IDENTIFICATION OF MODELS FOR MULTICRITERIAL OPTIMIZATION OF SAILING VESSEL DRIVING SYSTEMS

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Abstract

This paper deals with models of driving system of sailing vessels developed by applying methods of regression analysis and artificial neural networks. In particularly, a general form, identification process, and comparison of these models are presented.

Keywords: *driving system, sailing vessel, optimization, fuel consumption*

1. Introduction

In 1902, the largest, fastest sailing ship the world had ever seen was launched. The legendary Preussen dominated the seas, only to be gone in a few short years. Neither before nor since has the world seen such a magnificent sailing ship. Until today... Inspired by the legendary Tall Ship, Preussen, the new Royal Clipper has the proud distinction of being the largest and only five-masted sailing ship built since her predecessor was launched at the ending of the last century. With her complement of 42 sails, Royal Clipper is a splendid sight to behold. You might think she was an apparition from the grand age of sail, but Royal Clipper is as new as tomorrow. She boasts state-of-the-art navigation systems and all the comforts of today.

We can observe the tendency of increasing such a type of grandiose vessels year after year. In order to assure the passengers’ safety, the sailing vessels have to be equipped with engines enabling sailing in any wind conditions. As a rule, such vessels are equipped with adjustable propellers. In order to assure the operating effectiveness, the sailing vessels have to have the reasonable operating costs. But most important factors influencing these costs are expenses connected with engine fuel consumption. We can state that this consumption depends mainly on the following factors:

- the sailing conditions,
- the adjustable propeller speed and pitch.

The first group of factors is out of our control, whereas the adjustable propeller speed and pitch can be controlled by the ship operator. In order to control the engine fuel consumption, we should build an appropriate optimization model enabling selection of optimal settings of the adjustable propeller speed and pitch for various sailing conditions. This, in turn, requires to develop models combining the operating effectiveness of sailing vessels with the mentioned parameters.

In the subject bibliography, for example in [1], [2], [3], [4] and [5], we can find many models of driving system developed for the trade vessels. These models combine the vessel effectiveness with the engine rotation speed and propeller pitch. To combine all factors influencing the vessel effectiveness, methods of regression analysis are applied in these models. As a rule, relations

applied in these models have the form of nonlinear multiple regressions determined for only for three sailing conditions: light, variable and heavy.
In the case of sailing vessels, such an approach is unsatisfactory due to their sensitivity to changes of sailing conditions. It results from the following factors:

- as a rule, sailing vessel engines are auxiliary having a low margin of power,
- tall masts and rigs cause for increasing of air resistance which, in turn, depends on strength and direction of wind,
- hull shapes are sensitive to sea wave influences,
- sometimes a sea navigation is supported by sails.

Due to these factors, applying of classical methods for modeling of the sailing vessel driving system could not provide the expected effects. Therefore, we should develop models, which will take additionally into account:

- the changeability of sailing conditions in a wider range,
- the possibility of a sea navigation supported by sails.

Such models will be applied in the computer-aided system supporting the sailing vessel operator in a decision-making process concerning selection of the most suitable sailing parameters.
This paper deals with some issues connected with identification of models, which could be used for the optimization purpose of sailing vessel driving systems.

2. Concept of optimization model

In the sea navigation of sailing vessels can appear the variety of navigation situations depending on: sea and weather conditions, a time designated to reach the desired target, etc. In generally we could specify the following situations:

- sailing with the maximum speed in order to be just in time in the planned navigational point,
- sailing with the minimum fuel consumption in order to save the operating expenses,
- fast and cheap sailing to the planned navigational point.

In the last situation, we should find the compromise solutions. In order to do it, we should develop a method allowing for the optimal setting up of driving system parameters that is the propeller rotation speed and pitch. These settings, in turn, should assure the desirable values of parameters determining the cheapness and quickness of sailing to the planned navigational point.
Such a method can be developed based on the multicriterial optimization model of sailing vessel driving systems. It, in turn, requires to solve a few partial tasks as follows:

- formulation of the multicriterial optimization objective function together with determining its partial (criteria) functions and constraints,
- choose of the dependent and independent variables of the partial functions,
- selection of the method for identification of models setting up the partial functions,
- development of optimization algorithm (including selection of a method for finding of compromise solutions and computer representation).

In our approach, we have taken into account the following form of the multicriterial optimization objective function:

$$F_{obj} = w_1 \cdot F_{c1} + w_2 \cdot F_{c2} \ , \tag{1}$$

where:

F_{obj} - an objective function of the multicriterial optimization,

w_i - weights determining of the partial function importance; ($w_1 + w_2 = 1$),

F_{ci} - partial (criteria) functions of the multicriterial optimization.

As the partial functions, which should characterize the sailing cheapness and quickness, we have taken in mind relations combining the propeller rotation speed and pitch, and the sailing conditions with the both the engine fuel consumption or the vessel speed. In general description, we can express these functions as follows:

$$B = f(n_p, h_p, X_{sc}), \tag{2}$$

and

$$v = f(n_p, h_p, X_{sc}), \tag{3}$$

where:

B - an engine fuel consumption,
v - a vessel speed,
n_p - a propeller rotation speed,
h_p - a propeller pitch,
X_{sc} - sailing conditions.

A schematic diagram presenting of application of such relations in the optimization model is shown in Figure 1. In this Figure, the partial functions used to the optimization are distinguished by thick lines.

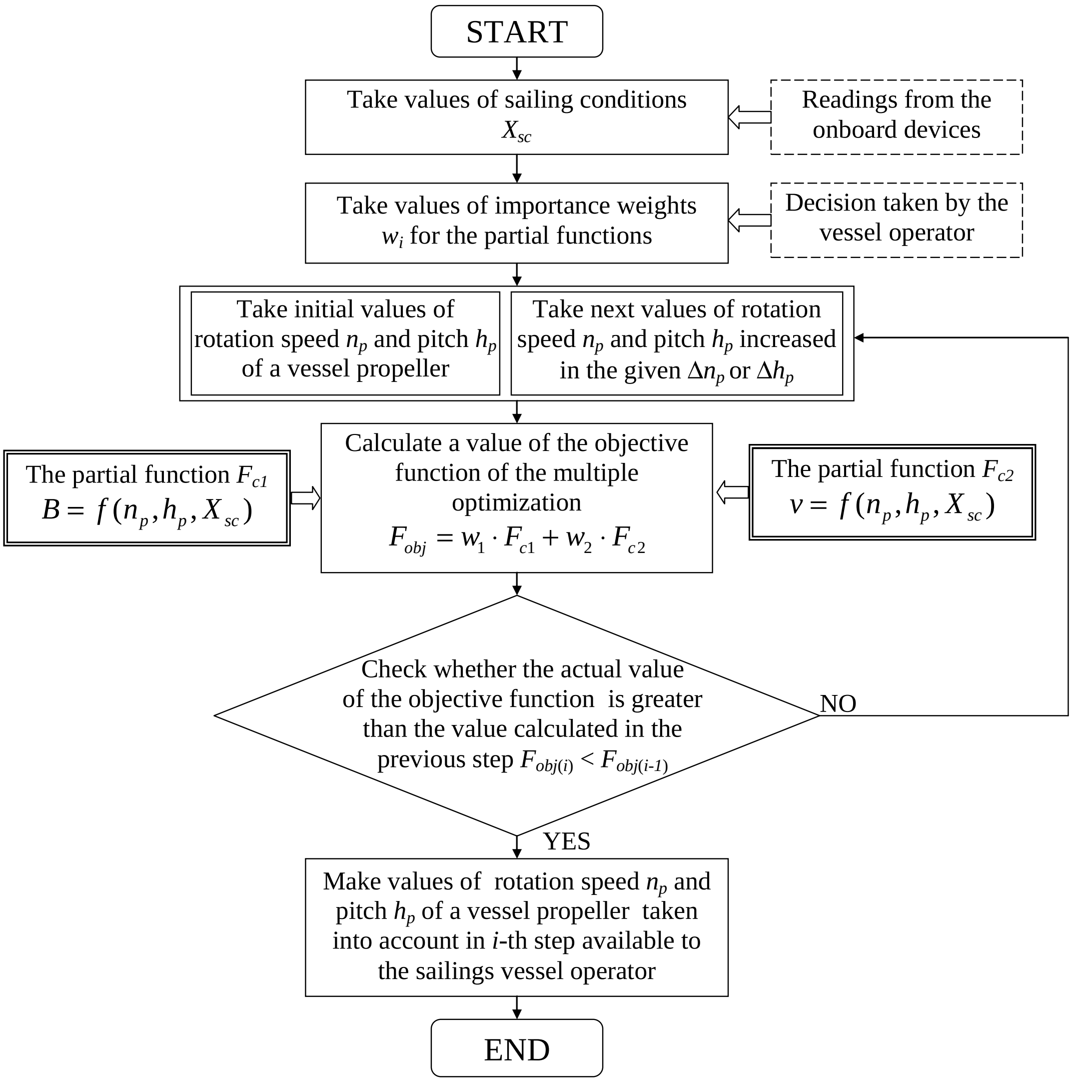

Fig. 1. The simplified schematic diagram of the optimization algorithm

In the further parts of this paper, we consider only modeling issues, which could assist in determining of the distinguished functions.

3. Modeling of driving system

3.1. General form of models

From a mathematical point of view, determination of these relations combining the propeller rotation speed and pitch, and navigational conditions with the engine fuel consumption or the vessel speed is a problem of approximation of multiple functions. This problem we can formulate as follows: for a given set of multiple function values $X_i = [x_1, x_2, \ldots, x_n]$ and their corresponding value y_i, where $i = 1, 2, \ldots, m$, we should determine a function combining a variable y called the dependent variable (a model output) and a vector of variables X called the independent variables (model inputs):

$$y = f(X) + \varepsilon \tag{4}$$

where:

y - a dependent variable,
X - independent variables,
ε - a value of an error term.

In the developed models, as dependent variables Y we selected parameters of determining the sailing cheapness and quickness that is the engine fuel consumption and the vessel speed respectively.
The independent variables X in these models are:

- factors characterizing sailing conditions (the wind direction and strength, state of the sea, etc.),
- parameters determining a work of sailing vessel driving system (the engine rotation speed and the propeller pitch).

The last parameters set up the decision-making variables being in disposal of the sailing vessel operator.
Disturbances ε of a model are caused by many factors for example: rig arrangements in relation to a wind direction, sea wave frequencies, mistakes made during readings from measurement devices, etc.
A schematic diagram of these models is presented in Figure 2.

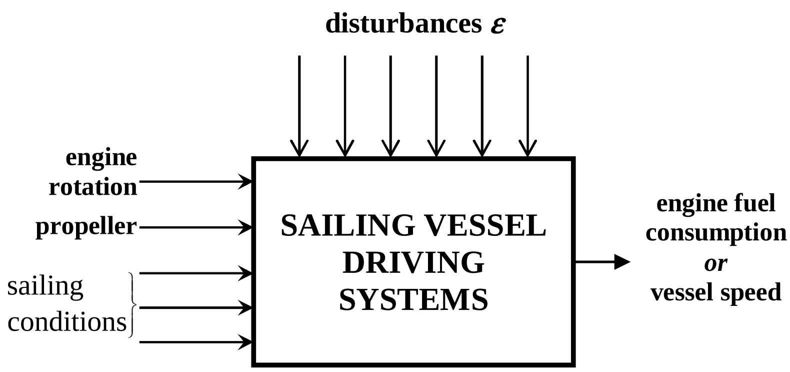

Fig. 2. A schematic diagram of sailing vessel driving system

3.2. Model variables and their acquisition

In the developed models, we have taken into account only such factors which could be read, estimated or calculated by vessel operators (a master or officers in watch) without any problems by readings their values from the onboard measuring devices.

As dependent variables, we select criteria which determining the sailing cheapness and quickness (spending of material and time resources) and can be used in the developed optimization model, namely:

- a specific fuel consumption B [dm^3/min], calculated as difference between indications of fuel gauges installed in the engine inlet and the outlet from injectors,
- a vessel speed v [knots], reading form the GPS receiver.

As the independent decision-making variables which can be controlled by a master or officers in watch, we take into account the following factors:

- an engine rotation speed n [rpm] , reading form the engine tachometer,
- settings of a propeller pitch H [scale intervals] reading form a scale of the propeller pitch lever.

The remaining independent variables are factors characterizing sailing conditions as follows:

- a wind speed v_w [m/s], reading from the anemometer,
- a wind direction K_w [^{o}], reading from the anemometer,
- a state of the sea s_m, [degree], carried out by the indirect estimation according to the Beaufort's scale,
- a tide speed v_p [m/s], calculated on a base of nautical charts and annual tide tables,
- a tide direction K_p [^{o}], calculated on a base of the nautical charts and annual tide tables,
- a vessel compass course KK [^{o}], reading from the magnetic compass,
- a vessel true course (with respect to the sea bottom) KDD [^{o}], reading form the GPS receiver.

In order to collect the appropriate set of data enabling to develop our models we carried out the special experiment on board of the sailing vessel 'POGORIA' during her regular voyages. Our observations were completed in various weather conditions, on variety geographical regions, and for different engine rotation speeds and settings of a propeller pitch. We obtained more than 800 observations, where about 50 percent of them concerned voyages without supporting of sails.

During our experiment we assumed that:

- voyages are realized with stable courses according to the smallest way to the intended point,
- wind and tide directions are orientated perpendicularly to the vessel symmetry axis (it takes into consideration increasing or decreasing dependent variables according to changes of the wind and tide directions - 0^0 perpendicularly to vessel boards, 90^0 from a bow, and -90^0 from a stern).

To solve the identification task for the considered models, we applied methods of regression analysis and artificial neural networks. For a testing purpose of neural networks we separated 37 observations (about 10% data) from the data set.

4. Identification of models

4.1. Regression models

To receive equations of regression models, we have applied methods of:

- the multiple linear regression in the form:

$$\hat{y} = a_0 + a_1 \cdot n + a_2 \cdot H + a_3 \cdot v_w + a_4 \cdot K_w + a_5 \cdot s_m + a_6 \cdot v_p + a_7 \cdot K_p , \tag{5}$$

- the multiple regression in the quadratic polynomial form:

$$\hat{y} = b_0 + b_1 \cdot n + b_2 \cdot n^2 + b_3 \cdot H + b_4 \cdot H^2 + b_5 \cdot v_w^2 + b_6 \cdot K_w + b_7 \cdot s_m + b_8 \cdot v_p + b_9 \cdot K_p , \quad (6)$$

– the multiple regression in the quadratic polynomial form limited to the decision-making variables:

$$\hat{y} = c_0 + c_1 \cdot n + c_2 \cdot n^2 + c_3 \cdot H + c_4 \cdot H^2 + c_5 \cdot n \cdot H , \quad (7)$$

The form of the multiple nonlinear regressions we have considered on a base of existing solutions, which can be found in the domain bibliography. All calculations we carried out by using the appropriate modules of STATISTICA programs.
Equations of multiple linear regressions combining the specific fuel consumption B and vessel speed v with the independent variables taken into account received the forms respectively:

$$\begin{aligned} \hat{B} = &-(7{,}43\mathrm{E}+01) + (5{,}67\mathrm{E}-02) \cdot n + (1{,}86\mathrm{E}+00) \cdot H + (1{,}24\mathrm{E}-01) \cdot v_w + (3{,}05\mathrm{E}-02) \cdot K_w + \\ &+ (2{,}21\mathrm{E}+00) \cdot s_m - (4{,}04\mathrm{E}+00) \cdot v_p + (6{,}45\mathrm{E}-02) \cdot K_p \end{aligned} \quad (8)$$

and

$$\begin{aligned} \hat{v} = &(2{,}62\mathrm{E}-01) + (2{,}48\mathrm{E}-03) \cdot n + (2{,}74\mathrm{E}-01) \cdot H - (3{,}67\mathrm{E}-02) \cdot v_w + (2{,}33\mathrm{E}-03) \cdot K_w + \\ &- (4{,}23\mathrm{E}-01) \cdot s_m - (3{,}99\mathrm{E}-01) \cdot v_p - (1{,}47\mathrm{E}-02) \cdot K_p \end{aligned} \quad (9)$$

For the presented models, we obtained values for the multiple determination coefficient R^2 equal 0,751 and 0,442 accordingly. It means that only 44% of the dependent variable variability is ‘explained’ by the multiple regression equation in the second model.
In a case of the multiple nonlinear regressions, their equations received the forms respectively:

$$\begin{aligned} \hat{B} = &(1{,}53\mathrm{E}+02) - (2{,}25\mathrm{E}-01) \cdot n + (1{,}09\mathrm{E}-04) \cdot n^2 - (5{,}32\mathrm{E}+00) \cdot H + (2{,}76\mathrm{E}-01) \cdot H^2 + \\ &+ (5{,}63\mathrm{E}-03) \cdot v_w{}^2 + (3{,}15\mathrm{E}-02) \cdot K_w + (2{,}41\mathrm{E}+00) \cdot s_m - (4{,}00\mathrm{E}+00) \cdot v_p + 5(,41\mathrm{E}-02) \cdot K_p \end{aligned} \quad (10)$$

and

$$\begin{aligned} \hat{v} = &-(7{,}47\mathrm{E}+00) + (1{,}44\mathrm{E}-02) \cdot n - (4{,}52\mathrm{E}-06) \cdot n^2 + (2{,}26\mathrm{E}-01) \cdot H + (1{,}71\mathrm{E}-03) \cdot H^2 + \\ &- (1{,}41\mathrm{E}-03) \cdot v_w{}^2 + (3{,}33\mathrm{E}-03) \cdot K_w - (3{,}65\mathrm{E}-01) \cdot s_m - (4{,}32\mathrm{E}-01) \cdot v_p - (1{,}43\mathrm{E}-02) \cdot K_p \end{aligned} \quad (11)$$

For these models, we obtained values of the multiple determination coefficient R^2 equal 0,813 and 0,443 accordingly. It means that only 44% of this dependent variable variability is ‘explained’ by the multiple nonlinear regression equation in the second model.
In order to check the legitimacy of our assumption taking in mind the sailing conditions, we carried out calculations for the multiple regression limited only to the decision-making variables because of its using in the classical approach presented in [[3]], [[4]] and [[5]]. We received the following equations respectively:

$$\begin{aligned} \hat{B} \; = &(1{,}26\mathrm{E}+02) - (1{,}16\mathrm{E}-01) \cdot n + (1{,}00\mathrm{E}-04) \cdot n^2 - (6{,}92\mathrm{E}+00) \cdot H + \\ &+ (5{,}83\mathrm{E}-01) \cdot H^2 + + (5{,}90\mathrm{E}-03) \cdot H \cdot n \end{aligned} \quad (12)$$

and

$$\begin{aligned} \hat{v} = &-(3{,}35\mathrm{E}+00) + (2{,}07\mathrm{E}-02) \cdot n - (1{,}00\mathrm{E}-06) \cdot n^2 - (9{,}11\mathrm{E}-01) \cdot H + \\ &+ (2{,}21\mathrm{E}-03) \cdot H^2 + 4{,}70\mathrm{E}-04 \cdot H \cdot n \end{aligned} \quad (13)$$

In these cases, we obtained values of the multiple determination coefficient R^2 equal 0,651 and 0,203 accordingly. Such low values of this coefficient confirmed the legitimacy of our assumption taking the sailing conditions into consideration.

Nevertheless, analysis of values of the multiple determination coefficient R^2 calculated for the best forms of multiple regressions shows that the models based on such methods are not suitable for the considered optimization purpose due to not enough explanation of the dependent variable variability.

4.2. Neural network models

To develop neural network models, we applied two independent nets. They represented the same dependences like in a case of regression models. In both models, we used a neural network structure including two hidden layers (Fig. 3). The output layer has one neuron representing a model output (the vessel speed *v* or the specific fuel consumption *B*), whereas the input layer has seven neurons representing model inputs (all independent variables introduced in order). During a teaching process of the neural networks we changed a number of neurons comprised in the hidden layer and their activation function in order to obtain more desirable results.

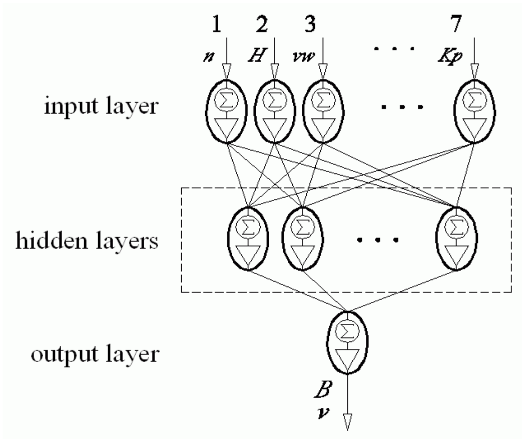

Fig. 3. Two-layer neural network

Values of a teaching set subjected to linear normalization in a range from 0,1 to 0,9. In this teaching process, we applied the backpropagation method. All calculations have been carried out by using the appropriate modules of MATLAB programs.
As it was mentioned, from the data set we separated 37 observations (about 10% data) for a testing purpose of neural networks. The highest differences between values obtained from both the testing set and the primary set were equal 15 % for the specific fuel consumption *B* and 11% for the vessel speed *v* respectively**.** Comparison of both networks is presented in Figure 4.

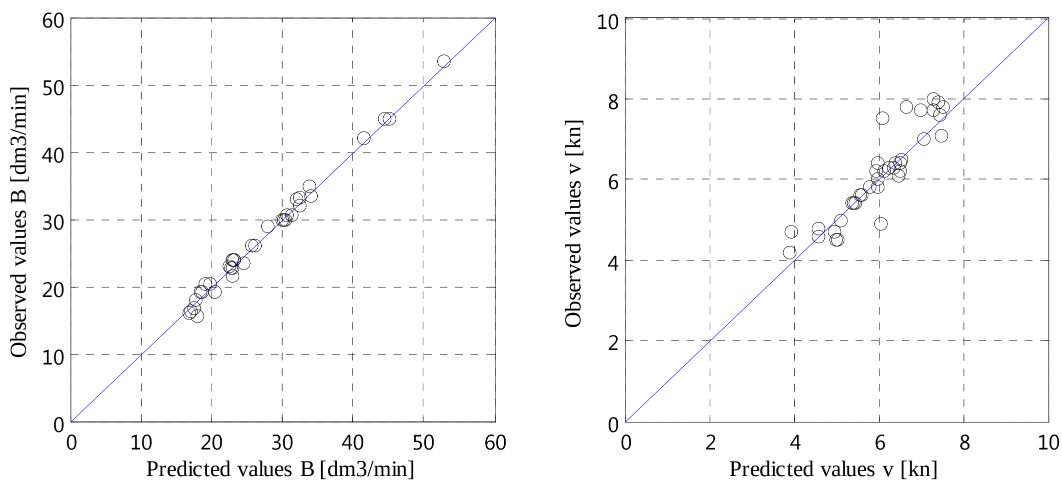

Fig. 4. Comparison of the primary and testing networks

5. Comparison of models and conclusion

In the first step we try to assess differences expressed as percentage between the observed and estimated values of the dependent variable. The estimated values of specific fuel consumption *B* outnumbered the observed values more than 10% in 22 cases for the multiple linear regression and 21 cases for the multiple nonlinear regression. We obtained the same results for the second model where the dependent variable is a vessel speed *v*. In a case of neural network models, we noticed that the estimated values outnumbered the observed values more than 10% in 2 cases for the first model and 7 cases for the second one. Analysis of these results allowed us to state that the greatest differences appeared in atypical operating situations, for example in heavy wind conditions with large settings of a propeller pitch.
In the second step we carried out comparison of the considered model by using index estimating of variances between the observed and estimated values of the dependent variable frequently termed as the standard error of estimate [6]:

$$\hat{\sigma}_{\varepsilon} = \sqrt{\frac{\sum (y_i - \hat{y}_i)^2}{n-2}} , \tag{14}$$

where:

$\hat{\sigma}_{\varepsilon}$ - the standard error of estimate,
y_i - the observed value of the dependent variable,
$\hat{y}_i$ - the estimated value of the dependent variable,
n - a number of observations.

The standard error of estimate allows to compare all used methods because of its universality. Results of such comparison are presented in Table 1.

Tab. 1. The standard error of estimated models.

Method	Specific fuel consumption B_h [dm^3/min]	Vessel speed v [knots]
Multiple linear regression	15,00	1,39
Multiple nonlinear regression	14,74	1,38
Multiple nonlinear regression limited to decision-making variables	23,78	1,20
Neural networks	1,08	0,74

Analysis of Table 1 shows that the most suitable models of the sailing vessel driving system are models based on neural networks. However, these models can not be presented in the analytical forms, even so they will be taken into consideration in the future optimization procedure enabling selection of optimal settings of sailing vessel operating parameters for various sailing conditions.

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