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Ship Operational Efficiency from AIS Data Using Big Data Technology

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Abstract: The Energy Efficiency Design Index (EEDI) is a necessary benchmark for all new ships to prevent pollution from ships. MARPOL has also applied the Ship Energy Efficiency Management Plan (SEEMP) to all existing ships. The Energy Efficiency Operational Indicator (EEOI) provided by SEEMP is used to measure a ship's operational efficiency. The shipowner or operator can make strategic plans, such as routing, hull cleaning, decommissioning, new construction, and so on, by monitoring the EEOI. Fuel Oil Consumption is the most important factor in calculating EEOI (FOC). It is possible to measure it when a ship is in operation. This means that the EEOI of a ship can only be calculated by the shipowner or operator. Other stakeholders, such as the shipbuilding firm and Class, or those who do not have the measured FOC, can assess how efficiently their ships are working relative to other ships if the EEOI can be determined without the real FOC. We present a method to estimate the EEOI without requiring the actual FOC in this paper. The EEOI is calculated using data from the Automatic Identification System (AIS), ship static data, and publicly available environmental data. Big data technologies, notably Hadoop and Spark, are used because the public data is huge. We test the suggested method with real data, and the results show that it can predict EEOI from public data without having to use actual FOC
Keywords: Ship operational efficiency, Energy Efficiency Operational Indicator (EEOI), Fuel Oil Consumption (FOC), Automatic Identification System (AIS), Big data

I. INTRODUCTION

A. *Energy Efficiency Operational Indicator (EEOI)*

Ships must comply with Annex VI of the International Convention for the Prevention of Pollution from Ships (MARPOL). Any ship with a gross tonnage of 400 or more must have a Ship Energy Efficiency Management Plan (SEEMP) on board, according to these regulations (International Maritime Organization, 2009). In addition, the SEEMP should use the Energy Efficiency Operational Indicator (EEOI), which can be calculated using Eq. (1).

$$EEOI = \frac{\sum_i \sum_j F_{ij} \cdot C_j^F}{\sum_i (m_{cargo,i} \cdot D_i)}, \tag{1}$$

where i is the voyage number, j is the fuel type, F_{ij} is the mass of consumed fuel j at voyage i, $C^F{}_j$ 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. Unlike the Energy Efficiency Design Index (EEDI), the value of which is determined in the design stage, EEOI changes during operation because of the performance of the ship changes. By tracking changes in EEOI, it enables shipowners or operators to make informed decisions in areas including routing, hull cleaning, decommissioning, and new building. From the point of view of a shipyard, EEOI can be used to compare efficiency between ships, and the result can be used for marketing or technical development purposes.

B. *EEOI Estimation without Operational Information*

Shipowners and operators can easily calculate EEOI because they have real-time operating data about their ships, such as fuel use. Shipyards, on the other hand, struggle to compute EEOI since obtaining sufficient operational data after a ship is delivered is challenging. As a result, shipyards must estimate EEOI using just publicly available data rather than real operating data. Shipyards can access public data such as ship dynamic data, ship static data, and ocean environmental data. Time, position, speed, drafts, and other factors that are time and situation dependent are included in the ship dynamic data.

The Automatic Identification System can provide these details (AIS). The ship's static data includes the ship's main size, engine specifications, and other constants that do not change with time or situation. Weather data such as wind, waves, and currents are included in the ocean environmental data. In order to estimate EEOI using these available data, the following variables in Eq. (1) must be estimated: CFj, D, mcargo, and Fij. The constant CFj is determined by the kind of fuel. Heavy Fuel Oil (HFO) has a CFj of 3.114 and Liquefied Natural Gas (LNG) has a CFj of 2.750. (LNG). The distance between two points on a voyage defines D, which may be determined using real-time position from ship dynamic data. The deadweight at design draught of the ship static data and the actual draught of the ship dynamic data can both be used to calculate mcargo. The ratio of design draught to actual draught is presumed to be the same as the ratio of design cargo mass to actual cargo mass. As a result, multiplying this draught ratio by deadweight yields mcargo. When the hull shape is taken into account, the estimation of mcargo can be more precise. Fuel Oil Consumption (FOC) is defined as

$$\sum_i \sum_j F_{ij} = \text{Power} \times \text{SFOC} \times \text{Hours}, \quad (2)$$

The terms SFOC (Specific Fuel Oil Consumption), Hours (Operation Hours), and Power (Actual Engine Power) are used interchangeably. The ship dynamic and static data can be used to calculate SFOC and operation hours, but real engine power cannot be calculated because it is measured when the ship is in operation. As a result, we present a method for estimating actual engine power and calculating EEOI without having access to operating data.

C. Main Results

We present an EEOI estimate approach in this paper. The following are the main findings:

1) EEOI is calculated using public data rather than operating data.
2) In order to determine precise FOC, the state of the ocean environment is taken into account.
3) To estimate power consumption, a modified Direct Power Method is provided,
4) big data technologies are employed to reduce data processing and computing time for EEOI calculation.

The proposed approach for estimating EEOI is summarised in Fig. 1. The following parts will go over this strategy in depth.

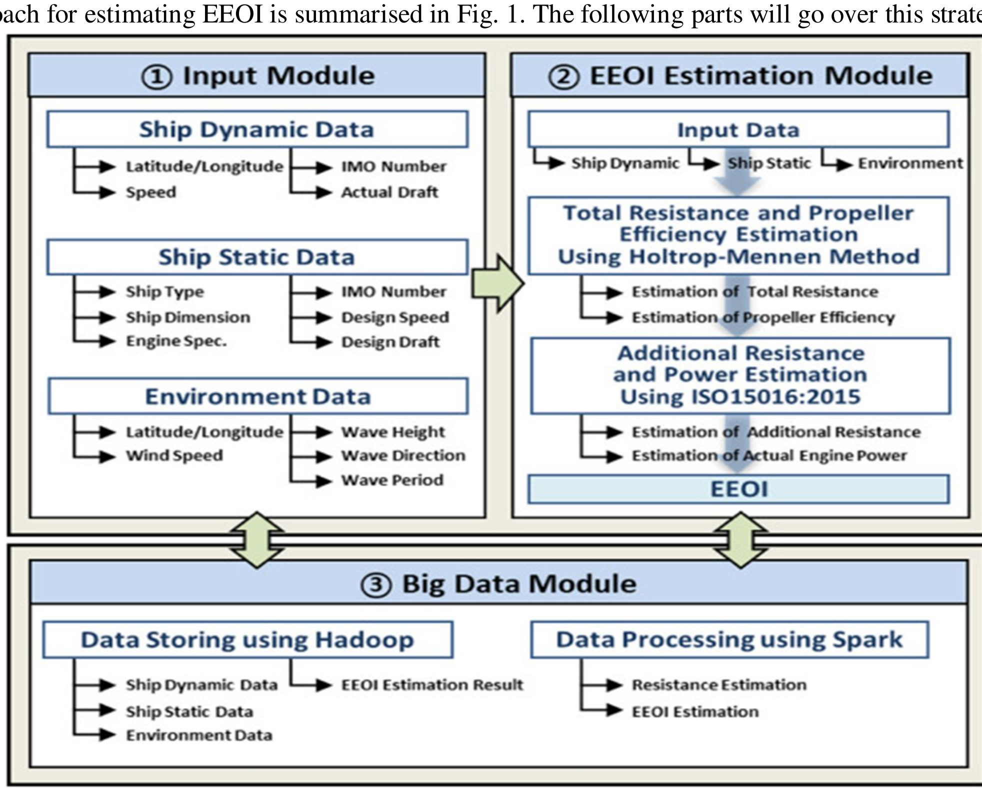

Fig.1.

II. INPUT DATA FOR EEOI ESTIMATION

The input data for EEOI estimation is described in this part, which includes ship dynamic data, ship static data, and environment data. AIS data, which is an automatic tracking system for ships, is used to gather ship dynamic data. Ship constants, such as main dimensions and engine parameters, are used to generate static data. The environmental data, such as wind, waves, and current, is derived from weather data. Table 1 contains all information about the data used in this study.

Item	AIS data	Ship static data	Environment 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 the 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

Table 1.

A. *Automatic Identification System (AIS) data*

All ships must carry an AIS capable of automatically communicating information about the ship to others, including coastal authorities, according to International Maritime Organization standards (International Maritime Organization, 2003). AIS sends 27 different types of signals to satellites, numbered 1 through 27, and the suggested technique employs Messages 1 and 5. Maritime Mobile Service Identity (MMSI), time, position, heading angle, speed, and other information are provided by Message 1. Message 5 contains information such as the MMSI, the International Maritime Organization (IMO) number, the time, and the actual draught. The EEOI is calculated by combining Message 1 and Message 5 by matching the MMSI and time information.

B. *Ship static data*

The ship static data relates to details about the vessel and its engines. The Class or research company can provide ship data such as principal dimensions and IMO number, and the engine catalogue can provide engine data. Principal measurements such as length, width, depth, design draught, design speed, and engine specifications such as Nominal Maximum Continuous Rating (NMCR) and Specific Fuel Oil Consumption are among the data needed to calculate the EEOI (SFOC). Based on the IMO number, ship static data can be linked to AIS data.

C. *Environment data*

To compute a ship's engine power, the additional resistance acting on the ship must first be estimated. The amount of power consumed varies depending on the ship's speed and the weather conditions on the ocean. The environment data (weather data) of the ship's position are necessary for the assessment of additional resistance. The weather data, which includes time, position, wind speed and direction, waves, and current, can be received via meteorological data centres. Based on time and position information, weather data can be linked to AIS data..

III.ENERGY EFFICIENCY OPERATIONAL INDICATOR (EEOI) ESTIMATION

A. *Overall Process for EEOI Estimation*

Eq. (1) of the EEOI formula includes fuel usage, carbon factor, cargo mass, and distance. FOC estimation is the most essential aspect in the calculation of EEOI because other numbers are not difficult to obtain. Eq. (2) can be used to calculate FOC . As a result, one of the most important aspects of estimating is determining how to determine engine power from publicly available data. The resistance acting on a ship and the propeller efficiency can be used to determine engine power. Except for current, total resistance arising from the shape and movement of a ship is divided in this study into total resistance and additional resistance resulting from environmental variables. After accounting for current speed, the overall resistance and propeller efficiencies are computed using the Holtrop-Mennen method (Holtrop, 1988). Rakke (2016) used the Holtrop-Mennen method to compute total resistance, but included a 17 percent sea margin to account for increased resistance due to ocean environmental conditions. We used ISO15016:2015 to compute the extra resistance in this investigation (International Organization Standardization, 2015). Then, to estimate engine power, we suggest the modified Direct Power Method (DPM), which is based on the Direct Power Method in ISO15016:2015. Finally, using the estimated engine power and other data, EEOI may be calculated. The overall procedure of EEOI estimate is depicted in Figure 2. In the following part, we'll go through this process in further depth.

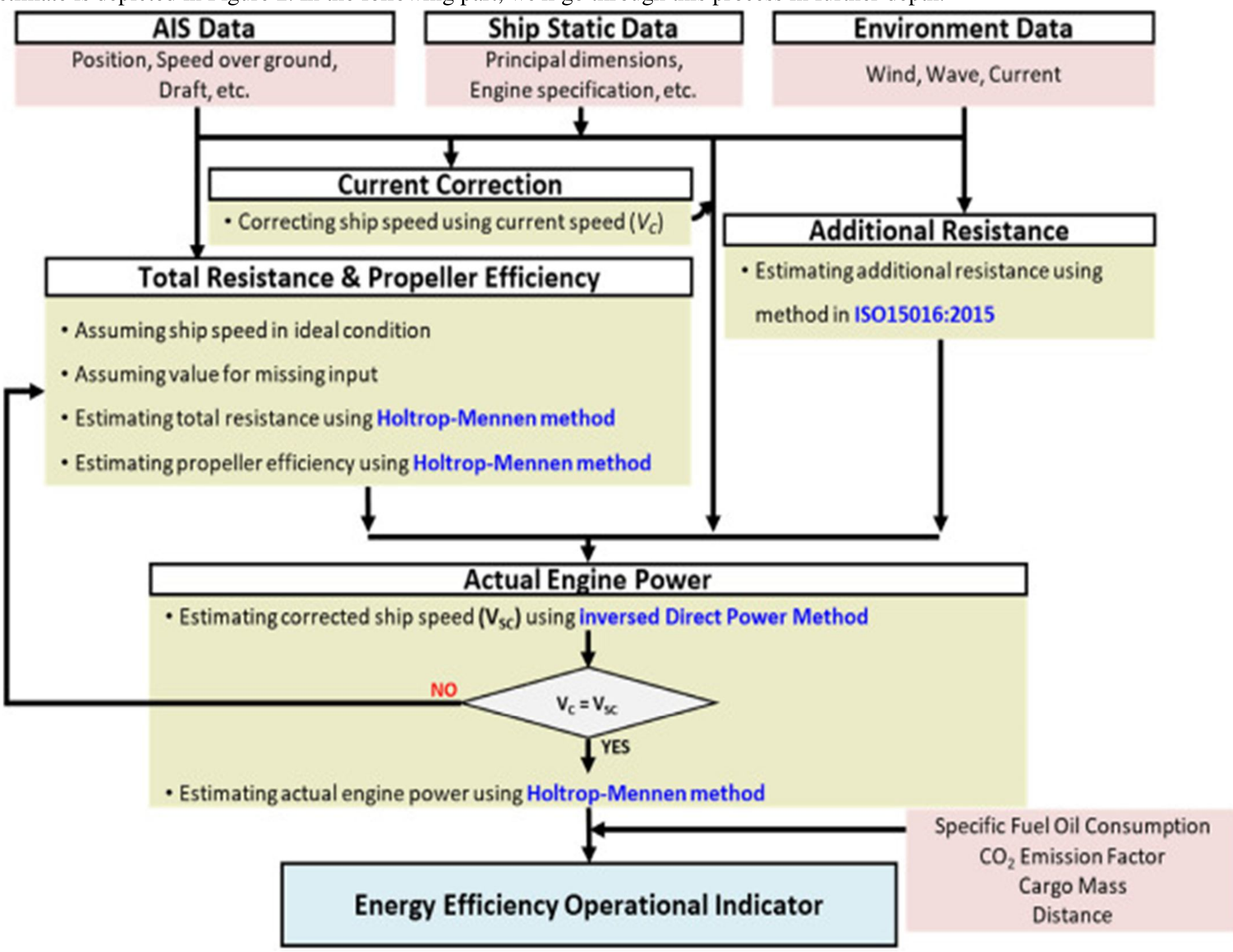

Fig.2.

B. *Engine Power Estimation*

For the purpose of calculating EEOI, the actual engine power is calculated in this study. The Holtrop-Mennen method is used to estimate the actual engine power, and the DPM is amended and applied to the predicted speed changed by the weather. AIS data and ship static data provide almost all of the necessary inputs for engine power calculation. In addition, the findings of the overall resistance, propeller efficiencies, and additional resistance estimations are included.

1) *Direct Power Method:* In ISO15016:2015 the engine power recorded in actual environmental conditions during a sea trial test is corrected to the power in ideal conditions (i.e., deep water, no wind, no waves, and no current) using DPM, and then the ship's ideal speed is calculated. By subtracting the impacts of ambient circumstances from the recorded engine power, the DPM calculates engine power under ideal conditions. The following approach, depicted in Fig. 3, is used to evaluate a ship's performance in ideal conditions.

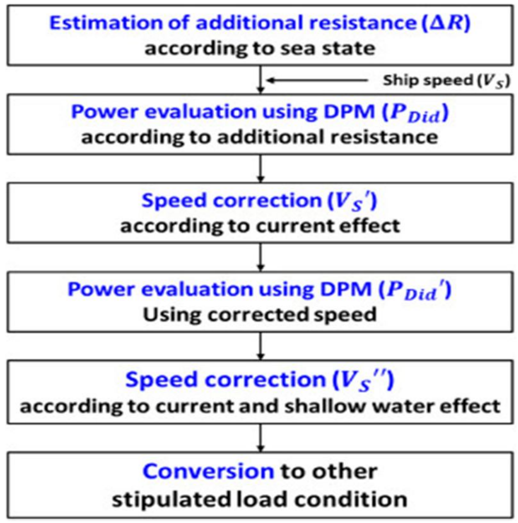

Fig. 3. Ship performance evaluation based on the Direct Power Method in ISO15016:2015.

However, because the goal of our method is to estimate engine power under environmental conditions, no measured power data is used. As a result, the DPM approach is reversed in order to estimate engine power, and the Holtrop-Mennen method is used. The ship's speed in ideal conditions is considered to be Vid = VC, and total resistance, propeller efficiency, and additional resistance in ideal conditions are all used as inputs in the estimating technique. The load factor is calculated by taking into account the surrounding conditions. The load factor is then used to compute the propeller advance ratio. The adjusted speed of the ship is then determined using the propeller efficiency. Finally, when the ship's adjusted speed equals the ship's speed corrected by the current, the real engine power is determined using the Holtrop-Mennen method. Change Vid if the ship's speed is not equal to the adjusted speed of the ship. The overall procedure is shown in Fig.4.

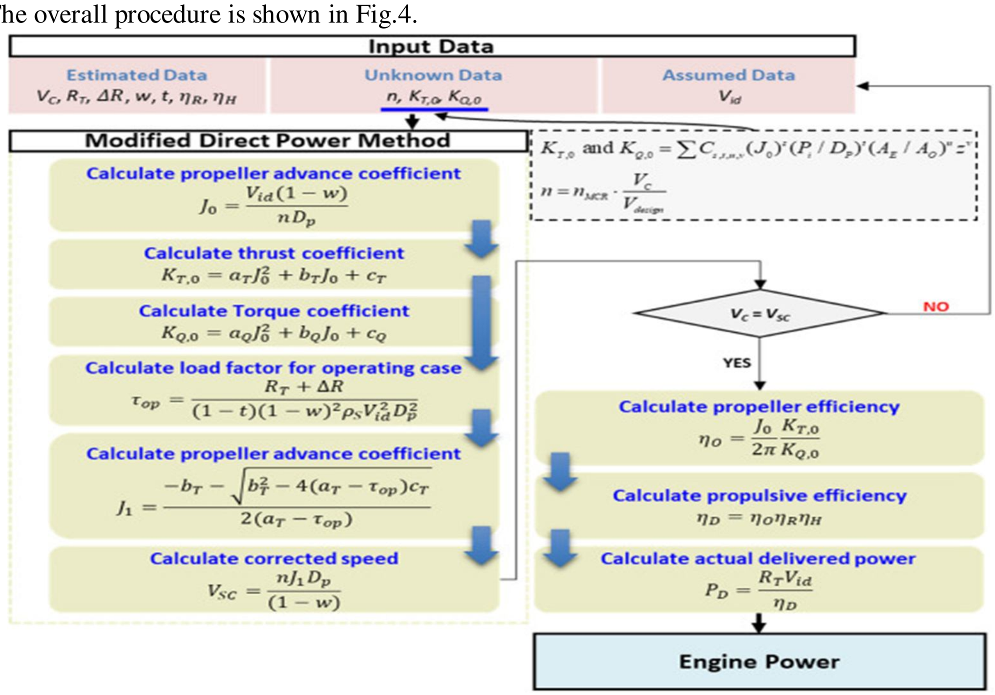

Fig.4.

C. EEOI Estimation

Figure 5 depicts the EEOI estimation technique with input data. The EEOI is calculated using AIS data, ship static data, and estimated information. Eq. can be used to calculate FOC (2). Finally, utilising FOC, carbon factor, cargo mass, and distance travelled, EEOI can be determined.

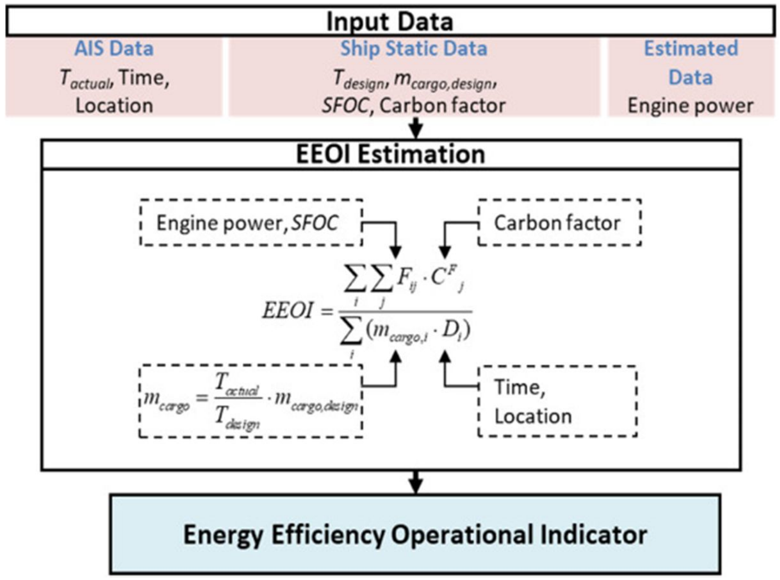

Fig. 5. Procedure for estimation of Energy Efficiency Operational Indicator.

IV. BIG DATA TECHNOLOGY FOR EEOI ESTIMATION

The Hadoop and Spark large data frameworks are described in this section. These frameworks were used to estimate EEOI and the applicability of this estimation was investigated.

A. Size of the Public Data

A year's worth of AIS data for 5500 ships consumes over 150 terabytes (GB). To compute the EEOI of a target ship, we must first select one from the AIS data. Furthermore, a year's worth of environmental data is nearly 1.2 terabytes (TB). As a result, just the weather data from the relevant time period should be loaded from these files. Table 2 summarises the sizes of the above-mentioned public data. Normally, a general computing system would struggle to process this amount of data. As a result, we estimate the EEOI using the above-mentioned big data architecture.

Item	AIS data	Ship static data	Environment data
Size	150 GB (for 5500 ships, 1 year)	20 MB (for 5500 ships)	1.2 TB (for 1 year)

Table 2 shows the size of the publicly available data.

B. Hadoop and Spark

Hadoop and Spark are the two most popular big data frameworks today. Hadoop is a platform for distributed data storage and computing that employs a basic programming model. HDFS (Hadoop Distributed File System) and MapReduce are the two core Hadoop technologies. HDFS facilitates the use of several servers as a single unified storage system, allowing for more efficient use of server storage space. Similarly, MapReduce makes it feasible to use several servers as if they were a single computer and to make efficient use of server resources.

Spark is a big data-focused open-source distributed processing technology. All data operations are performed in memory, and all data is processed at the same time. When compared to MapReduce, Spark has three significant advantages. For starters, Spark is 10–100 times faster than MapReduce. Second, Spark comes with a number of libraries that can be used in a variety of domains. Third, Spark supports various types of programming languages such as Scala, Java, and Python. Because of these advantages, we applied HDFS and Spark to our estimation of EEOI.

C. Application of Big Data Framework

A big data cluster must be built in order to apply a big data framework to EEOI calculation. Using Hadoop and Spark, we build a huge data cluster with numerous machines (Park et al., 2019). The master server uses the executor, which distributes computational tasks, and the name node, which distributes data to storage spaces. The worker, which performs the actual processing, and the data node, which serves as the actual storage, are also applied to the slave server, as illustrated in Figure 7.

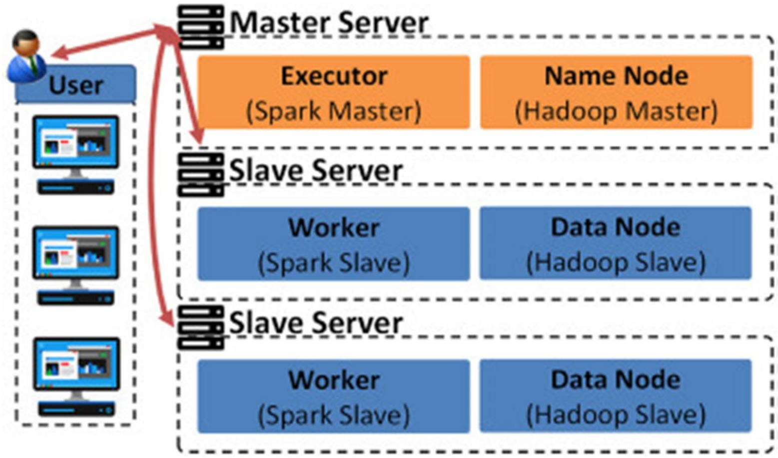

Fig. 7. Configuration of a big data cluster.

The large data cluster is used to store public data and conduct the estimation for EEOI estimation. HDFS is used to store AIS data, ship static data, and environmental data. The EEOI estimation result is likewise saved in HDFS. The estimation of total resistance and EEOI is also done with Spark.

V. CONCLUSIONS

Based on the Holtrop-Mennen approach and ISO15016:2015, a method for estimating EEOI using public data is proposed. The Holtrop-Mennen method is used to calculate total resistance and propeller efficiency, additional resistance is calculated according to ISO15016:2015, and engine power is calculated using the modified Direct Power Method and the Holtrop-Mennen method.

In the case of average EEOI, including additional resistance from environmental data is critical for determining actual engine power. Without real operating data, the suggested method can estimate the EEOI. Furthermore, it is recommended that big data technologies, such as the ones utilized in this study, be used to handle a vast amount of publicly available data.

A. Appendix A. Nomenclature

A_{BT} cross-sectional area at the fore perpendicular
A_E/A_O propeller expanded area ratio
A_M midship section area
A_T transom area under the waterline
A_{XV} transverse projected area above the waterline including super-structures
a_Q, b_Q, and c_Q factors for the torque coefficient curve
a_T, b_T, and c_T factors for the thrust coefficient curve
B breadth of the ship
C_{14} prismatic coefficient based on the waterline length
C_6 coefficient for additional pressure resistance of immersed transom immersion
C_A coefficient for model-ship correlation resistance
C_{AA} wind resistance coefficient
$C_{AA}(0)$ wind resistance coefficient in head wind
C_B block coefficient
C_F coefficient of frictional resistance
C^F_j fuel mass to CO_2 mass conversion factor for fuel j
C_M midship section area coefficient

C_P prismatic coefficient
C_{WP} waterplane area coefficient
D depth
D_i nautical miles corresponding to the cargo carried or work done for voyage number i
DWT deadweight
F_{ij} mass of consumed fuel j at voyage i
Fr Froude number
Fr_i Froude number based on immersion of bulbous bow
G gravitational acceleration, 9.8 m/s^2
H_{l3} significant wave height
J propeller advance ratio
J_0 propeller advance ratio in ideal conditions
K_Q torque coefficient
$K_{Q,0}$ torque coefficient in ideal conditions
K_T thrust coefficient
$K_{T,0}$ thrust coefficient in ideal conditions
k_1 form factor of hull
k_2 appendage resistance factor
L_{BP} length between perpendiculars
L_{BWL} distance of the bow to 95% of maximum breadth on the waterline
LCB longitudinal centre of buoyancy
L_R length of run
L_{WL} waterline length
MCR Maximum Continuous Rating
m_{cargo} cargo carried (tonnes) or work done (number of TEU or passengers) or gross tonnes for a passenger ship
n propeller revolution per second
n_{MCR} engine revolution per second
P_B measure for the emergence of the bow
T, T_{design} design draft
T_{actual} actual draft of the ship
T_{wave} mean wave period
t thrust deduction fraction
V and V_{design} ship's speed
V_A speed of advance
V_C ship's corrected speed using the current speed
V_G ship's measured speed over ground
V_{id} ship's assumed speed in ideal conditions
V_{SC} ship's changed speed by the weather
V_{WRef} relative wind velocity at the reference height
$v_{current}$ v component of current velocity
v_{ship} v component of ship velocity
v_{wind} wind velocity to the North
w wake fraction
z number of propeller blades
ΔR total increased amount of resistance
$\alpha_1(\omega)$ function of the circular frequency ω of regular waves provided in ISO15016:2015
η_D propulsive efficiency
η_H hull efficiency
η_O propeller efficiency in open water
η_R relative rotative efficiency

v_{sea} kinematic viscosity of seawater, 0.00000118 m^2/s
ρ density of the sea
ρ_{air} density of air, 0.0012 ton/m^3
ρ_{sea} density of sea, 1.025 ton/m^3
τ_{op} load factor for operating condition
ω circular frequency of regular waves
ψ_{WRef} relative wind direction at the reference height
ζ_A wave amplitude
∇ displacement volume of the ship

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