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A framework for the application of shipboard energy efficiency monitoring, operational data prediction and reporting

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ABSTRACT

In this study, a framework for the application of shipboard energy efficiency monitoring, operational data prediction and reporting based on the ship's measurement data and meteorological and oceanographic data by the geographic position and time of navigation is presented. General system theory in synergy with machine learning (ML) is used to construct the framework. The general system theory is utilized for identification and transition of components of the proposed framework of energy efficiency monitoring and prediction. A systematic investigation of the internal and external environment is conducted, and the definition of information flow between the individual components provided. Then, the external opportunities and threats that the system faces were opposed to internal strengths and weaknesses to formulate strategies in which weaknesses and threats of the system are offset by existing strengths and probabilities. After assessing the results of the strengths, weaknesses, opportunities and threats (SWOT) and threats, opportunities, weaknesses and strengths (TOWS) analysis, it can be concluded that the proposed framework is feasible and widely applicable in the maritime industry. The novelty is that the proposed framework is using on-board data processing and is integrated into the existing ship monitoring, decision-making and reporting system, thus satisfying the prerequisites for simple application.

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1 Introduction

Nowadays ships collect a large amount of data in measuring signals (temperature and pressure sensors, fuel flowmeter, anemometer, etc.) to supervise and manage ship systems. Measurement data represent a long series of numerical values; they serve for current system monitoring and are rarely used for deep learning and extraction of additional information. Information is the meaning attributed to data, that is, the result of data processing, manipulation and organization so that the user gets the associated meaning, relevance and knowledge [1]. Without the help of computer processing, especially with big data over a more extended period, it is difficult to extract knowledge and make quality decisions based on it. The subject of this research is construction of a framework for the application of shipboard energy efficiency monitoring, operational data prediction and reporting based on the actual ship[1] measurement data and meteorological and oceanographic data by the geographic position and time of navigation in the real conditions of the ship's operation.

Maritime traffic is one of the fastest-growing carbon dioxide atmospheric pollution sources and the International Maritime Organization (IMO) has taken a leading role by implementing a rapid action of enforcing various countermeasures targeting the reduction of fuel consumption. The Ship Energy Efficiency Management Plan (SEEMP), adopted by the IMO, is an operational measure that establishes a mechanism to improve the energy efficiency of a ship in a cost-effective manner. As of January 1, 2019, the SEEMP is divided into two parts. Part I provides a sustainable approach to monitoring ship and fleet efficiency over

[1] Ship and the Company details are known to the authors.

time and options for optimising the ship efficiency. Under the Article 22A, Chapter 4, Annex VI, MARPOL 73/78, Part II contains binding requirements for ships of 5000 gross tonnage or more, relating to the collection of ship data for each type of fuel used and data related to cargo transport methodologies used by ships of 5000 gross tonnage or more [2]. At the end of each calendar year, the shipowner shall compile the data collected in that calendar year or one of its parts, and within three months after the end of each calendar year report to the Administration, i.e. the Authorized Organization (Classification Society), on the total value for the previous period. Collected data will be used when deciding on future carbon dioxide emission limitations, and first results are expected in 2022. The IMO Marine Environment Protection Committee (MEPC) at its regular session MEPC73 launches work on the fourth GHG study initiated by the Baltic and International Maritime Council (BIMCO) according to the actual projections of GHG discharges from ships. Namely, they believe that the current estimates of 50-250% increased GHG emissions by 2050 are excessive and do not take into account the actual projection of world economic growth and gross domestic product (GDP) as a basis for estimating the future need for maritime transport. The fourth GHG Study 2020 (MEPC75/7/15) finds that total greenhouse gas (GHG) emissions from maritime shipping rose about 10% from 2012 to 2018. Most striking are 12% increase in black carbon emissions and a 150% increase in methane emissions. Methane slip is not yet regulated and in the next phase emissions limitations from new LNG-fueled ships are expected. The study highlights that it will be challenging to meet IMO's goal of cutting GHG emissions from international shipping by at least 50% from 2008 levels by 2050 and that innovative technologies shell be employed to achieve the goals [3].

The European Union, in its Monitoring, Reporting and Verification Regulation (MRV Regulation 2015/757) that came into force on 1 July 2015 adopted three strategies: (1) Monitoring, reporting and verification of carbon emissions from ship, (2) GHG reduction targets for the maritime transport sector and (3) further measures, including Market-Based Measures (MBM) [4, 5, 6, 7]. First MRV strategy requires all ships of more than 5000 gross tonnage visiting ports of the European Union or EFTA to provide data on carbon dioxide emissions into the atmosphere. Data collection began on January 1, 2018. Database is managed by the European Maritime Safety Agency (EMSA), which publishes carbon dioxide emissions data every year.

Since large amounts of data are present on seagoing ships and yet not used for deep leaning or automated reporting, and with the mentioned requirements for reduction in energy use, emissions, and reporting, there is a need for an appropriate framework that would address these gaps by (1) describing data utilization, (2) providing a comparison of the current situation with previous recordings (testbed, sea trial, previous voyages), (3) predicting shipboard energy efficiency in the future and (4) assisting with reporting on energy efficiency and carbon dioxide or other emission data.

Typically, performance calculation models are divided into those based on (1) physical laws (white models), (2) those that process measurement data by mining or machine learning (black models), and (3) those that combine the two approaches mentioned (grey models). Publication ISO 19030-1: 2016 [8] describes general principles for the measurement of changes in hull and propeller performance and defines a set of performance indicators for hull and propeller maintenance, repair, and retrofit activities. Unlike methods based on physical laws, data mining and machine learning methods are not so prevalent in reference works. At the same time, only a few published papers deal with the framework of the application of such methods in real ship operation conditions.

Lajic et al. [9] set up a model of support when deciding to change navigation direction or speed in critical situations by identifying upcoming events (such as changing the direction and magnitude of waves and wind) through redesigning the existing mathematical model as part of the SeaSense system. According to the proposed fault-tolerant system with fault diagnosis and the method of evaluation and selection of the most appropriate combination of data (sensor fusion quality test, SFQ test), i.e., the possibility of continued prediction, and in the event of an error in measuring different states of the sea, waves, etc., the data being processed were collected from existing SeaSense systems installed on several container ships of the Danish Navy. SFQ can be successfully used to increase the accuracy of measuring the state of the sea, and thus increase the reliability of predicting the response of the ship when changing the speed and direction of navigation.

Petersen et al. [10] present an efficiency model of coastal ferry navigation developed using an artificial neural network (ANN) and a Gaussian process (GP) based on measurement data from voyages in a 1 hour and 55 minute period. The results obtained by artificial neural networks are better than those obtained by the Gaussian process. The relative propulsion power error is 1.65%, while the error in predicting fuel consumption is 1.50%.

Nielsen and Jelsen [11] describe a support system in deciding to change the speed of a ship and the direction of navigation in poor weather conditions in real-time, using a prediction model with the assessment of the wave impact. The proposed model estimates the wave spectrum by combining hydrodynamic modeling and statistical processing of retrieved data. The authors use linear spectral analysis in the statistical processing of the normal distribution (Gaussian curve). At the same time, the Monte Carlo simulation (MCS) and the first-order reliability method (FORM) process the data that monitor the discrete functions. The model is based on data collected from eight sensors installed on the deck of the test ship. The measured data were acceleration, wave height, green water sensor data, and data retrieved from the stress sensor. The system gives promising results, but a much larger amount of data is needed to validate it fully.

As part of his doctoral thesis, Hansen [12] presents a model for predicting operating parameters and the necessity for cleaning the hull and propeller of a container ship using the "Bond Graph" method and regression analyses. He uses data from ship sensors, namely data from the motion sensor installed on the bow and data from daily reports from a period of 380 days. Data sent from the ship via daily reports are insufficient to notice the need for hull cleaning, while such a necessity is discernible by processing measurement data. Despite the author not having sufficient data on external influences, by filtering the input data, he successfully determines the steady-state condition to measure the degree of hull and propeller fouling.

Trodden et al. [13] present a model for planning the fuel consumption and exhaust emissions of tugs and analyzing the initial state, which can then be used to assess the degradation of efficiency during extraction by a software filter algorithm to eliminate all states that do not correspond with the initial. The model processes 43,143 specimens of tug speed and fuel consumption measurements over 30 days in different operating modes. The authors show that the use of eco-speed of the propulsion engine reduces fuel consumption by about 20%, so the presented model was introduced on the tugs where the research was conducted.

In his work, Perera [14] deals with the topic of sensory data processing with an emphasis on the framework of their collection, transmission, and processing. Data are taken from a bulk carrier and processed by clustering, using unsupervised Gaussian mixture models (GMM) algorithm with expectation maximization (EM). The corresponding data sets are then displayed graphically, using diagrams. The clustering results are promising, while the collection framework is elaborated in detail.

None of these sources deals with on-board data processing and integration into the existing ship monitoring, decision-making, and reporting system, which is one of the main determinants of the proposed framework. The on-board processing of measurement data significantly reduces the model dependence on the amount of data, and the ability of satellite communication between ship and land.

The proposed implementation of energy management and reporting model is assisting in the identification of energy fuel saving with the expected scientific contribution in identifying relevant parameters affecting energy efficiency, determining parameters impact and developing a new methodological approach for monitoring and predicting emissions. The developed methodology is implemented for the case of liquefied petroleum gas carrier. Furthermore, it is not uncommon for various manufacturers of solutions to reduce energy consumption and optimize navigation to go through the states of system transition without a proper quality analysis of the current situation hence such systems are not fully consistent with the ship's procedures and current measures in place. This paper deals with such gaps in detail.

2 Materials and Methods

In this paper, a liquefied petroleum gas carrier, similar to the recent series of a South Korean shipbuilder with a capacity of 54,340 DWT, length 225 m, and width 37 m, is used. The type and size of the ship were selected based on the fact that its size is consistent with the average size of vessels commonly used in ocean navigation and that the results can be therefore widely applied to ocean-going ships. Since the proposed framework involves deep learning, the learning time depends on the vessel and the voyages. The fastest learning time will be with those ships that are on permanent routes, and with tankers, especially for liquified gas transportation, where the vessel is in ballast or cargo condition. On a case ship, there are procedures and measures in place for efficient use of energy resources and control of carbon dioxide emissions. Procedures and measures are assumed from binding legislation and relevant maritime industry standards. On a particular ship, in its safety management system (SMS), the shipowner defines and documents the sources, roles, responsibilities, and authorities of all persons or departments that manage, perform and verify procedures and influencing factors related to the implementation and management of environmental components to achieve effective control. Under the provisions of the SMS, the master of the ship is responsible for the implementation and maintenance of all elements of the energy management system and environmental protection. He is obliged to ensure the implementation of binding environmental requirements. The chief engineer is responsible for monitoring performance, plant maintenance, and implementing corrective actions after assessing the consumption value by the requirements of the SEEMP. The shipowner establishes a formal process of identifying energy consumers and variables that affect consumption in all conditions of ship operation. The process includes a feasibility study of measures to improve energy efficiency using technical or operational means. The level of success of such measures is assessed by energy efficiency indicators concerning defined goals. Energy planning is managed by the shipowner's energy management department and is carried out with the help of available resources. The result of that is an action plan for the implementation of energy savings, leading to specific goals.

The current SEEMP contains simple energy efficiency measures, technical measures, and modernization of existing equipment, or changes in existing company procedures, and can be summarized into six action groups:

1. establishing and maintaining documented procedures for situations in which deviations from the policy and objectives of the shipowner may occur,
2. determining operational criteria in the procedures,
3. establishing and maintaining procedures related to the shipowners' identification of significant environmental

aspects for goods and services and communication of the relevant procedures and requirements to contractors and suppliers,

4. avoiding or minimizing environmental risks,
5. establishing a procedure either formally (through energy planning and action plans) or in the form of simple instructions for efficient equipment handling, on-board energy management, vessel navigation (conditioning) and modification of existing equipment, and
6. ensuring compliance with legal requirements and other binding regulations.

On a particular ship, external weather forecast service is used to plan the trip and optimize navigation procedures. Measurement data from the ship's monitoring and control system, as well as the navigation system, are processed but are not stored nor used to discover new information, i.e., revealing hidden behavior patterns. Data related to the control of energy consumption and the amount of carbon dioxide emitted are entered manually in the forms prescribed by the shipowner. An external (ship) communication system has been installed on the ship in question, which enables the transmission and reception of instructions, orders, commands, reports, as well as communication and exchange of data with the office and other participants in the maritime venture.

The shipowner's energy management department meets within the interval no longer than one year. However, if the target achievement period for a particular measure is defined for a shorter interval (e.g., quarterly), then the assessment is carried out at the end of the period that coincides with the target framework.

For the purposes of defining the new framework for the application of shipboard energy efficiency monitoring, operational data prediction and reporting based on the ship's measurement data and meteorological and oceanographic data by the geographic position and time of navigation, the general system theory is used [15]. In the broadest sense, general system theory refers to a collection of general concepts, principles, tools, problems, methods, and techniques directly related to the systems. Although the term "system" may have different meanings in different circumstances, it usually refers to the arrangement of specific, interconnected components within a model, in such a way that they form a whole [16, 17]. General system theory suggests a distinction between open and closed systems. The openness of the system is pointed out by one of the creators of the general system theory, Ludwig von Bertalanffy, who believes that the dynamic interaction of the components of the open system model is its essential feature. If the system were closed and did not exchange matter, energy and information with the environment, the environment would not be able to recognize such a system [15]. The definition of the system starts from the basic definition according to which the system must be understood extremely formally, as a group of identities that are preserved in a complex and changing environment by stabilizing the difference between interior and exterior. The system is created from unchanged and environmentally oriented meaningful structures whose task is to reduce complexity [18]. Since, logically, each system strives to establish a balance between these opposing principles, there is a phenomenon in which each system, by its very existence and the consistency of its balance, resists change [19]. The system can be unambiguously defined based on two groups of data: universe of discourse and couplings (UC structure) and the state structure and transition (ST structure) [16, 20]. When examining the UC structure, it is noticeable that the connections between two elements represent a set of all common attributes between these elements, i.e. their cross-section, while the ST structure is used to define all possible states and all possible transitions between elements, and, if possible, the probabilities of these transitions or the system is lead from one state to another when the transitions are not stochastic. Therefore, the connections between the elements are information flows.

3 Results and discussion

Noticing the shortcomings of the existing system, in which the input variables are corrected with a time lag (related to the time of achieving the set goals), and using data that are manually entered into the system, taking into account statutory changes in reporting related to energy consumption and carbon dioxide emissions, as well as insufficient processing of available measurement data, a new framework for the application of shipboard energy efficiency monitoring, operational data prediction and reporting based on the ship's measurement data and meteorological and oceanographic data by the geographic position and time of navigation is proposed. The framework or model implementation is defined by the UC (Figure 1) and ST structure (Figure 2) of the model.

3.1 UC model structure

The proposed model (Figure 1) introduces dynamic interaction between system components, which is enabled by feedback on input variables such as, for example, main propulsion shaft revolutions, navigation direction, trim of the ship, or the necessity for cargo liquefaction, whose changes can affect fuel consumption. Feedback is achieved by applying machine learning algorithms to data that are converted into information (C4) and whose output predictive values can be compared with the current state and thus make the necessary correction of input values (Figure 1). Information on more efficient ship management and ship systems is available at the shipowner's office (C24). It can be used when correcting an existing shipboard energy efficiency plan (C19), concluding cargo contracts, and creating business policy. The introduction of new information into the system reduces uncertainty, which is a fundamental feature of the proposed model. By organizing information, they become knowledge about energy saving procedures and measures, which can be used to optimize fuel consumption, to introduce new systems at the project level, as well as to improve the energy system. Another feature of the proposed model is the reduction of environmental complexity achieved by automated completion of SEEMP and EU Monitoring, Reporting, and Verification of CO 2 emissions (EU MRV) reports. Data entry control is still left to the machine operator but can be omitted after being confirmed in practice.

It is important to note that the UC structure of the model (Figure 1) shows the key elements of the system (components) that share common attributes at the same level of resolution and exchange information related to the proposed system (model). The proposed model follows the existing legislative and institutional preconditions, as well as the operating authorities, necessary for their implementation and the existing technological preconditions. The new physical components of the proposed model are a data collection and storage system (a2), computer data processing (a3), and graphical user interface (GUI), through which information is available to the end-user in the form of characters, images, and diagrams (a4). To perform the given process and adequately exchange information with other system components, (dedicated) software is required. Such software includes data filtering (automated quality control algorithms), data mining, and machine learning algorithms and is connected to other parts of the system using input and output variables. The focus of this paper is the elaboration of the derived model rather than a description of machine learning solution.

Further elaboration of used machine learning methods, experiments and results are available in [21] and [22]. Usually, those are neural networks (ANN) [23], support vector machines (SVM) [22, 24] and random forests (RF) [21]. In ANN, whose prediction results are similar to SVM and RF, there is a demanding pre-processing procedure, as well as finding optimal parameters for building a successful model. In any case, the choice primarily depends on the type and amount of data, the output variable, the objectives (classification, regression, or detection of outliers) and the processing speed [21]. The control elements of navigation (a7) and energy systems (a8) are taken from the existing system because they appropriately aggregate the procedures to a higher level of resolution.

External challenges mainly relate to communication regarding the retrieval of meteorological data (a12), submission of reports to the Flag State Registry Administration (a13), and communication with the shipping company (a14). Given that these issues have been resolved within the existing system, they will not be addressed specifically. When choosing an adequate marine weather forecast, the amount of data and their reliability should be taken into account. Internal and external challenges in working with large data sets are often categorized in recent literature as ''the challenges of big data'' [25]. However, it should be noted that in the proposed model most of the data is retained on board, so the issue of transfer and challenge of a large amount of data is thus resolved.

The number of data instances, i.e., the period of data collection on ship performance and navigation data, collected in the data collection and storage unit (a2), is one of the most important challenges within the set limits of the model. This is solved by adequately selected algorithms in synergy with expert selection, while the question of data quality is elegantly solved by filtering in six stages: (A) global range test, (B) local range test, (C) stuck value test, (D) spike test, (E) gradient test, (F) trend test [26]. Six automated quality control algorithms are applied to each parameter. The algorithms are written in Python and available in an open-source GitHub repository [26].

Impacts on the system can be divided into two primary groups: (1) impacts within the model limits, i.e. input value of the main propulsion shaft revolutions, ship's course, cargo liquefaction order, decision on the number of generators connected to the switchboard, number of cooling pumps in operation, etc., and (2) impacts beyond the limits of the model (system), such as weather and sea conditions, voyage order, binding provisions of international legislation.

Continuous processing of a large number of measurement data conditioned computer processing on board, while the Internet of Things (IoT), a prerequisite for remote control of the ship, or autonomous navigation, remained as an option in the future, after broadband data exchange with the possibility of real-time management is confirmed in practice.

Individual elements of the UC model structure explained:

a1 – integrated automation system (IAS),

a2 – data collection and storage, x_{1-n} (t) (Table 1) retrieves data from the IAS system, the ship's navigation system, data from the ship's noon reports and meteorological and oceanographic data from external sources; access to the original data set is provided,

a3 – pre-processing by filtering and preparing data for processing, and data processing by machine learning procedures that combines selection of relevant input parameters, time equalization, reduction of the number of required instances and recovery of lost or incomplete data, as well as the application of appropriate machine learning algorithm to given parameters, model learning and evaluation, prediction, i.e. carrying out data mining procedures,

a4 – a decision support system (DSS) displays the results of predicting the output variables y_{1-n} (t) (fuel consumption of the main propulsion engine, specific fuel consumption of the main propulsion engine, slip, speed over ground, trim and the necessity for cargo liquefaction) in parallel with the set values (SEEMP, test drive, transport contract, etc.), which allows targeted corrective action,

a5 – the ship's master is the highest decision-making authority regarding the safety of navigation, environmental protection, cargo transport, voyage, reporting and implementation of company policy and cost control; in performing the above duties, he is assisted primarily by the chief engineer, chief mate and other crew members,

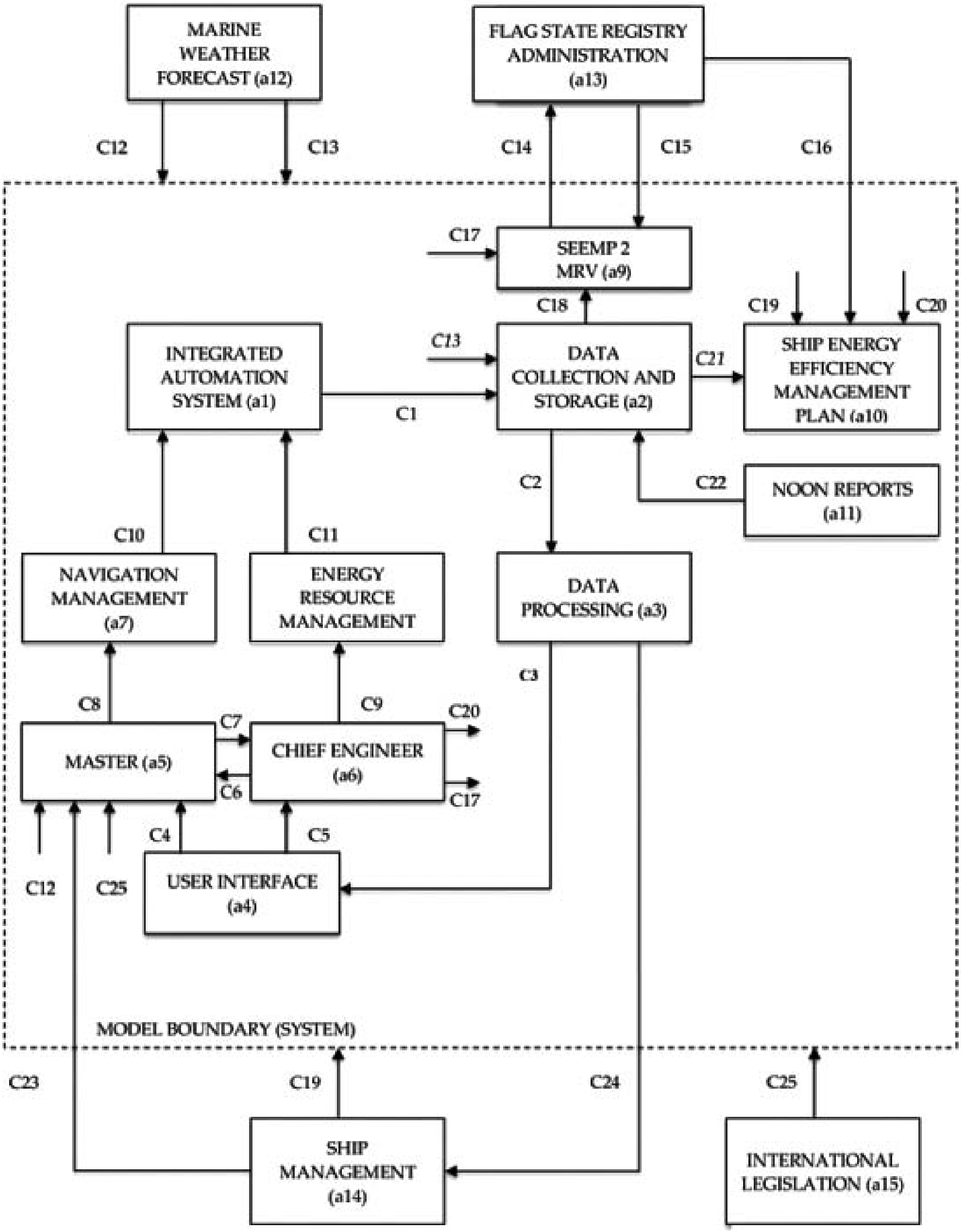

Figure 1 UC structure of the model

Source: Authors

a6 – the chief engineer is in charge of plant maintenance on deck and in the engine room, supervising the transfer and bunker fuel, controlling maneuvering from the engine room (if necessary), controlling and ordering spare parts and implementing the SEEMP plan,

a7 – navigation management contains the organizational and technical elements of management and reporting as well as the relevant procedures to ensure the safety of navigation, contained in the ship's safety management system; when the safety of the crew, ship and cargo is jeopardized, the master of the ship is given the opportunity to override the procedures and make a final decision,

a8 – energy resource management contains organizational and technical elements of management and reporting in accordance with the guidelines for optimal use of energy resources (contained in the ship's safety management system),

a9 – SEEMP (2) and MRV ship reporting plan,

a10 – the Ship Energy Efficiency Management Plan (SEEMP),

a11 – noon reports,

a12 – marine weather forecast.

a13 – Flag State Registry Administration, i.e. Recognized Organization (RA),

a14 – shipowner with ship and energy efficiency management system and business policy,

a14 – international legislation and its executive elements.

C1 – data x_{1-n} (t) from the integrated automation system, i.e. monitoring and alarm system and the ship's navigation system (Table 1): main propulsion shaft revolutions, speed and wind direction from the anemometer, air temperature, sea temperature, the trim of the ship, the heel of the ship, the mean draft along the length and the ship's course over ground,

C2 – data from data collection and storage (a2) to processing unit (a3),

C3 – output data set y_{1-n} (t) after machine learning algorithms (Table 1) for the user interface: main propulsion engine fuel consumption (3), Energy Efficiency Operational Index (EEOI), Energy Performance Indicator (EnPI), specific fuel consumption, slip, speed over ground, the trim of the ship and the necessity for cargo liquefaction. It is important to note that EEDI and EnPI are calculated from listed variables in (Table 1) and known values. The effective power of electricity required to liquefy cargo is higher than any other operation on a liquefied petroleum gas carrier; hence it is used to monitor the cargo liquefaction.,

C4 – graphical display of output values for perusal of ship's master,

C5 – graphical display of output values for perusal of chief engineer,

C6 – suggestion of the chief engineer to the master, regarding shipboard energy efficiency advancement,

C7 – master's order to the chief engineer regarding optimization of utilizing energy resources (propulsion shaft revolutions, ship's course, necessity for gas cargo liquefaction),

C8 – master's navigational orders towards navigation management,

C9 – the chief engineer's decision on the energy resources management system (number of generators in the grid, number of operating cooling pumps, etc.),

C10 – output values from the navigation control and decision-making system,

C11 – output values from the energy resources management system,

C12 – meteorological and oceanographic data for perusal of ship's master,

C13 – meteorological and oceanographic data input for the data collection and storage system: u/v component of wind, gust, significant wave height, wave direction, wave period, swell direction and sea current speed,

C14 – data from SEEMP (2) and MRV towards Flag State Registry Administration, i. e. Recognized Organization (RA),

C15 – approval, periodic review and changes in the regulations of SEEMP (2) and MRV plan by the Flag State Registry Administration, i.e. RA,

C16 – approval, periodic review and changes in the regulations of SEEMP (1) plan by the Flag State Registry Administration, i.e. RA,

C17 – control and correction of data entered in SEEMP (2) and MRV reports by the chief engineer,

C18 – data to the ship's SEEMP (2) and MRV from the data collection and storage system,

C19 – setting goals and monitoring the implementation of energy saving measures by the shipowner's energy management department,

C20 – control and correction of data entered in SEEMP reports by the chief engineer,

C21 – data from the data collection and storage system to SEEMP,

C22 – observational data from ship's noon reports to the data collection and storage system: wave height, swell, and wind observation,

C23 – voyage order and other operating procedures,

C24 – output data set y_{1-n} (t) directed to the shipowner's energy efficiency management system as well as vessel management system, after machine learning algorithms: main propulsion engine fuel consumption, EEOI, EnPI, specific fuel oil consumption (SFOC), slip, speed over ground (SOG), the trim of the ship (11) and the necessity for cargo liquefaction, in parallel with the set values (SEEMP, sea trial, charter party, etc.),

C25 – requirements of international legislation and the various executive bodies enforcing them towards the master of the ship.

Table 1 List of variables that enter data collection and storage – input variables (a2) and exit the data processing unit (a3) – output variables

VARIABLE	INFORMATION/ UNIT	UC MODEL STRUCTURE LABEL
Pickup11	ME revolutions per minute (min^{-1})	C1:x_1(t)
SFOC	Specific fuel consumption (g/kWh)	C1:x_2(t), C3:y_1(t)
ME_tot_FL	ME total FO consumption (mT)	C1:x_3(t), C3:y_2(t)
Nav_02	Ship's speed over ground (knots)	C1:x_4(t), C3:y_3(t)
Nav_04	Wind speed from anemometer (knots)	C1:x_5(t)
Prop_slip	Apparent slip ratio (%)	C1:x_6(t), C3:y_4(t)
MSB0-TOT-LOAD	Total load on busbars (kW)	C1:x_7(t), C3:y_5(t)
MS114	Ambient air temperature (°C)	C1:x_8(t)
MW014	Sea water temperature (°C)	C1:x_9(t)
Trim in meters	- fore, + aft (m)	C1:x_{10}(t), C3:y_6(t)
List in degrees	(°)	C1:x_{11}(t)
Draft- mean	(m)	C1:x_{12}(t)
ECDIS COG	course over ground (deg)	C1:x_{13}(t)
ECDIS wind direction	(deg)	C1:x_{14}(t)
Uwind	(m/s)	C13:x_{15}(t)
Vwind	(m/s)	C13:x_{16}(t)
Wind gust	(m/s)	C13:x_{17}(t)
Significant wave height	(m)	C13:x_{18}(t)
Wave direction	(°)	C13:x_{19}(t)
Wave period	(s)	C13:x_{20} (t)
Sea direction	(°)	C13:x_{21}(t)
Sea current speed	(m/s)	C13:x_{22}(t)
Sea	Douglas sea scale (ship's logbook) (DSS[2])	C22:x_{23}(t)
Swell	Douglas sea scale (ship's logbook) (DSS)	C22:x_{24}(t)
Wind	Beaufort scale (ship's logbook) (Bft[3])	C22:x_{25}(t)

Source: Authors

3.2 ST model structure

The ST structure (Table 2 and Figure 2) defines possible states and possible transitions between states, and the probabilities of these transitions. S0 is the condition without the implemented decision support system, i.e. state as found on the case vessel. For the system to move to a higher state S1, it is necessary to establish the framework for the application of shipboard energy efficiency monitoring, operational data prediction and reporting. Next step is data collection, data processing, and running a machine-learning algorithm to learn the model from the data. It is often required to move back and forth until the amount and quality of data are sufficient for quality machine learning prediction and until reaching the S2 state. Continuous monitoring the and model maintaining brings us to the final state S3. For the system to achieve the set goals, it must be supervised throughout the steps.

Table 2 and Figure 2 provide an overview of possible system states (models) and transitions between states, where the system states are as follows:

S0 – lack of model or database (current situation),

S1 – a model that enables the collection of relevant operational data has been set up,

S2 – the initial (zero state) has been determined, whereby the model achieves the full functionality of pre-

[2] The Douglas sea scale (DSS) is a measure of the height of the waves and the state of the swell. The scale is expressed from 0 to 9.

[3] The Beaufort scale (Bft) is used to evaluate wind strength in the scale from 0 to 12.

Table 2 Transitions between states

STATE	TRANSITION	OUTPUT
S0 – lack of model	I1 – setting up a scientifically accepted model that describes, predicts and enables adjustment of the relevant operating parameters of the ship	S1 – set up and accepted model
S1 – accepted model	I2 – data collection	S2 – determined initial (zero) state
S2 – determined initial (zero) state	I3 – continuous model monitoring and maintenance	S3 – full functionality of the model

Source: Authors

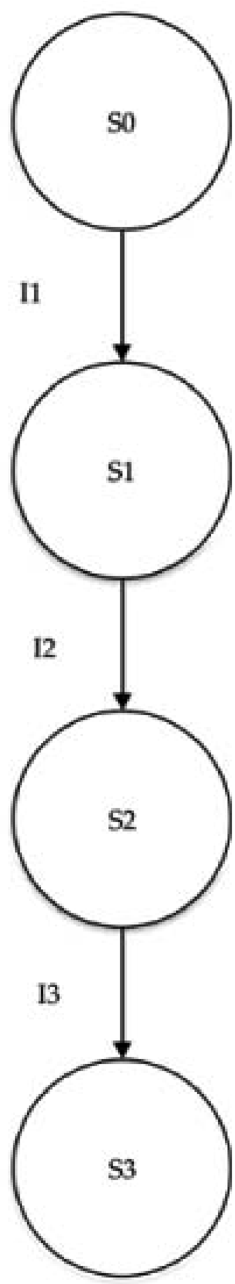

Figure 2 ST structure of the model

Source: Authors

diction and support in making decisions on optimizing energy consumption and reducing carbon dioxide emissions into the atmosphere, and

S3 – continuous model monitoring and maintenance.

3.3 SWOT and TOWS analyses

According to the presented model it is evident that continuous monitoring of relevant operating parameters, the ability to predict them, and feedback on input values will contribute to more efficient management of energy resources and reduce carbon dioxide pollution of the atmosphere, provide insights into the real situation, as well as possible measures to reduce fuel consumption and prevent pollution, which all parties in the maritime venture will benefit from in many ways. With continuous changes in external conditions, the challenge is in choosing an appropriate structure that reduces the disintegrative effects of the environment to the lowest possible level. Lack of information increases the entropy of the system, which is why, accordingly, it is appropriate to evaluate the assessment of the applicability of the model through strengths, weaknesses, opportunities and threats (SWOT) analysis. Strengths and weaknesses represent the internal characteristics of the system (model), while opportunities and threats come from the environment. Due to its integrative and comprehensive role, it is often referred to as internal-external analysis, while the SWOT matrix is also called the matrix of internal and external factors [27].

The procedure for building a SWOT analysis (Table 3) is as follows [28]:

1. identifying strengths, weaknesses, opportunities and threats,
2. determining the importance and probability of occurrence,
3. analysing the opportunities' relation to strengths and weaknesses, as well as the threats' relation to strengths and weaknesses,
4. identifying strategic alternatives.

Table 3 SWOT elements identification

STRENGTHS (S)	WEAKNESSES (W)	OPPORTUNITIES (O)	THREATS (T)
S1. Prediction of relevant operating parameters and continuous monitoring	W1. The initial learning time from the data prevents prediction at an early stage of system implementation	O1. Integration of ship and office into a common IT monitoring and decision-making system	T1. The proposed model is not recognized as a useful tool for monitoring operational parameters and decision making
S2. Impact on the correction of the existing SEEMP	W2. For the purposes of quality prediction, it is necessary to cover all external conditions and operational procedures scenarios	O2. The proposed model involves preparation of remote or automated ship management	T2. Changes in external factors, such as relevant regulations, guidelines and standards
S3. Improvement of the energy system and EEDI at the project level	W3. Part of the data retrieved from the ship's noon reports is based on subjective perception	O3. Proposal of a new approach to ship management and navigation advancement to weather forecasters	T3. SWOT element identification may be obsolete in changed conditions of application (environment)
S4. Adjustment of the shipowner business policy towards greater environmental friendliness	W4. The interpretation of predictions and the resulting procedures depend on the human factor	O4. The collected data and processing results may be used by the shipowner when concluding a charter party	
S5. Determining initial (zero) state		O5. The collected data and processing results can be used by the shipowner to propose a new methodological approach to the IMO and its committees	
S6. Use of existing infrastructure with minimal interventions		O6. The results of the model can be used in a planned maintenance system	
S7. Compliance with relevant regulations, guidelines and standards		O7. The collected data and processing results can be used in future research	
S8. Establishing an automated system for monitoring and predicting fuel consumption and CO_2 emissions		O8. Further use of external weather forecast service	
		O9. The collected data can be applied to ships from the same series	

Source: Authors

In order to identify strategies that will best emphasize strengths and minimize weaknesses, as well as capitalize opportunities and neutralize threats, an analysis of the opportunities' relation to strengths and weaknesses, as well as the threats' relation to strengths and weaknesses, was performed, and a TOWS matrix of the system (model) was compiled. The TOWS matrix (Table 4) helps identify the links between strengths (S), weaknesses (W), opportunities (O) and threats (T) and provides a basis for formulating strategies on those relationships. It shows how the external opportunities and threats, faced with a particular system, can be countered by internal strengths and weaknesses to result in four sets of alternative strategic recommendations [29]:

1. S-O strategy: maximizing strengths to maximize opportunities in the environment (maxi-maxi),
2. S-T strategy: maximizing strengths to minimize threats (maxi-mini),
3. W-O strategy: minimizing weaknesses in an opportunity-rich environment (mini-maxi),
4. W-T strategy: minimizing weaknesses and threats (mini-mini).

In order for the TOWS matrix to perform with quality, it is necessary to systematically investigate the internal and external environment and define the information flows used in the analysis and identification of key relationships between internal and environmental variables. Repeating combinations or those without a clearly identified strategy are excluded.

Following the SWOT identification of internal and external system factors and the TOWS matrix of uncertainty

Table 4 TOWS matrix

		INTERNAL FACTORS	
		STRENGTHS (S)	**WEAKNESSES (W)**
EXTERNAL FACTORS	**OPPORTUNITIES (O)**	S1O1 System integration is possible after meeting the technological prerequisites related to data traffic speed. S1O2 By expanding the number of input and output variables, it is possible to create a foundation for remote or autonomous ship management. S1O3 Collaborating with weather forecasters to improve the service. S1O4 Corrections to standardized charter party are possible by including measured operating parameters. S2O5 An initiative towards the IMO and other stakeholders is possible in order to change the methodological approach to reporting on fuel consumption and carbon dioxide emissions. S1O6 The prediction and monitoring output data can be used comparatively with the manufacturer's data, with the aim of early detection of faults or maintenance needs (hull cleaning, propeller polishing, etc.). S1O7 The presented results can enable further scientific research and improvements. S5O6 The initial state of the operating parameters can be compared to the manufacturer's data as an input to the planned maintenance system. S6O2 Developing software and infrastructure for the future system of remote or autonomous management. S7O5 Participating in the development of legislation and guidelines of relevant institutions.	W1O8 The existing navigation support system continues to be used until sufficient data is collected by the model. W1O9 The collection time of the initial data number can be minimized if it is the second or the n^{th} number from the same series. W2O8 The existing navigation support system continues to be used until all external conditions and operational procedures scenarios are covered. W2O9 The collection time of the initial data number can be minimized if it is the second or the n^{th} number from the same series. W3O2 In model development and future research, data based on subjective perception will be excluded. W4O1 By integrating the ship – office system, software improvements are possible in different external conditions and operational procedures scenarios. The decision-making system continues to function as it is.
	THREATS (T)	S1T1 Predicting relevant operational parameters is new information in the existing decision-making system; it can be accepted or rejected as such. S2T1 The existing SEEMP can be corrected in a shorter time interval than the existing one. S3T1 The collected knowledge can be used to improve the energy system and EEDI at the project level. S4T1 The business policy of shipowners towards greater environmental sensitivity has been recognized by all stakeholders in the maritime venture. S5T1 The initial state is used for future comparisons; an existing model with an initial state from a test drive or test bed may be unrealistic. S6T1 Implementing the new system does not require significant resources. S7T1 The proposed system is in line with existing regulations, guidelines and standards. Obtaining type approval will be requested after the completion of the software system development process and the selection of the physical components of the system. S7T3 The SWOT and TOWS analysis needs to be repeated periodically at key developmental stages of the model. S8T1 Automation of the existing system; the human element can still be included.	W1T1 The use of the proposed model is non-binding; the model is an upgrade and support in the existing decision-making system with unchanged responsibilities and changes in information. W1T2 Changes in regulations, guidelines and standards are unlikely to limit support in deciding on the efficient use of energy resources or, in the case of more efficient navigation, if the competent authorities adopt standards for the application of such systems, the system may be modified to comply. Such an upgrade is relatively simple because the proposed model is fully integrated into existing legislation and existing infrastructure. W2T1 The proposed model is intended for use on tankers and all other ships where operational procedures are repeated within a reasonable period of time. Use on ships for, for example, the transport of heavy cargo, would require a longer period of retrieving data and learning from it. W3T1 The problem can be overcome by comparative monitoring of the same quantities with different readings, in order to reduce the input of unrealistic values. W4T1 The problem can be overcome by developing an adequate software and educating end-users.

Source: Authors

reduction strategies, it is possible to conclude that the set framework is applicable and takes into account specific environmental conditions. Assumed strengths and probabilities represent advantages and benefits, both in reducing energy consumption and preventing carbon dioxide pollution, and in sustainable development within environmental parameters, with a minimum of resource depletion and environmental pollution. Weaknesses and threats to the system have been offset by existing strengths and probabilities. Given that the TOWS structuring mechanism deals with the current situation and does not give rise to new ideas or insights, during the development of the model, it is necessary to repeat the analysis to consider possible changed relationships and correct the initial development strategy. This confirms the framework which, by the synergy of machine learning methods and general system theory, processes data retrieved from sensors during navigation, as well as data on external influences, and describes, predicts and enables adjustment of relevant ship operating parameters on the example of liquefied petroleum gas carriers to reduce energy consumption and emissions of the carbon dioxide. The introduction of new information on more efficient management of the ship and its systems has enabled more energy-efficient navigation and management of ship processes, as well as the correction of the existing shipboard energy efficiency plan.

4 Conclusion

In this research, a model framework is proposed that enables monitoring, prediction, and adjustment of the relevant operating parameters of the ship intending to reduce energy consumption and emissions of the carbon dioxide. The framework provides the possibility of automatic reporting to relevant organizations. In setting up the framework machine learning methods were used in combination with general system theory. For model learning, measurement data from the ship's automation system, as well as secondary data from the ship's navigation system, daily reports, and available meteorological and oceanographic data by geographical position and navigation time, were used. To describe the system, the UC structure was used, which determined the components of the system and their interconnectedness, and the ST structure, which recognized the states and described the transitions between individual states. SWOT identification and TOWS analysis of system strengths, weaknesses, opportunities, and threats were used to examine and identify strategies that would best identify strengths and minimize weaknesses. Following the mentioned analyses, it is possible to conclude that the proposed framework is applicable and that by processing data retrieved from sensors in navigation, including data on external influences, it is possible to set a model that monitors, predicts and enables adjustment of relevant ship operating parameters, leading to more efficient cargo transportation.

By monitoring the relevant operating parameters of liquefied gas carriers with a built-in liquefaction system, optimization can achieve significant energy savings. Equally, new knowledge can be used in the process of making decisions about scheduled maintenance, such as cleaning the underwater parts of the hull or cleaning and polishing the ship's propeller. By adopting the technical measures to improve energy efficiency, a comparison with the previous state and quality assessment of the newly installed system is enabled. The model also includes automated data collection for the SEEMP and MRV reports, which simplifies the ship's reporting system.

Over time, the collected data on relevant operating parameters, as well as recommendations and procedures for reducing energy consumption and carbon dioxide emissions, become knowledge that can be included in the installation of technological solutions and the development of procedures to improve energy efficiency and reduce carbon dioxide emissions on existing ships. Predicting the specific fuel consumption enables comparison with the initial and current state. It provides useful information on the efficiency of the combustion process by the set values of the manufacturer. The adopted technical and operational solutions can be incorporated into new shipbuilding projects, making it easier to achieve the required level of energy efficiency.

Reduced speed brings significant savings in fuel consumption and is chosen by many shipping companies, especially when the ship is in ballast, as an integral part of management policy. If energy efficiency is adequately rewarded, and the precondition is the possibility of presenting savings, then shipowners have an incentive to invest in reducing fuel consumption. As a result, there may be a market correction, which then helps to achieve a reduction in carbon emissions by rewarding environmentally friendly behavior. A further advantage of the proposed framework is in flexibility towards additional data implementation. An example is the future limitation of methane emissions from natural gas ships and those ships that use natural gas as a fuel.

This research has contributed scientifically in the developing a new methodological approach for application of monitoring, prediction and energy efficiency and carbon dioxide emissions reporting model. It is prerequisite to move from a state of lack of model to a higher model state.

Further research can focus on the development of software to optimize energy consumption and reduce carbon dioxide emissions by the needs of the end-user. Furthermore, based on the results of this research and by employing the machine learning algorithms, it is possible to prototype software that will fully implement the shipboard energy efficiency monitoring, operational data prediction, and reporting based on the ship's measurement data and meteorological and oceanographic data by the geographic position and time of navigation, allowing direct insight into the actual values of improved shipboard energy efficiency.

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