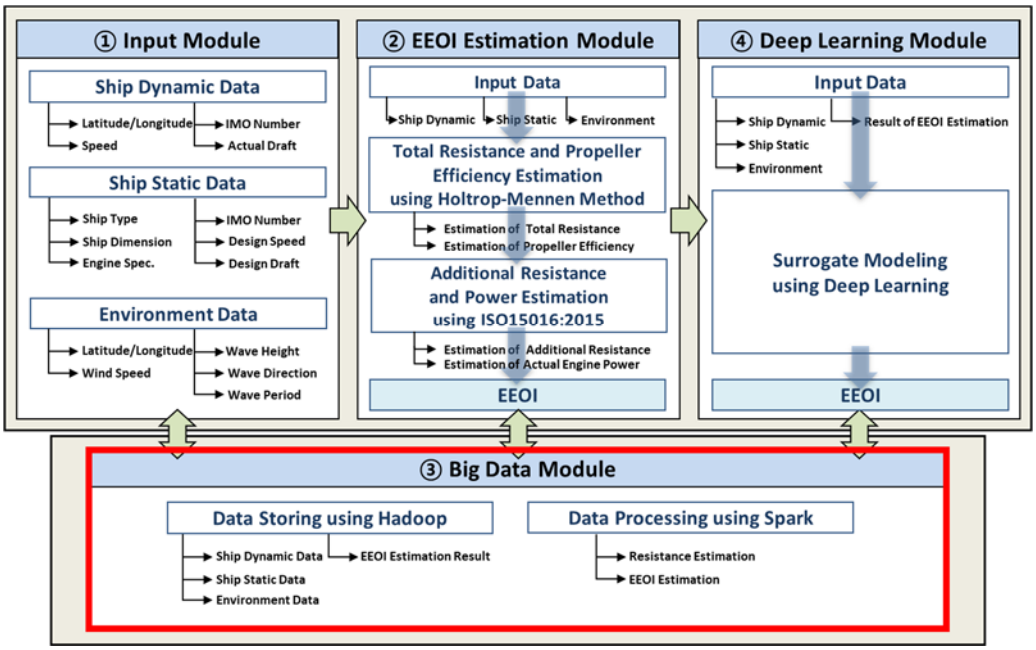

Figure 21 Big data module for EEOI estimation

As shown in the Figure 21, the big data technologies such as Hadoop and Spark were used for the EEOI estimation. This chapter describes concept of big data and introduces Hadoop and Spark which are representative big data frameworks. In this study, Hadoop and Spark were applied to the EEOI estimation because the size of the public data is very large.

4.1. Concept of big data

Although concept of big data has been discussed in recent years, there is no exact concept for big data yet. Generally, three concepts are mainly mentioned. Gartner (2012) defines big data as "a cost-effective, innovative, high-capacity, high-speed, and versatile information asset used for improved insight and better decision making." McKinsey (2011) defines big data as "data beyond the scope of a typical database SW that can be stored, managed, and analyzed," focusing on the size of the database. International Data Corporation (IDC) focuses on the business rather than the database. IDC (2011) defines big data as “new generation technologies and architectures designed to economically extract value from very large volumes of a wide variety of data by enabling high-velocity capture, discovery, and analysis.”

Generally, big data is compared to traditional data analysis based on '3V' such as 'Volume', 'Velocity' and 'Variety'. The first characteristic, Volume, refers to the amount of data that is large enough, both physically and conceptually. The second characteristic, Velocity, means that data is produced in real time and the distribution speed is also very fast. Lastly, Variety means that unstructured data such as photos and videos are included as well as structured data. Recently, 3V and ‘Value’ have been mentioned as characteristics of big data. Value means that new value is created from big data. Figure 22 shows characteristics of big data.

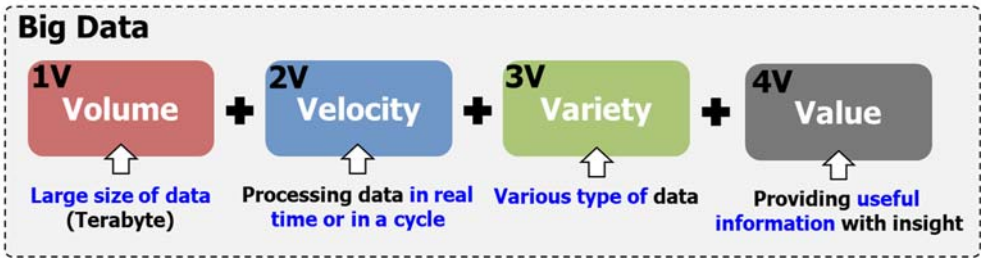

Figure 22 Characteristics of big data

In summary, big data processes more than 100 times more data than existing data analysis. And, big data includes not only structured data such as log data and purchase records but also unstructured data such as social media, location, and sensors. Additionally, big data is a data processing method that creates value by presenting various and reliable analysis results, applying new computing technology that can process the various data as soon as possible.

4.2. Big data technology

Hadoop and Spark, are technologies that enables distributed data storage and processing using multiple computer resources.

4.2.1. Hadoop

Hadoop is an open source framework that can efficiently distribute large amounts of data stored in computers using a simple programming model. Hadoop is designed to span

from a single server to thousands of devices. And it is designed to detect and tune the failure of each device, enabling a robust big data management.

Main technologies of Hadoop are HDFS (Hadoop Distributed File System) and MapReduce. HDFS enables to use many severs as one storage, and it is possible to use storage space of servers efficiently. MapReduce enables to use many servers as one computer, and it is possible to use resources of the severs efficiently.

Hadoop provides subprojects that make possible to apply Hadoop efficiently in various areas. The Hadoop subproject forms a Hadoop ecosystem with core projects consisting of HDFS and MapReduce as Figure 23. The hadoop subprojects includes Hive which is a Hadoop-based data warehousing solution, Sqoop which provides data transfer between Hadoop and a relational database, and Mahout which implements Hadoop-based data mining.

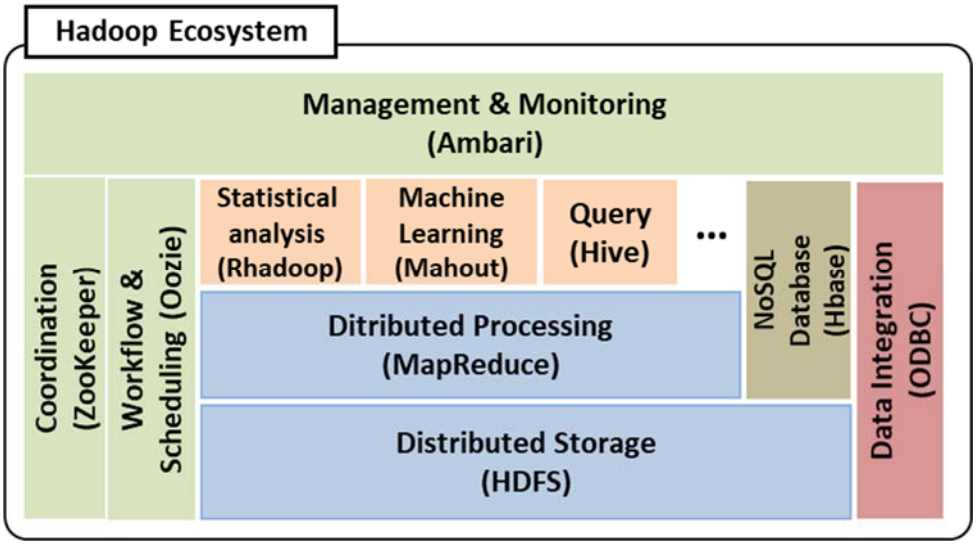

Figure 23 Hadoop ecosystem

4.2.2. Spark

Spark is a high-speed cluster computing technology designed for fast computation. Spark has been extensively optimized for interactive query and stream processing and uses memory cluster computing for fast processing.

Spark also provides libraries that allow it to be applied to a variety of applications as the Hadoop subproject. The Spark libraries forms a Spark ecosystem with core Application Program Interfaces (APIs) as Figure 24.

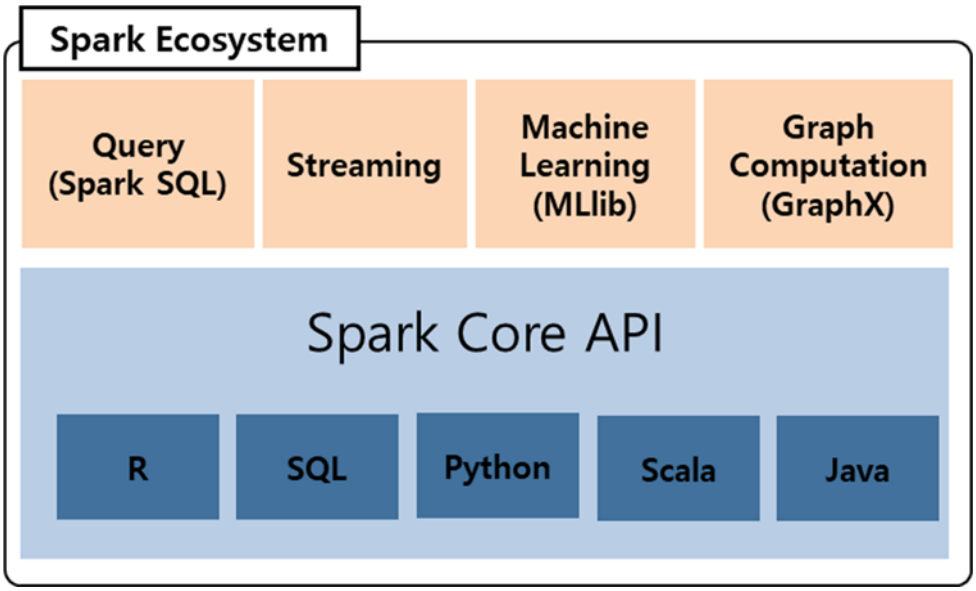

Figure 24 Spark ecosystem

Spark has two big advantages compared to MapReduce. First, Spark is faster than MapReduce 10 to 100 times. Second, Spark supports various types of programming languages such as Scala, Java, and Python. Because of the advantages, HDFS and Spark were applied to the EEOI estimation in this study.

4.3. Application of big data technology for EEOI estimation

For applying the big data technologies to EEOI estimation, it is required to construct big data platform. In this study, the big data platform with multiple servers was constructed with Hadoop and Spark. One server was configured to act as a master server to manage slave servers. And, the rest of servers were configured to distribute and process data as slave servers. Figure 25 shows the big data platform for EEOI estimation.

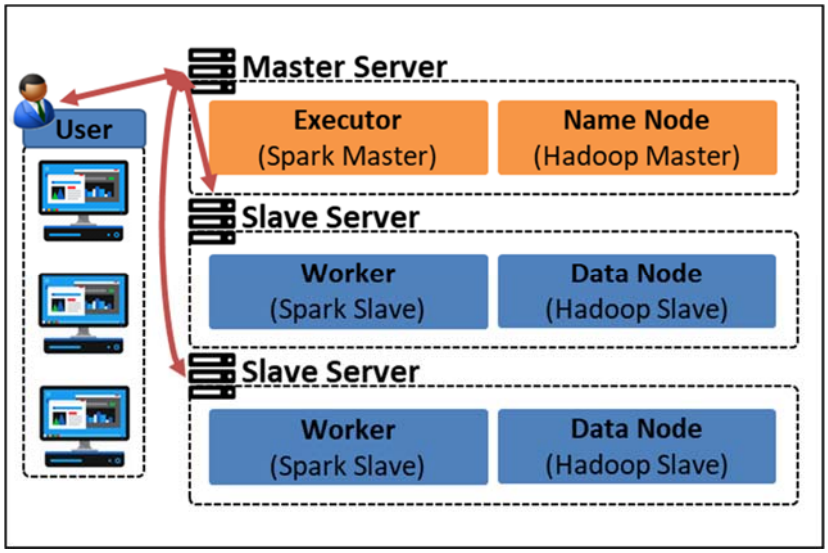

Figure 25. Big data platform for EEOI estimation

Moreover, Zeppelin was applied to use the big data platform. Zeppelin is a web-based notebook that enables data-driven interactive data analytics. Using Zeppelin, data stored in HDFS can be processed based on Spark in web environment. Figure 26 shows Zeppelin's web interface.

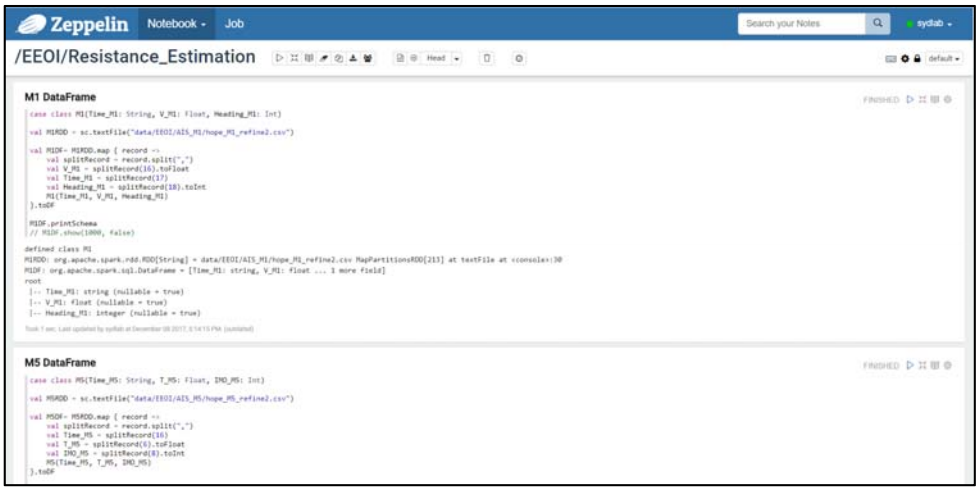

Figure 26 Web interface of Zeppelin

For the EEOI estimation, the big data platform was used to store public data and to process the estimation. The AIS data, ship and engine data, and weather data were stored to HDFS. The result of EEOI estimation was also stored to HDFS. Moreover, estimation of resistance and EEOI was processed using Spark. And, the whole process was performed in web environment using Zeppelin.

4.4. Utility of big data technology

To examine utility of the big data technologies, regression analysis which was used to EEOI estimation was performed using Spark and R which is a free software environment for statistical computing and graphics. Based on Spark, data was analyzed using a regression function on MLlib which is basically provided. Based on R, data was analyzed using a function which is basically provided and using Biglm which is a R package for regression analysis. Then, computation time depending on whether the big data technology is used or not was compared. Table 12 shows the computation time for analysis.

Table 12 Computation time for analysis

Data size	Without Big Data Technology		Using Big Data Technology	Difference in time (A-B)
	R	R (Biglm) (A)	Spark (B)	
300 MB	30 s	32 s	74 s	-42
600 MB	73 s	54 s	87 s	-33
900 MB	124 s	122 s	105 s	17
1.2 GB	·	241 s	113 s	128
2.0 GB	·	355 s	159 s	196
3.0 GB	·	494 s	183 s	311
4.0 GB	·	766 s	256 s	510

As shown in the Table 12, the regression analysis using the R basic function was not executed when the data size is bigger than 1.2 GB. Therefore, the computation times using Spark basic function and using Biglm were compared. Figure 27 shows the result of comparison.

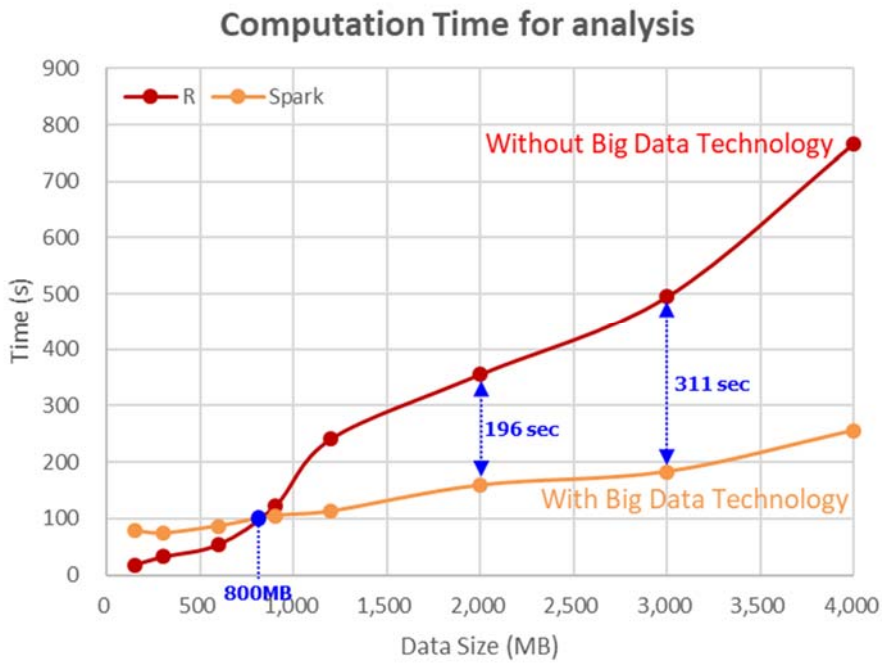

Figure 27 Comparison of computation time

As a result of comparison, from around 800 MB, Spark is faster than R. Moreover, the larger the amount of data, the greater the difference of computation time. Therefore, the larger the data size, the greater the effect of big data technology. In this study, data size of the public data for one year is almost 2 TB, and big data technology has utility for EEOI estimation.

5. Deep learning for EEOI estimation

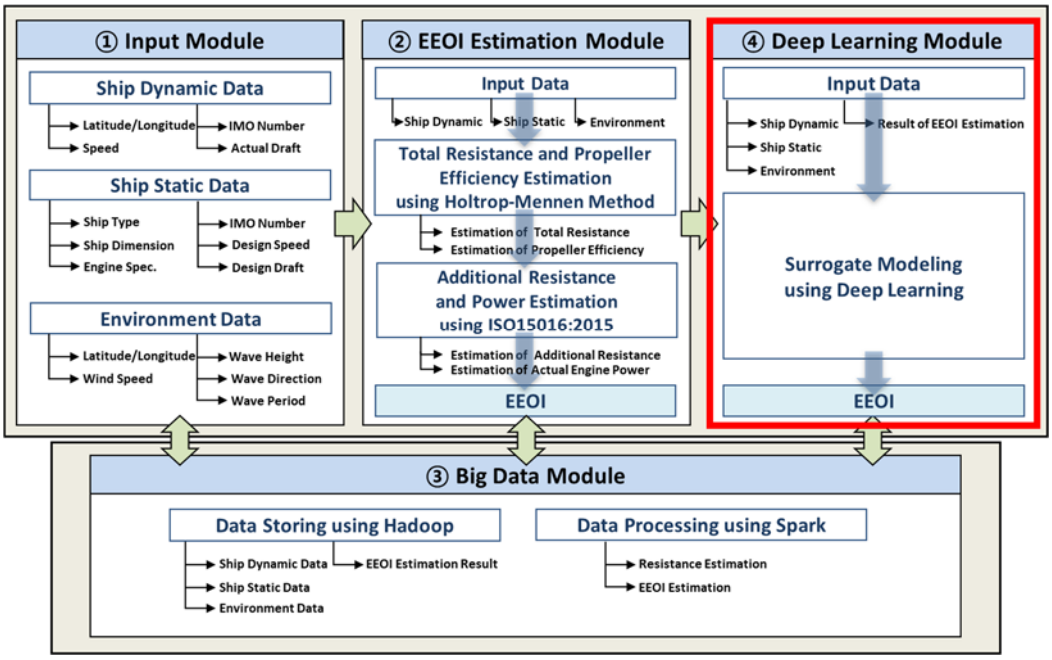

Figure 28 Deep learning module for EEOI estimation

As shown in the Figure 28, a surrogate model was used for the EEOI estimation. This chapter describes the surrogate model constructed using deep learning. In this study, the surrogate model was applied to the reference ship data and verified.

5.1. Concept of surrogate model

The surrogate model is simplified and approximated model which is created through statistical and mathematical methods. The surrogate model is used to store result of analysis in database and analyze it through mathematical methods to obtain similar results. The most popular surrogate models are Support Vector Machine (SVM), Gaussian Process Classification (GPC), Artificial Neural Network (ANN), Deep Neural Network (DNN).

5.2. Concept of deep learning

DNN is one kind of ANN which has multiple hidden layers, and it is constructed using deep learning. Deep learning is one of machine learning algorithms, and it can be defined by its characteristics (Deng et al., 2014);

1. Using a cascade of multiple layers
2. Learning in supervised or unsupervised manners
3. Learning multiple levels of representations
4. Using some form of gradient descent for training via back propagation

In this study, deep learning was used to construct the surrogate model for the EEOI estimation because DNN is known to have the highest accuracy for complex calculation as a surrogate model.

5.3. Overall procedure of deep learning for EEOI estimation

To create a DNN using deep learning, input and output layers of the DNN must be defined. And, training data which is suitable for the DNN structure is required. In this study, because the purpose of deep learning was construction of the surrogate model for EEOI estimation, the inputs of the EEOI estimation was used for the input layer, EEOI was used for the output layer. And, for the deep learning, the public data and EEOIs estimated using the proposed method were used for training. Then, the DNN, the surrogate model for EEOI estimation, was constructed. Figure 29 shows procedure of the deep learning for EEOI estimation.

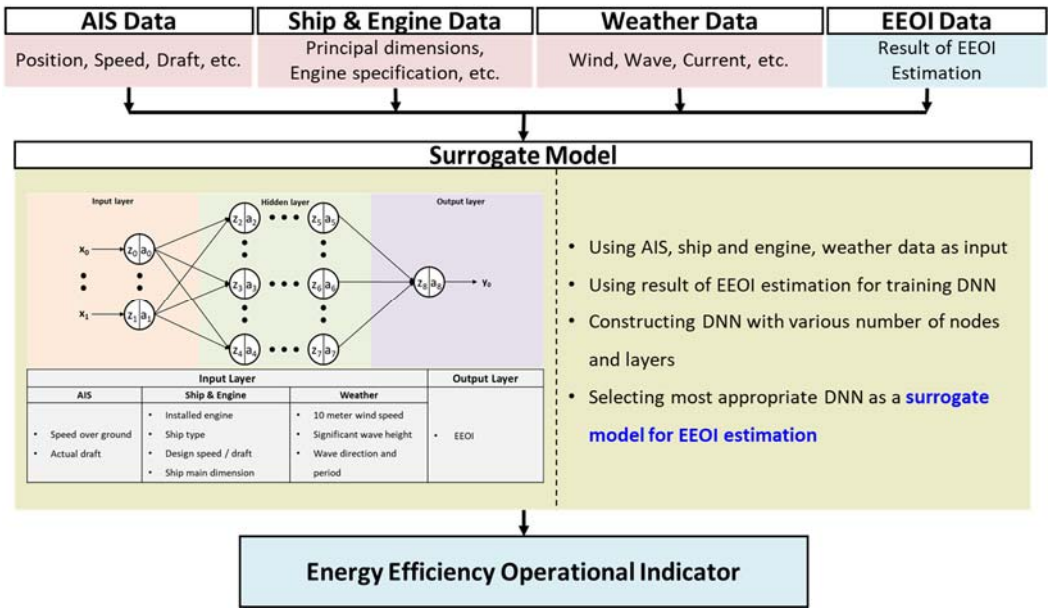

Figure 29. Procedure of deep learning for EEOI estimation

5.4. Application of deep learning for EEOI estimation

In this study, a DNN was constructed for the reference ship. The reference ship is a container ship, and a number of data is 3,067 for almost one year. For the deep learning, actual speed, heading angle, actual draft, wind speed, and significant wave height were used for input layer, but the ship static data for reference ship was excluded. And, the estimated EEOI using the proposed method was used for output layer. Table 13 shows information of training data for the deep learning.

Table 13 Training data for deep learning

Contents	Details
Target ship	Container ship (1 ship)
Number of data (Training / Validation)	3,067 (2,760 / 307)
Number of input nodes	6
Number of output nodes	1
Input variables	Actual speed, heading angle, actual draft, wind speed (x, y-direction), significant wave height
Output variable	Estimated EEOI

The DNN includes two hidden layers, and each layer has 60 nodes. Each node was activated following Rectified Linear Unit (ReLu), and 20 percent of nodes were dropout for each training epoch to prevent overfitting. Moreover, each DNN for each epoch was evaluated based on RMSE. Table 14 shows the DNN structure for the reference ship and hyper-parameters for the deep learning.

Table 14 Hyper parameter for deep learning

Contents	Details
Number of hidden layers	2
Number of nodes (for each layer)	60
Activation function	ReLu
Dropout ratio	20 %
Loss function	RMSE

In this study, the DNN was trained using the training data. Figure 30 shows the training result according to epoch.

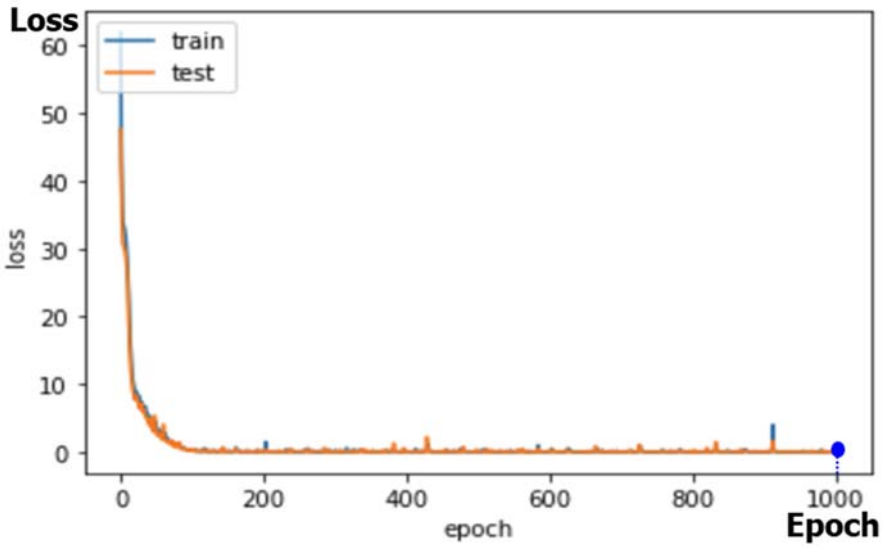

Figure 30 Training result according to epoch

In the Figure 30, as the epoch progresses, the loss, RMSE, decreases. And, since the loss is continuously decreased, it is possible to confirm that there is no overfitting

Then, EEOI was estimated using the DNN. Figure 31 shows EEOI estimation result using the DNN.

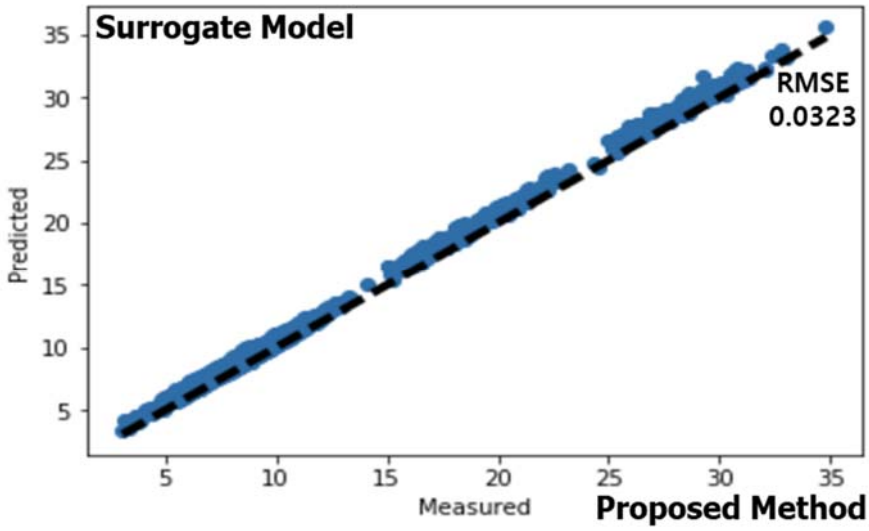

Figure 31 EEOI estimation result using DNN

In the Figure 31, the result of EEOI estimation using the DNN is almost same with the result using the proposed method. Moreover, RMSE is only 0.0323 which means that the DNN has high accuracy. This result implies that the surrogate model can substitute the proposed method.

5.5. Computation time for EEOI estimation using surrogate model

In this study, the surrogate model is applied because the proposed method requires a lot of computation time to estimate EEOI. Therefore, to confirm the utility of the surrogate model, computation time taken to estimate EEOI using the surrogate model was compared to computation time taken using the proposed method. Table 15 shows the result of comparison.

Table 15 Computation time for EEOI estimation

	Computation time
Reference	0.1 seconds
Proposed method	2,443 seconds
Surrogate model	0.2 seconds

As in the Table 15, it only takes 0.2 seconds to calculate EEOI using the surrogate model. It is almost same with EEOI calculation using the reference data. As a result, it is possible to reduce computation time dramatically using the surrogate model, and the surrogate model is appropriate to use in shipyards.

6. Conclusions and future works

In shipyards, EEOI estimation is required to compare the efficiency of ships and to check the time-varying efficiency of the ships. However, since it is difficult to obtain data required for EEOI estimation, it is necessary to calculate EEOI using the public data such as the AIS data, ship and engine data, and weather data.

In this study, the method for EEOI estimation using the public data was proposed based on the Holtrop-Mennen method and ISO15016:2015. In the proposed method, total resistance and propeller efficiencies are estimated using the Holtrop-Mennen method, additional resistance is estimated following the ISO15016:2015, and actual engine power is estimated using the modified Direct Power Method and Holtrop-Mennen method. The utility of the proposed method was verified using the reference data. EEOIs calculated using the reference data and estimated using the proposed method were compared. As a result of verification, the proposed method has high accuracy but take a lot of processing time. Therefore, the technologies of big data and deep learning was applied to EEOI estimation.

For EEOI estimation, Hadoop and Spark which are representative big data technology were applied. The public data was stored to HDFS, and the data was processed using Spark. To verifying the utility of the big data technologies, the computation times whether the big data technologies are used or not were compared. As a result of comparison, the bigger the data size, the bigger the effect of application of the big data technologies. And, it was confirmed that the big data technologies have application value to EEOI estimation.

To reduce computation time for the EEOI estimation, the surrogate model constructed

using deep learning was also applied. The surrogate model was constructed using data of the reference ship and verified. As a result of verification, the surrogate model has high accuracy, and it reduces the processing time dramatically.

In the future, the proposed model will be improved with considering harsh environment conditions. And, surrogate models for other types of ships will be constructed using more big data.

References

[1] Benford, H. (1963). Principles of engineering economy in ship design. *Society of Naval Architects and Marine Engineers*, New Jersey, USA.

[2] Bernitsas, M.M., Ray, D., and Kinley, P. (1981). K_T, K_Q and efficiency curves for the Wageningen B-series propellers.

[3] Charchalis, A. (2013). Designing constraints in evaluation of ship propulsion power. *Journal of KONES*, 20.

[4] Chi, H., Pedrielli, G., Kister, T., Ng, S.H., and Bressan, S. (2015). An AIS-based framework for real time monitoring of vessels efficiency, *Proceedings of 2015 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, 1218-1222

[5] Deng, L., and Yu, D. (2014). Deep learning: methods and applications. Foundations and Trends® in Signal Processing, 7(3–4), 197-387.

[6] Gartner (2012). The Importance of 'Big Data': A Definition.

[7] Holtrop, J. and Mennen, G.G. (1982). An approximate power prediction method.

[8] IDC (2011). Extracting Value from Chaos.

[9] IMO (2011). Resolution A.1078(28), *International Maritime Organization*, London, UK.

[10] IMO (2011). Resolution MEPC.203(62), *International Maritime Organization*,

London, UK.

[11] IMO (2014), Resolution A.917(22), *International Maritime Organization*, London, UK.

[12] IMO (2014). Resolution MEPC.245(66), *International Maritime Organization*, London, UK.

[13] IMO (2014). Third IMO GHG study 2014. *International Maritime Organization*, London, UK.

[14] IMO (2016). IMO train the trainer (TTT) course on energy efficient ship operation, *International Maritime Organization*, London, UK.

[15] ISO15016 (2015), Guidelines for the assessment of speed and power performance by analysis of speed trial data.

[16] Jensen, G. (1994). Moderne Schiffslinien, *Handbuch der Werften*, XXII, 93.

[17] MAN B&W (2014). MAN B&W S90ME-C9.2-GI-TII Project Guide.

[18] McKinsey Global Institute (2011). Big data: The next frontier for innovation, competition, and productivity.

[19] Park, J.H. and Lee, J.H. (2015). Analysis Method for Maritime Accident using Automatic Identification System, *Journal of Digital Forensics*, 9(2), 63-77.

[20] Perez, H.M., Chang, R., Billings, R., and Kosub, T.L. (2009). Automatic identification systems (AIS) data use in marine vessel emission estimation. *Proceedings of 18th Annual International Emission Inventory Conference*, 14, e17.

[21] Rakke, S.G. (2016). *Ship emissions calculation from AIS*, Master's thesis, NTNU.

[22] Schneekluth, H. (1987). Ship Design for Efficiency and Economy, *Butterworth-Heinemann*, Oxford, UK.

[23] Smith, T.W.P., O'Keeffe, E., Aldous, L., and Agnolucci, P. (2013). Assessment of Shipping's Efficiency Using Satellite AIS data.

[24] Wen, Y., Geng, X., Wu, L., Yip, T.L., Huang, L., and Wu, D. (2017). Green routing design in short seas. *International Journal of Shipping and Transport Logistics*, 9(3), 371-390.

국문 초록

빅데이터와 딥러닝 기술을 기반으로 한 선박 에너지 효율 운항 지표 예측 방법에 대한 연구

조선소 입장에서는 선박 간의 효율 비교, 시간에 따른 선박 효율 변화를 확인하기 위해서 에너지 효율 운항 지표 (EEOI: Energy Efficiency Operational Indicator)의 추정이 필요하다. 하지만 선박의 실제 운항 데이터를 취득하는 것이 어려운 상황이기에 선박 자동 식별 시스템 (AIS: Automatic Identification System) 데이터, 선박 및 엔진 데이터, 기상 데이터와 같은 공용 데이터를 이용해 에너지 효율 운항 지표를 추정해야 한다.

본 연구에서는 공용 데이터를 이용해 에너지 효율 운항 지표를 추정하는 방법을 제안하였다. 제안된 방법에서는 Holtrop-Mennen 방법을 이용해 선박의 전체 저항 및 프로펠러 효율을 추정하였고, ISO (International Organization for Standardization) 15016:2015 에서 제안된 방법을 사용해 선박의 부가 저항을 추정하였다. 그리고 수정된 DPM (Direct Power Method)과 Holtrop-Mennen 방법을

이용해 엔진 출력을 추정하였다.

에너지 효율 운항 지표 추정에 사용된 공용 데이터의 용량이 크기 때문에 Hadoop, Spark 와 같은 빅데이터 기술을 적용하였다. 공용 데이터는 Hadoop 상에 저장되었으며, Spark 를 이용해 처리되었다. 그리고 에너지 효율 운항 지표 추정에 걸리는 시간을 줄이기 위해 딥러닝을 이용해 대리 모델 (surrogate model)을 만들어 적용했다.

최종적으로 제안된 방법을 예제 선박에 적용하여 선박 에너지 효율 운항 지표를 추정해보았고, 추정 결과를 실제 결과와 비교해봄으로써 제안된 방법의 효용성을 검증하였다.

Keywords: 선박 자동 식별 시스템 (AIS), 빅데이터, 딥러닝, 선박 에너지 효율 운항 지표 (EEOI), Hadoop, Spark, 대리 모델 (surrogate model)

Student number: 2016-21130