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OPTIMIZATION MODEL TO MANAGE SHIP FUEL CONSUMPTION AND NAVIGATION TIME

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ABSTRACT

Owners of vessels are interested in the lowest possible operating costs. These costs are mainly related to fuel consumption during navigation. To manage it rationally, the main decision-making problem is selecting the proper parameters of the ship's propulsion system during navigation. In practice, operators of ships equipped with controllable pitch propellers controlled in manual mode make a selection of the commanded outputs based on their own knowledge, intuition, and all accessible information regarding sea conditions. In many cases, their decisions are unreasonable or incorrect. Therefore, it would be desirable to support their decision-making in selecting the commanded outputs.
For this reason, we have decided to develop a decision support system in the form of an expert system. This computer-aided system supports the selection of the commanded outputs of the ship's propulsion system. The most important component of this system is the two-criteria optimization model, allowing the rational management of the ship fuel consumption and navigation time.

Keywords: expert system, optimization model, ship fuel consumption, time of navigation

INTRODUCTION

Rational management of resources is the most important challenge facing our civilization in the modern world. It is also the fundamental postulate of the micro-economy. The immediate reason why various economic operators must behave rationally is the rarity and depletion of accessible resources. In the management of industrial processes, the operators use various resources, such as:
– human resources - people with their knowledge and practical skills,
– natural resources - land with its riches (hydrocarbons), water, air,
– artefact resources - tools, machines, buildings, financial resources.

The problem of rational resource management also affects the maritime industry, including the fleet carrying out maritime transport tasks. Owners of vessels such as commercial, passenger and fishing vessels, tugs, etc. are interested in the lowest possible operating costs. These costs are mainly related to the use of material resources, e.g. fuel consumption during navigation and the navigation time to reach the required destination. To manage these resources rationally, the main decision-making problem is selecting the proper parameters of the ship's propulsion system during navigation. This, in turn, can be reformulated as an issue of the optimal selection of the operating parameters (called the commanded output) of the ship's propulsion system, containing a source of mechanical power (engines), and propulsors transforming this power into propulsive force. The set-up of the propulsion system depends on the vessel size and type of operation.

In practice, two main types of propulsors are used for the propulsion of vessels: fixed pitch propellers (FPP) and controllable pitch propellers (CPP). A fixed pitch propeller is a propulsor with the pitch fixed. To increase or reduce the vessel speed, the propeller's rotational speed is increased or reduced. A CPP varies the angle of each blade (pitch) to control the amount of thrust produced by the propulsor. To increase or reduce the vessel's speed, the CPP pitch is altered. In the variable load conditions of navigation, this property allows for optimum use of the ship's engine power by selecting the propeller thrust force according to the ship hull resistances and operation in the area of maximum efficiency of the ship's propulsion system.

The CPP type of propulsor is most common on vessels where it is necessary to sail efficiently at two different load conditions, i.e. towing or running free, and on ships that sail to ports with limited or no tug assistance. Therefore, a CPP can mostly be used on tugs, cruise ships, ferries, cargo and fishing vessels. The pitch and rotational speed of the CPP may be controlled independently of one another, or together through a speed/pitch ratio controller. There are two modes of setting up commanded outputs:

– programmed control mode, when the speed/pitch ratio controller is utilized,
– remote manual mode, when the CPP pitch and rotational speed are controlled separately.

The programmed control mode of propulsion control automatically provides the optimum pitch and rotational speed combination for any given speed. The speed/pitch ratio controller calculates the CPP pitch and rotational speed that are required to achieve the desired ship speed under ideal conditions.

The remote manual mode is used in vessels that operate mainly in different load conditions, for example harbour tugs, fishing vessels, and sailing vessels running under an engine. Selection of the commanded outputs of their ship's propulsion system is made by setting up both the engine rotational speed and the CPP pitch. Combinations of two manipulated commanded outputs to realize the desired ship motion are very complex and complicated. Moreover, the permissible ranges for these outputs are limited by the maximum speed to be obtained from the ship engine and by the minimum speed ensuring the vessel's maneuverability. These ranges are not fixed and depend primarily on sea conditions, in particular the wind speed and direction and the sea current.

As was mentioned earlier, to manage ship fuel consumption and the navigation time to reach the required destination rationally, it is necessary to select proper commanded outputs of the propulsion system, that is, the engine rotational speed and the CPP pitch. To illustrate these relationships, we consider three options:

– moderate fuel-efficient navigation and ship speed is desirable,
– navigation with the lowest fuel consumption is desirable, whereas the time to reach the required destination is not important,
– navigation at the highest possible speed is desirable (e.g. in an emergency); in this case, fuel consumption is not taken into account.

In the presented options, both resources to be managed, that is, the fuel consumption and navigation time, are opposed to each other. In our opinion, it is desirable to find a compromise solution that will allow us to plan navigation more flexibly. In practice, the operators of ships equipped with the CPP controlled in manual mode make a selection of the commanded outputs based on their own knowledge, intuition, and all accessible information regarding sea conditions. In many cases, their decisions are unreasonable or incorrect. Therefore, it would be desirable to support their decision-making in selecting the commanded outputs.

For this reason, we have decided to develop a decision support system in the form of an expert system. This computer-aided system supports the selection of the commanded outputs of the ship's propulsion system. The most important component of this system is the two-criteria optimization model, allowing the rational management of the ship's fuel consumption and navigation time.

LITERATURE REVIEW

In the bibliographic resources available, there are many publications that present the application of optimization methods to various maritime problems. These methods have been used for various aspects of the maritime industry as well as different stages of the life cycle of vessels, including, *inter alia*, optimization of:

– routes and schedules of merchant ships from the point of view of travel time to the destination and fuel consumption,
– design of offshore floating units, including the design of the ship's hull and propulsion,
– ship's operation and maintenance.

To compete with large consortia and attract new customers, many shipping companies have started consolidating their efforts. Therefore, these companies need to develop new strategies for planning efficient routes and ship schedules. Some decisions that must be taken by shipping companies are contradictory in their nature. However, the existing models presented in the literature usually combine conflicting objectives into a single objective function, which aims to minimize costs. Such an approach does not allow the conflicting nature of certain cost elements to be taken into account, which additionally reduces the possibilities for analyzing relevant compromise solutions.

To avoid this shortcoming, the study [1] proposed a multi-objective mixed non-linear optimization model for the vessel scheduling problem that took all the main cost components presented in the literature into account and divided them into two opposite groups. The original nonlinear model was linearized by discretizing the vessel sailing speed reciprocal.

The Global Multi-Objective Optimization Algorithm was developed to obtain the Pareto Front vessel schedules.

The paper [2] presents the optimization of the ship's shipping route based on the dynamic programming method. The optimization was carried out in accordance with the minimum fuel consumption strategy, taking into account the ship's movements due to sea conditions. The ship's voyage was parameterized as a multi-stage decision-making process to formulate a dynamic programming optimization problem. Waves and wind conditions were estimated for each route segment based on weather forecasting maps, then seakeeping related indexes and fuel oil consumption were computed taking into account wave-induced ship motions and added resistance.

In [3] the authors pointed out that the majority of published works on the optimization of the ship's shipping route almost exclusively use a single-objective optimization approach, making it practically impossible to successfully achieve safety and economy-related goals. Their method represents an attempt to develop such solutions by applying an evolutionary multi-objective optimization to pursue three objectives: minimization of the risk of collision, minimization of fuel consumption due to collision avoidance maneuvers, and minimization of the extra time spent on collision avoidance maneuvers with regard to autonomous surface ships.

Instead, a similar method of optimization but with regard to the sailboats in [4] has been used.

Issues concerning multi-objective optimization of offshore floating units, including the design of the ship's hull and propulsion are presented in many publications as well. For example, in [5]shipping companies spend good efforts in improving the operational energy efficiency of existing ships. Accurate fuel consumption prediction model is a prerequisite of such operational improvements. Existing grey-box models (GBMs a genetic algorithm-based gray-box model for predicting the ship's fuel consumption based on ship operation data was proposed. The methodology of model development consists of a ship's fuel consumption modeling procedure based on the basic principles of the ship's propulsion, a GA-based estimation procedure, and a performance assessment procedure. According to the paper's authors, the proposed model provides a more reliable relationship between the fuel consumption rate of the ship and the factors affecting it than existing models. Unfortunately, this model has two major deficiencies: it has been tested for only one ship and neglects the impact of hull and propeller biofouling.

The authors of the paper [6] proposed the use of different methods of single- and multi-objective optimization of the specific characteristics of a liner shipping service. In particular, they proposed a multi-objective optimization model based on maximizing profit, minimizing CO_2 emissions and minimizing SO_x emissions, for which all components of the substitute objective function are a function of the ship's speed.

Many publications, in turn, are dedicated to issues of the ship's design process, in a particular selection of the optimal shape of a hull, the geometry of a propeller, or the cooperation of the hull–propeller system.

The parametric design and multi-objective optimization of ships under uncertainty applying the Holistic Optimization Design Approach are presented in [7]. The developed optimization procedure begins with setting up a detailed parametric model that captures both the external and internal geometric characteristics of the ship, along with the integration of several numerical tools. This allowed the evaluation of a multitude of merit functions and design constraints, all as part of the optimization problem.

Multi-objective surrogate-based hull-form optimization using high-fidelity Reynolds-Averaged Navier–Stokes Equations is presented in [8], whereas computational fluid dynamics-based hull form optimization using the approximation method is reported in [9] and [10]. To quickly obtain practical ship forms with good resistance performance, the optimal design method of ship forms by using the non-linear programming method is presented in [11].

A global view for the multi-objective combinatorial optimization (MOCO) problems in ship design, where the main focus is on evolutionary computation, particularly genetic algorithms, and posterior evaluation of Pareto-optimal solutions, is presented in [12]. A two-stage hybrid approach is proposed for an extremely hard MOCO problem in ship design, the subdivision arrangement of a ROPAX vessel. A multi-objective genetic algorithm technique is employed in the first stage, which enables the combinatorial tree to be explored, resulting in better solutions for the MOCO problem in a reasonable processing time. In the second stage, a classical multiple attribute making technique is used to determine the ranking order of the Pareto-optimal solutions. The application of the proposed approach was explained through a real case study from ship design.

Attempts are also made to use multi-objective optimization methods to design the ship room arrangement. For example, a method combining systematic layout planning and a genetic algorithm to optimize the cabin placement within ships is presented in [13], [14], [15], whereas application of the particle swarm algorithm to optimize the ship's vertical passage layout problem is presented in [16].

The optimal ship power plant solutions for different fuel types by applying cost, emission, and safety objectives based on the product life-cycle are analyzed in [17]. For this purpose, a two-objective optimization method was used to determine the optimal configurations of the cruise ship's power plant, taking into account the actual operational profile of the ship and several design parameters of its energy system. The results obtained showed, inter alia, that the cruise ship's power plants with dual-fueled engines working with natural gas show lower life-cycle costs and emissions while demonstrating a level of system safety comparable to the basic configuration of a power plant.

The design method proposed in [18] provides a comprehensive approach to multi-objective optimization of the hull–propeller system of a ship. Two objective functions, i.e. lifetime fuel consumption and operating cost functions, are taken into account. An evolutionary algorithm based on NSGA-II was adopted. The results showed that the proposed method is the right and effective approach to finding Pareto optimal solutions distributed uniformly and is able to improve both of the objective functions significantly and other performances of the system.

The paper [19] presents a parametric model of the ship's propeller geometry which, in combination with the nondominated sorting genetic algorithm II, was used to optimize the ship's propeller profiles. The radial distribution functions of the propeller pitch and other propeller components were varied. According to the authors of this paper, the optimization procedure presented can provide a well-balanced starting point for the design of high-efficiency propellers, while meeting the conflicting requirements on cavitation inception and other factors characterizing the operation of the propeller.

The work [20] presents ideas and an assessment of two methods using evolutionary algorithm techniques to optimize the marine propeller from the point of view of its cavitation. The particle swarm optimization (PSO) algorithm was used in the multi-objective optimization. Three PSO algorithms were developed and tested to optimize four design solutions of marine propellers for different types of ships. The results were evaluated by a study of the generation medians and the Pareto front development.

In [21] Multi-objective Particle Swarm Optimization was applied to achieve the effective shape of the ship's propeller. Maximizing efficiency and minimizing cavitation were chosen as partial optimization objectives.

The paper [22] proposes a design solution for a high-speed ship propeller. A specially developed optimization procedure was used and the necessary data were obtained from studies of reduction models carried out in the towing tank. The propeller design is solved using a multi-objective approach to numerical optimization and combines the Boundary Elements Method, a viscous flow solver based on the Reynolds-Averaged Navier-Stokes Equations approximation, a parametric 3D description of the blade, and a genetic algorithm.

Relatively few publications are available related to the multi-objective optimization of the ship's operation and maintenance problems. For instance, a hybrid multi-criteria decision making and optimization approach to the issue of support-and-repair ship allocation on a deep-sea route is presented in [23]. This approach was based on an aggregation of evaluation information of quantitative criteria (i.e. weight and economics) and qualitative criteria (i.e. repairability, reliability, and convenience). The authors built a mathematical model of the allocation of this equipment in the form of a mixed-integer nonlinear model. A removal strategy based on a greedy algorithm modifies impossible solutions. According to the authors, the proposed method achieves better solution accuracy and global search performance than three widely used penalty-based methods by several test instances generated randomly. The NSGA-II algorithm based multi-objective optimization approach to arrive at an optimum maintenance plan for the vast variety of machinery to improve the average reliability of a ship's operations at sea at minimum cost is presented in [24].

The analysis carried out here of the issues related to the application of multi-objective optimization methods to the various problems that arise in the operation and design of ships shows that:

– this concerns a wide range of maritime industry areas, for instance: optimizing the ship's routes and schedules [1]-[6], design of the ship's arrangement [7], [12]-[17], hull and propeller shape [8]-[12], optimizing the ship's hull and propeller cooperation [18]-[22], and optimizing the maintenance process [23], [24],
– these methods are based on analytical models, for example [1], [17], [25] or numerical models, for example [12], [19], [22], and in the majority, they are parametric studies, where data were obtained from the ship's historical logs or specifications of the existing ships,
– these methods used various optimization algorithms, for example: exact algorithms in [1], [17], [25], approximation algorithms in [9], and metaheuristic algorithms (evolutionary algorithm [18]; genetic algorithm [13], [14] [15]; particle swarm optimization [16], [20]).

Unfortunately, from the perspective of the problem discussed in this paper, i.e., supporting the selection of the commanded outputs of the ship's propulsion system, the literature review performed found no methods based on data collected during the planned sea trials regarding ship fuel consumption and speed prediction.

COMPUTER-AIDED SYSTEM SUPPORTING THE SELECTION OF THE COMMANDED OUTPUTS

In the most general sense, selection of the commanded outputs considered as the decision-making problem can be formulated as follows: *what should be the CPP rotational speed and pitch to ensure both the desired fuel consumption necessary for the ship's propulsion and the ship's speed for the observed meteorological conditions at sea.*

To build an expert system supporting the selection of the commanded outputs, it is necessary to pre-define the form of functions connecting the presented parameters. The form of these functions is very important because it determines the further actions associated with the essential elements of the developed decision support system, including data acquisition and function mapping. The analysis presented in [26] showed that the most useful solution to do this is the use of a mathematical apparatus based on artificial neural networks (ANNs) and the theory of multi-criteria optimization.

The developed expert system supporting the selection of the commanded outputs consists of the following main components:

– a data acquisition module,
– a module of the ANN functions, and
– a module of the commanded output selection.

Data acquisition module

The main tasks of the data acquisition module are:

– determination of the developed system variables,
– acquisition and collection of relevant data necessary for the building of the ANN functions.

In line with the postulate for rational use of resources, the fuel consumption necessary for the ship's propulsion and the ship's speed were taken as the system output variables.

As the system input variables, the following factors were taken into account:

– the operating parameters of the CPP, namely its rotational speed and pitch,
– the parameters affecting the ship's motion, the values of which are subjected to change with variations in sea conditions.

For the building of the ANN functions, the following variables were taken into account (Table 1):

– input variables: ship's engine rotational speed, CPP pitch, wind direction, wind speed, state of the sea, tidal current direction, and tidal current speed,
– output variables: hourly fuel consumption rate and instantaneous ship speed over the ground.

To verify the correct selection of the commanded outputs, the torsional torque of the drive shaft was used as the constraint in the optimization module. Therefore, it was decided to measure a torque on the driveshaft to determine: a torque and minimum engine rotational speed values when friction clutch slipping is detected, and the maximum torque value when exceeding the permissible gear oil temperature is observed during long-term operation of the ship's propulsion system.

A detailed analysis of the factors affecting the ship motion and the method of selecting the system variables are presented in [26] and [27].

To collect the relevant data necessary for the construction of the ANN functions, we conducted a dedicated experiment at sea on a ship equipped with a two-blade CPP. The experiment was carried out on the ship Pogoria launched in 1980. Her length overall is 40.59 meters and her width is 8 meters. Pogoria's propulsion system consists of a 255 kW main engine, which drives a CPP with a 356 rpm nominal rotational speed through a 1:4.5 reduction gear ratio. This experiment was conducted with the engine as the main source of power (without using sails) for various conditions at sea. To obtain suitable data, we used various navigational and meteorological instruments aboard the ship, and a specially developed measuring device for measuring fuel consumption and shaft torque.

The data necessary for building the ANN functions were obtained from 315 observations carried out during sea trials that lasted nearly two years. A total of 18 variables were recorded and 11 variables were used to construct the ANN functions. The remaining parameters were used to check and verify the correctness of the collected data. The experiment resulted in a dataset that was converted to the output and input values of the ANN models.

More information concerning the measuring devices and procedures of the sea trials can be found in [27], and the detailed description of the tested vessel in [28].

During the long-running sea trials, it was noted that the occurrence of hull biofouling has a significant impact on ship speed reduction. Therefore, we decided to include this factor as an additional input variable named 'time since the last docking of the ship' (Table 1). More information regarding the biofouling phenomenon and the influence of the biofilm layer on the ship hull resistance is presented in [29].

The module of ANN functions

As was mentioned, to build a computer-aided system supporting the selection of the commanded outputs, it is necessary to build ANN functions connecting the selected input and output variables. Such functions allow us to solve problems formulated not very well formally and, to replace the 'manual' process of building functions with a network learning process. In [30] Authors stated that the ANN model could supply a relatively high determination coefficient as compared between predicted results and experimental data, showing that the ANN model could have a good ability to predict the engine behaviors with an accuracy higher than 95%.

The STATISTICA software was used to assess the quality of the collected dataset necessary for the construction of the ANN models. A central agglomeration procedure and six combinatorial methods were used to analyze the correctness of the factor space

Tab. 1. Variables used in two-criteria optimization model

Type of variable	Variable name	Variable identifier	Ranges of variable		Observed values (taken into account in optimization simulation)
			min	max	
Decision-making variables (commanded outputs)	rotational engine speed [rpm]	X_1	from 1000 to 1800 with steps of 50		
	pitch of CPP [pitch scale]	X_2	from 2 to 18 with steps of 1		
Observed variables (conditions of sea and ship hull)	wind direction angle in relation to the longitudinal axis of the ship [°]	X_3	−90	90	−90
	wind speed [knot]	X_4	0	40	17
	state of the sea [degree in Douglas scale]	X_5	0	10	4
	tidal current direction angle in relation to the longitudinal axis of the ship [°]	X_6	−90	90	−15
	tidal current speed [knot]	X_7	0	10	1
	time since the last docking of the ship [months]	X_8	0	24	8
Output variables	hourly fuel consumption rate [dm³/h]	X_{1obs}	2	60	to be calculated
	instantaneous speed over the ground [knot]	X_{2obs}	2	12	

structure. In the considered space, all data were separated by the metrics that proved their appropriate selection [31].

As a rule, the data processed employing the ANN techniques are derived from observations and therefore they cannot be entered into networks directly. For this reason, data preparation by using the normalization and standardization techniques to rescale the input and output variables prior to training neural network models was applied. In particular, a linear normalization with a 10% stock in the range of 0.1 to 0.9 for data with positive variable values and -0.9 to 0.9 for data with negative variables values, respectively, was used. Normalization in this way allows data to be extrapolated, that is, to go beyond the range of observed values, e.g., greater than the observed values of the wind speed or sea state.

To build the ANN models, we used the MATLAB software package and carried out many actions required by the ANN techniques and namely:

– division of the data set into three sets (training, testing, and validation),
– determination of the ANN model architecture (choosing the number of hidden layers and epochs of network learning),
– assessment of the ANN model quality (using MATLAB regression plots that displayed the network outputs with respect to targets for training, validation, and testing sets).

Following the suggestions presented in [32], two networks were created for output variables, that is, for the hourly fuel consumption rate and instantaneous ship speed over the ground respectively. In both cases Multilayer Perceptron (MLP) networks were implemented with the following structures:

– eight neurons in the input layer, representing the input variables for both ANN models,
– two hidden layers with different numbers of neurons, and
– one neuron in the output layer representing the output variables separately for each of the ANN models.

These two networks differ only in the number of neurons in their hidden layers.

The quality of the received networks was proved using MATLAB regression plots. In both cases, the quality of fit is reasonably good for all datasets, with R^2 values above 0.95. More detailed information regarding the application of artificial neural networks for modeling ship speed and fuel consumption can be found in [31]. Examples of the relationships between the output variables and input variables of the received ANN functions for both the entire range of decision-making variable values and the selected meteorological sea conditions presented in Table 1 are shown in Fig. 1 and 2.

The conducted analysis of the modeling results for both ANN models of the MLP type allowed us to assert that:

– **although the data obtained from sea trials have inherently discrete values, they let us set up the neural networks result in continuous functions,**
– **the networks built are well matched to the real data, as evidenced by the relatively high correlation coefficients and the lack of so-called 'sigmoid-cliffs' [33],**
– **there are some problems in matching with the sea trial observations, especially in areas where relatively few data have been collected or a lack of them is observed.**

Information regarding the constructed ANN functions is saved as a matrix and stored in the computer memory as a set of a weight factor matrix assigned to all neuron inputs, from which the obtained networks consist of information about the structure of the connections between neurons in each layer. The size of such a matrix is very large.

Taking into account the above statements, we have decided to apply the ANN functions developed to build a module of two-criteria optimization allowing for the management of both the ship fuel consumption and the navigation time through selecting the commanded outputs.

The module of the commanded output selection

As was mentioned earlier, to support a selection of the commanded outputs of the ship's propulsion system, we have developed a decision support system in the form of

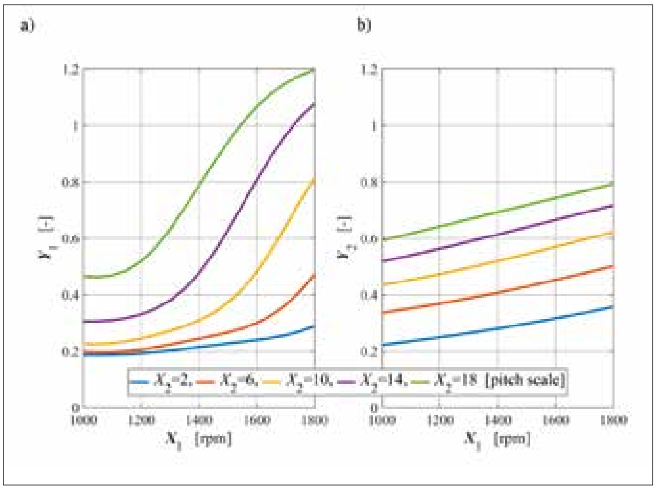

Fig. 1. Relationships between the decision-making variable X_1 'rotational speed of the engine' and the normalized output variables: a) Y_1 'normalized hourly fuel consumption rate'; b) Y_2 'normalized instantaneous speed over the ground' (for values of the observed variables presented in Table 1)

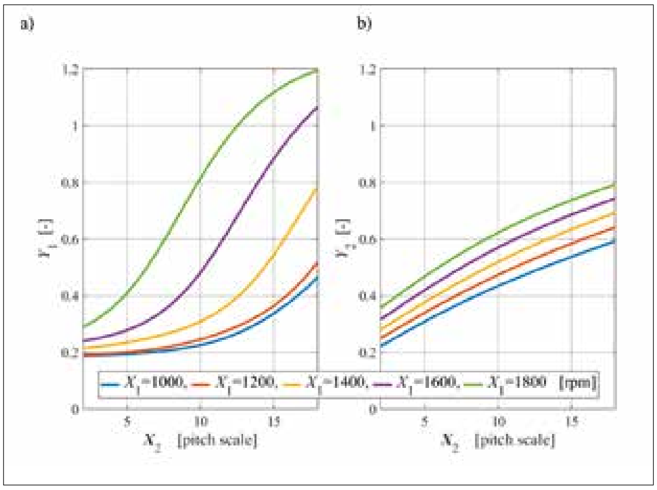

Fig. 2. Relationships between the decision-making variable X_2 'pitch of the propeller' and the normalized output variables: a) Y_1 'normalized hourly fuel consumption rate'; b) Y_2 'normalized instantaneous speed over the ground' (for values of the observed variables presented in Table 1)

a computer-aided system. The developed system allowed the selection of the decision-making variables (the commanded outputs) that should ensure that the ship reaches the required destination with reasonable fuel consumption. Moreover, we assumed that the most appropriate way to build such a system is through the use of two-objective optimization methods based on ANN functions. Thus, the developed ANN functions were used as criterion functions in the considered module of the commanded output selection.

The general idea of the module of the commanded output selection is presented in Fig. 3 in the form of a 'black box'. In it, three inputs interact with the process of commanded output selection and produce two outputs.

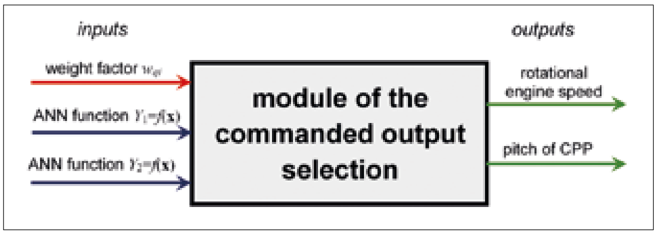

*Fig. 3. Module of the commanded output selection in the form of a 'black box' (**x** – a vector of the input observed variables in ANN function development)*

Two inputs refer to the received ANN functions $Y_1=f(\mathbf{x})$ and $Y_2=f(\mathbf{x})$ respectively, whereas the third input is a set of weight factors w_{qi} of the optimization function. On the other hand, two outputs specify values of the commanded output selection, i.e. the desirable values of the ship engine rotational speed X_1 and CPP pitch X_2.

To build the commanded output selection module, we have developed the mathematical optimization model of the considered two-objective optimization problem. In general, it consists of an objective function and a set of constraints in the form of a system of equations or inequalities.

The objective function of two-objective optimization

As was mentioned, both the developed ANN functions $Y_1=f(\mathbf{x})$ and $Y_2=f(\mathbf{x})$ will be used as criterion functions in the two-objective optimization. The values of the first criterion should be as small as possible. This is connected with fuel consumption, whereas the values of the second criterion should be as large as possible because it is related to wasted navigation time. Therefore, the Weighted Sum Method was used as the substitute objective function Z in the proposed two-objective optimization. This method minimizes a positively weighted convex sum of both the selected criterion functions. The essence of this substitute objective function Z_{sof} is to assign appropriate weights w_{qi} to both criteria Y_1 and Y_2, then adding the products of the weights and criteria values:

$$Z_{sof} = w_{q1} \cdot Y_{N1} + (1 - w_{q1}) \cdot Y_{N2} \rightarrow MIN \tag{1}$$

$$0 \leq w_{qi} \leq 1 \tag{2}$$

$$w_{q1} + w_{q2} = 1 \tag{3}$$

where:

Z_{sof} – the substitute objective function of a two-objective optimization problem,
Y_1 – the normalized hourly fuel consumption rate,
Y_2 – the normalized instantaneous speed over the ground,
w_{q1} – the weight factor of criterion 1,
w_{q2} – the weight factor of criterion 2.

The accepted form of this function is in accordance with the logic of managing the ship fuel consumption and navigation time to reach the required destination, and it is intuitively understandable and decision-maker-friendly for ship operators. Moreover, the adoption of this approach is recommended in many publications dealing with issues of multi-criteria optimization, for example in [34], [35].

When the Weighted Sum Method is used, the calculation is performed by gradually changing the values of the weights, which leads to a better understanding of the relationship between the selected criteria.

In the considered module of the commanded output selection, the ANN functions were used as criterion functions. Unfortunately, the graphic charts of both the selected criterion functions have consistent slopes (Fig. 1 and 2). Therefore, the substitute objective function Z_{sof} (Eq. 1) was modified by introducing a new output variable Y_{lss} representing the loss of ship speed:

$$Y_{lss} = Y_{2max} - Y_{2obs} \tag{4}$$

where:

Y_{lss} – the output variable expressing the loss of ship speed,
Y_{2max} – the maximal instantaneous ship speed over the ground read from the measuring device,
Y_{2obs} – the instantaneous speed over the ground read from the measuring device.

As already mentioned, the normalization and standardization techniques were applied to rescale the input and output variables prior to training the neural network models. In particular, a linear normalization was used across the range from 0 to 1 for positive values of the variables Y_2, which means that $Y_{2max}= 1$ and

$$Y_{Nlss} = 1 - Y_2 \tag{5}$$

where:

Y_{Nlss} – the normalized output variable expressing the loss of ship speed,
Y_2 – the normalized variable Y_{2obs}.

In this case, the normalized criterion function Y_{Nlss} (representing the loss of speed by the ship) has a slope opposite to the normalized criterion function Y_1 characterizing the fuel consumption (Fig. 4).

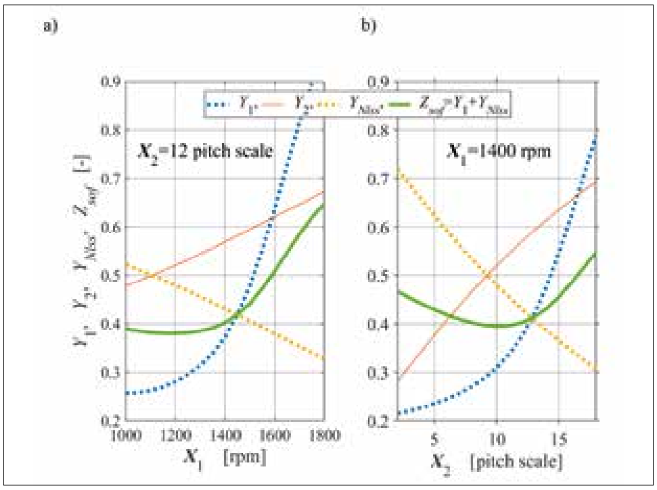

Fig. 4. Relationships between the normalized output variables Y_2, Y_{Nlss}, Z_{sof} and: a) the decision-making variable X_1 'rotational speed of the engine'; b) the decision-making variable X_2 'pitch of the propeller' (for values of the observed variables presented in Table 1)

After performing the appropriate substitutions and transformations, the substitute objective function Z takes the following form:

$$Z_{sof} = 1 + w_{q1}(Y_{N1} - 1) + (w_{q1} - 1)Y_{N2} \rightarrow MIN \quad (6)$$

This is a convex function where the minimum occurs (Fig. 4). This is a purely technical approach that facilitates graphical analysis of the optimization results and does not change the results of the optimization in any way.

Set of acceptable solutions

One of the important stages in the development of the optimization model is the determination of a set of acceptable solutions. In the general case, this set imposes inequality and equality constraints on possible solutions. In the considered module of the commanded output selection, the set of acceptable solutions includes constraints imposed on:

– decision-making variables,
– permissible operating ranges of the ship's propulsion system. In the first case, the operating ranges of the ship engine rotational speed and the pitch of the CPP set the optimization constraints on the values of the decision-making variables, that is, the commanded outputs. These constraints are directly related to the working principles of mechanisms controlling the settings of the engine rotational speed and the CPP pitch. The ship operator controls the rotational speed of the engine (and consequently, the shaft speed) and the CPP using two command levers situated on the navigation bridge (Fig. 5a). These levers remotely control the engine injector pumps and the angles of the CPP blades. An example of the blade angle is shown in Fig. 5b.

The decision-making variable X_1 'rotational speed of the engine' is controlled remotely by the first lever, which changes the positions of the control rod of the engine inline injector. The command values are read as indications n of the rpm indicator (with 50 rpm accuracy) as standard equipment of the propulsion engine system. The allowable ranges for these values set the first inequality optimization constraint:

$$1000 \leq n \leq 1800 \text{ [rpm]} \quad (7)$$

The decision-making variable X_2 'pitch of the CPP' is controlled by the second lever, which remotely changes the blade angles of the CPP, employing a mechanism equipped with hydrostatic transmission. The position of the lever clearly determines these angles with respect to the propeller hub. The command values are read as indications of the lever position with respect to the disc engraved scale H marked from –25 to +25 (negative values mean vessel motion backwards). However, for operational reasons the allowable ranges for these values set by the second inequality optimization constraint are:

$$2 \leq H \leq 18 \text{ [}\textit{pitch scale}\text{]} \quad (8)$$

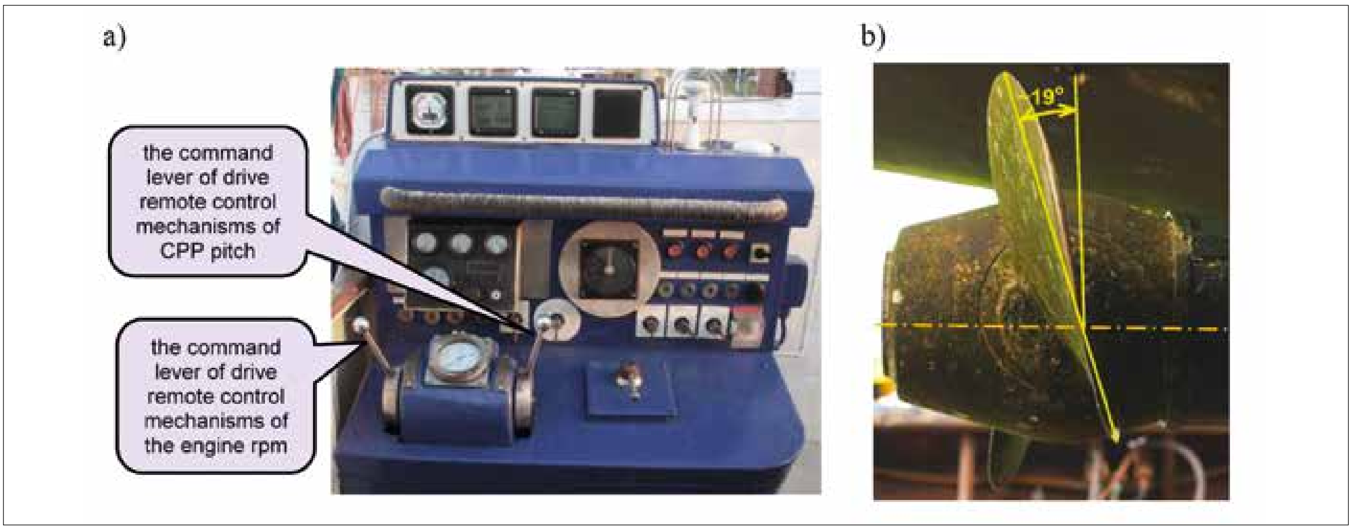

Fig. 5. Mechanisms controlling settings of the engine rotational speed and CPP pitch: a) command levers; b) example of the CPP blade angle

Nevertheless, there is no direct relation between the position of the command lever and the engine rotational speed. This is due to the fact that setting the rotational speed may correspond to different positions of the control rod of the inline injector pumps depending on the current load. The current load, in turn, depends on the orientation of the CPP blades to the propeller hub. Therefore, to control the current load of the ship engine, we introduce the shaft torque M as the next optimization constraint.

In general, the operating range of the engine is determined as follows:

$$M_{min} \leq m \leq M_{max} \tag{9}$$

where:

- M – the current value of the torque on the ship's propulsion shaft,
- M_{min} – the minimal permissible value on the ship's propulsion shaft,
- M_{max} – the maximum permissible torque value on the ship's propulsion shaft.

The minimum permissible torque M_{min} is determined by the minimum torque required to overcome resistance in the engine, gear, shaft bearings and CPP with the zero pitch angle.

As a rule, the maximum permissible torque is determined based on characteristics called the engine operating ranges. Unfortunately, we do not have any access to such characteristics. Therefore, the torque values were read from strain gauges mounted on the ship's propeller shaft by wireless transfer of the signal [26].

To determine the relationships between the torque M and the command outputs, separate functions were built using ANN techniques. To develop these functions, the same approach and observations were used as those used to develop the ANN functions (Fig. 6).

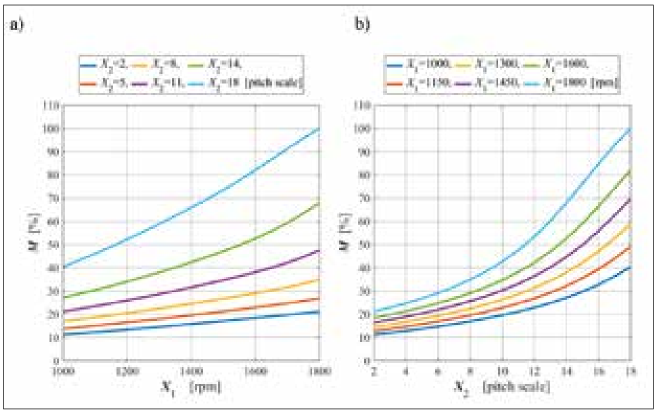

Fig. 6. The relationships between shaft torque M and: a) 'rotational speed of the engine'; b) 'pitch of the CPP' (for values of the observed variables presented in Table 1)

The minimum maneuvering speed of the ship v_{min} was selected as the additional constraint. Based on years of ship operator experience, we have taken into account the following inequality as the optimization constraint:

$$v_{min} \leq 2 \text{ knots} \tag{10}$$

This minimal ship speed plays an important role in avoiding possible damage resulting from collisions, contact with berths or other ships.

Two-criteria optimization algorithm

The two-criteria optimization algorithm procedure (Fig. 7) was created based on the mathematical optimization model developed, including both the objective function and the set of acceptable solutions.

To determine the optimum values of the output commands, the complete search method was used. This method was selected because of the small number of possible combinations of commanded outputs, that is, combinations of the decision-making variables X_1 'rotational speed of the engine' and X_2 'pitch of the CPP' respectively. This resulted in 289 combinations of possible settings of the commanded outputs. For each combination, the minimal values of the objective function were calculated.

To prevent the selection of an unacceptable solution, we applied a special technical approach based on significant enlarging of the value of the substitute objective function Z. In such case, this value Z was multiplied by a rate called the 'penalty factor'.

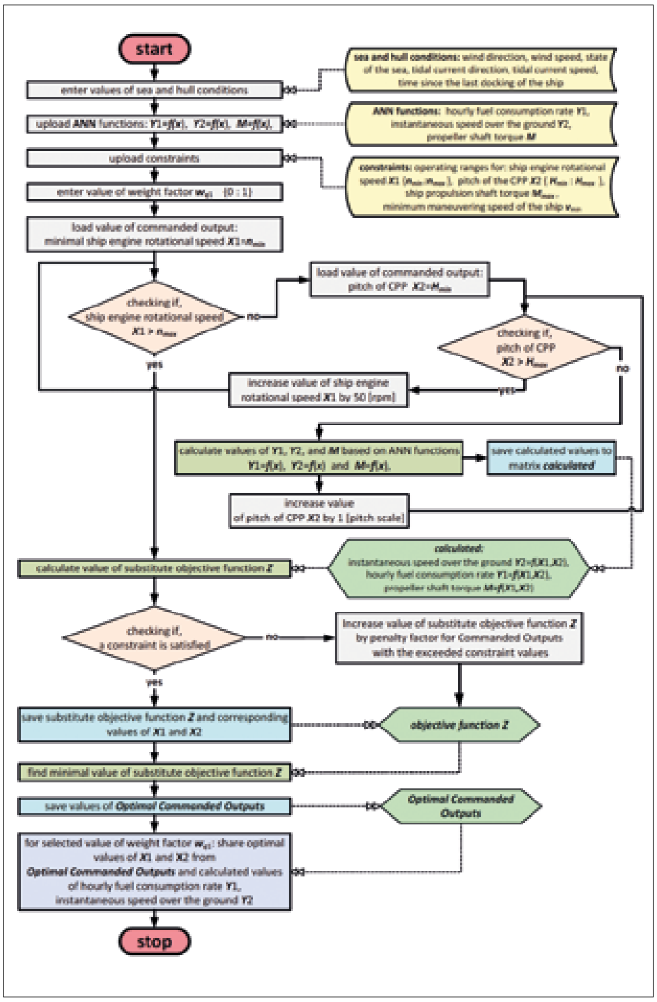

Fig. 7. Algorithm procedure of two-objective optimization

Optimization calculations were performed using standard mathematical functions and mathematical operations on matrices of the MATLAB package.

RESULTS AND DISCUSSION

To validate the correctness of the form of the substitute objective function Z_{sof} (Eq. 6), it was investigated before basic optimization calculations. An example of such an investigation is presented in Fig. 8 as the 3D plot where this function is mapped by the surface in a tradeoff curve form. The calculation was performed for the weight factors $w_{q1} = w_{q2} = 0.5$ for the entire ranges of the decision-making variables X_1 and X_2, taking into account the selected meteorological sea conditions presented in Table 1. The function obtained has a long, narrow, and bent shaped flat valley, where the minimum of the substitute objective function Z occurs. For other meteorological data, similar 3D plots were obtained that confirmed that the substitute objective function was chosen correctly.

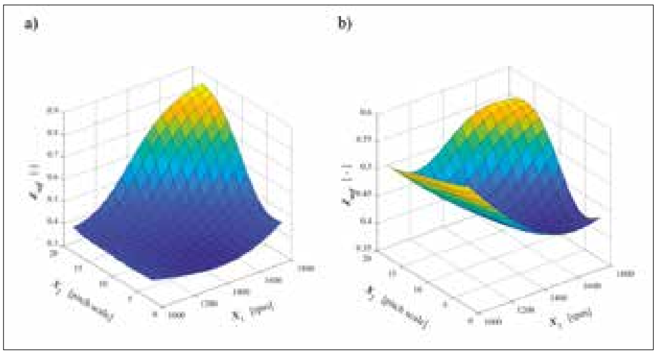

Fig. 8. Three-dimensional visualization of relationships between the substitute objective function Z and both the decision-making variables X_1 'rotational speed of the engine' and X_2 'pitch of the propeller': a) $w_{q1} = 0.35$; b) $w_{q1} = 0.65$ (for values of the observed variables presented in Table 1)

In our research, we performed calculations to carry out the analysis of the substitute objective function values for weight factors w_{qi} changing from 0 to 1 with a step of 0.1 for the various meteorological conditions and the entire range of decision variables X_1 and X_2 based on the developed two-criteria optimization algorithm procedure (Fig. 7).

Some examples of the results obtained by the optimization calculations are presented in Fig. 9 in the form of 2D graphs. All calculations were performed for selected weight factor values $w_{q1} = 0.2$, 0.4, 0.6, and 0.8 and selected meteorological and hull conditions presented in Table 1. The curves shown in the 2D graphs have marked points demonstrating the minima of the substitute objective function Z_{sof}.

In some cases, these points lie at the graph edges due to the constraint (Eq. 7) imposed on the decision-making variable X_1, which limits the allowable ranges of the ship engine speed. For example, in cases of the decision-making variable value of a pitch of the CPP:

– X_2 equals 2, the allowable maximum engine speed moved the substitute objective function minimum to the graph left edge (Fig. 8b),
– X_2 equals 14, the allowable minimum engine speed moved the substitute objective function minimum to the graph right edge (Fig. 8c).

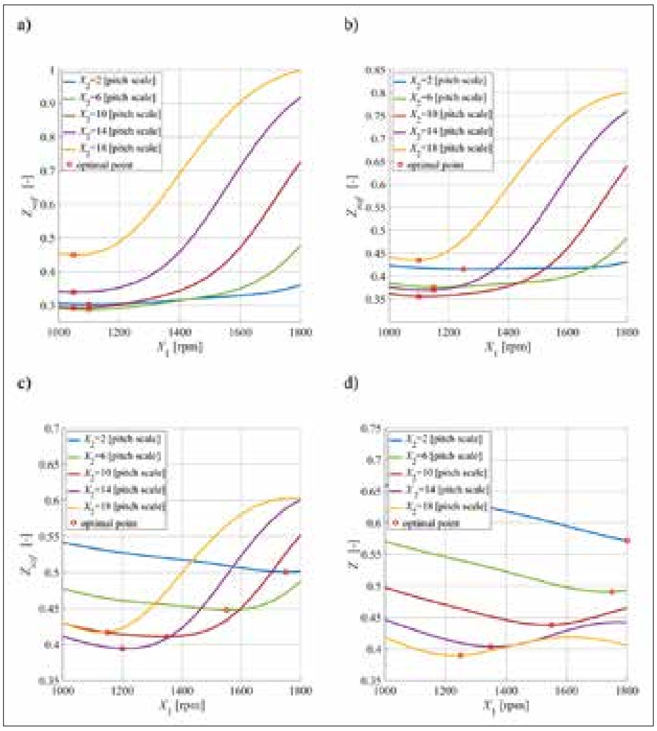

Fig. 9. The substitute objective function Z for values of the observed variables presented in Table 1 for the whole ranges of decision-making variables: rotational speed of the engine X_1 and pitch of CPP X_2 in relation to the weight factors: a) $w_{q1} = 0.2/0.8$; b) $w_{q1} = 0.4/0.6$; c) $w_{q1} = 0.6/0.4$ and, d) $w_{q1} = 0.8/0.2$.

Table 2 presents the estimated values of the output variables Y_1 (hourly fuel consumption rate) and Y_2 (instantaneous speed over the ground), together with the estimated value of the torque on the ship's propulsion shaft. These were calculated based on the developed algorithm procedure of two-criteria optimization presented in Fig. 7:

– for the optimal values of the command outputs (rotational speed of the engine and pitch of the CPP),
– for the weight factors wqi from 0 to 1 with a step of 0.1, and
– taking into account the selected meteorological conditions presented in Table 1.

Based on the optimization simulations and analysis of the obtained results carried out, we can state that the developed two-criteria optimization model strongly supports the selection of the commanded outputs of the considered ship's propulsion system. The minimum values of the substitute optimization function Z_{sof} (Eq. 6) occur for most of the range of decision-making variables (commanded outputs). However, in the case of selection of the border values of the weight factor close to 0 or 1, the minimum values of this function are moved to the left or right periphery of its parts due to the imposed constraints.

It is clear that with a weight factor of 0 or 1, the considered two-criteria optimization problem comes down to the issue of single-criterion optimization. Then the minimum hourly fuel consumption rate or maximum ship speed over the ground should be sought.

Tab. 2. Observed values of resource use predicted by the two-criterion optimization model

Weight factor w_{qi}	Optimal values of commanded outputs		Observed values of resource use		
	Optimal setting of rotational speed of the engine	Optimal setting of pitch of the CPP	Hourly fuel consumption rate	Instantaneous speed over the ground	Torque as a percentage of nominal torque
[-]	[rpm]	[pitch scale]	[dm^3/h]	[knot]	[%]
0.0	1050	3	10.76	2.22	12.30
0.1	1100	5	11.01	3.14	15.48
0.2	1100	7	11.45	3.90	18.38
0.3	1100	9	12.26	4.61	21.82
0.4	1100	11	13.71	5.27	26.04
0.5	1200	12	15.69	5.89	32.11
0.6	1200	14	18.38	6.49	39.40
0.7	1250	15	21.54	6.95	46.78
0.8	1300	16	26.64	7.41	55.86
0.9	1500	18	51.10	8.65	89.19
1.0	1800	15	60.62	8.92	92.69

In addition, for the given meteorological conditions and adjacent values of the weight factors, the two-criteria optimization model provides different combinations of the optimal values for the commanded outputs. Moreover, the estimated values of the output variables Y_{1obs} (hourly fuel consumption rate) and Y_{2obs} (instantaneous speed over the ground) are close to each other. This allows the introduction of additional optimization criteria, e.g. harmful pollutants contained in the exhaust gases emitted from the ship engine (NO_x, CO_2, ppm, etc.).

CONCLUSIONS AND FINAL REMARKS

Based on the results obtained, we can conclude that the developed model of two-objective optimization supporting a selection of commanded outputs for a ship's propulsion system:

– allowed us to develop an expert system that, in turn, supports a setting of the commanded outputs that ensures the set time to reach the required destination with rational fuel consumption,
– has minimum values of its substitute objective function for the vast majority of the range of decision-making variables, which makes it very useful for optimal selection of both the pitch and rotational speed of the CPP.

Moreover, the developed decision-making system:

– allows the selection of the commanded outputs in the dialogue between the decision-maker and the computer, where the decision-maker takes the appropriate decisions, and the computer processes the collected data and makes available a proposal for the selection of the commanded outputs,
– ensures cooperation with other systems used in the ship operation to receive the actual data,
– provides the possibility of continuously updating the parameters of the decision-making system resulting from the acquisition of the new data.

The developed methodology can also be applied to other types of vessels with a similar design solution to their propulsion systems. Developing such a system requires an experiment to be performed in the form of sea trials for the acquisition of new data specific to the tested vessel.

During the study, it was noted that, for some meteorological and operational conditions and adjacent values of the weight factors, the developed system provides various combinations of optimal commanded outputs and for which the projected values of the output variables (ship speed and fuel consumption) are close enough. Therefore, there is an opportunity to introduce additional optimization criteria, e.g. emissions of harmful pollutants (NO_x, CO_2, pollutant concentration) from the ship engine. This issue sets the direction for further research.

The research findings were also used in practice. Since the ship's operator did not allow the use of the installed measuring apparatus (torque meter, fuel consumption meter) outside the prescribed sea trial period, it was dismantled. Therefore, it was not possible to continue operating the computer system to select the proper parameters of the ship's propulsion system during navigation to the present date. To use the research findings, a special assisting table was drawn up for the ship operators. This table contained the ranges of the typical observed variable values and the corresponding commanded outputs, ensuring optimal values of both the ship speed and the fuel consumption values.

In the opinion of the shipowner of the tested ship, a noticeable reduction in fuel consumption was observed. Of course, this is only a qualitative opinion and cannot be considered as a reliable scientific confirmation of the results of the research findings.

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