Selection of optimal forecasting models in the navigation safety decision support system

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Abstract. One of the most important components of the navigation safety decision support system (NS DSS) is the forecasting block. The results of his work have an impact on the type of control actions formed by the system. The effectiveness of this block depends on the forecasting methods used. The accuracy of the result of the forecasting block depends largely on the choice of the forecasting method. To develop reliable forecasts, it is necessary to determine forecasting methods, in relation to the specifics of the functioning of the NS DSS. Several ways of solving the problem of choosing the appropriate forecasting method in relation to the NS DSS are proposed. Two methods are demonstrated: Artificial neural networks (ANN) using precedents and Intelligent process analysis (IPA). Solving the problem of choosing the optimal method will guarantee obtaining a forecast with a certain level of accuracy, which will significantly increase the reliability of the forecast and, as a result, the effectiveness of the NS DSS. Solving the problem of choosing the optimal method will guarantee obtaining a forecast with a certain level of accuracy, which will significantly increase the reliability of the forecast and, as a result, the effectiveness of the NS DSS, which allows us to assert the relevance of this problem and further research.

1. Introduction

Without a predictive monitoring system, the decision support system (DSS) can only make decisions regarding the consequences of an event that have already occurred. This will inevitably lead to late, untimely actions, which means that the value of such a DSS is completely insignificant. If there is a predictive monitoring system, the NS DSS can promptly recommend to the boatmaster the best measures to avoid the risk of ship collisions, grounding, etc. The presence of a predictive function is one of the essential characteristics of the NS DSS being developed, which allows solving the following tasks:

- identification of undesirable trends in the development of the current situation;
- assessment of the consequences of the application of control actions developed by the decision-making block.

The main task of the forecasting model is that it should have such properties that are sufficient to monitor the real process during the transitions of the ship’s state from dangerous to safe with a given accuracy.
2. Formalized representation of predictive functions in the NS DSS

The activities in the NS DSS being developed for the purpose of ensuring global security are carried out simultaneously at the following levels of interaction:

- interaction of the ship's internal subsystems ("by subsystems");
- interaction with the environment ("ship-nature");
- interaction with other ships ("group of ships").

A feature of the functioning of the NS DSS is a conflict that occurs when there is a danger of collision or convergence of ships at an excessively close distance. The conflict caused by a security violation (maintaining the integrity of the system) forces the ship to constantly solve the tasks of finding a new safe state, \( S_{\text{есмонажное}} \), taking into account classical and non-classical control and transferring the system from a dangerous state to a new equilibrium safe state in accordance with the concepts and principles of the NS DSS being developed [1]. With this approach, the behavior of the ship, both in the presence of a control action and without it, is a discrete process, each step of which, in general, is the transition of the ship's state from one class of states to another [2] (Figure 1).

If it is possible to form generalized or aggregated images based on a priori information - classes of states \( \{ S_1, S_2, \ldots, S_n \} \) with a known reaction of the ship in each class, then the control action can be considered as a display of the state of the ship from class to class (including to the original class).

In the NS DSS architecture, one of its most important components is the forecasting block [3], where the main information for the forecast is time series, and the forecast tool is a predictive model or predictor. The results of his work have an impact on the type of control actions formed by the system.

Let's consider the basic concepts of forecasting [4], which should be applied in the NS DSS being developed. Let's imagine that the time series \( x_t \) generated by some model can be represented as two components:

\[
x_t = \xi_t + \varepsilon_t,
\]

where the value \( \varepsilon_t \) is generated by a random process with zero mathematical expectation and a finite (not necessarily constant) variance, and the value \( \xi_t \) can be generated either by a deterministic function, or by a random process, or by some combination of them.

The value \( \xi_t \) is called the level of the series at time \( t \), and the development of the level in time is called a trend. The trend can be expressed by both deterministic and random functions, or a

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**Figure 1.** A simplified view of the state transitions of the ship, where in the designation of the state of the ship, the upper index means the class of the state of the ship, and the lower index means the number of the state of the ship.
combination of them. Trends can have a variety of series with a random level or a random spasmodic growth pattern, for example:

$$\xi_t = a_1 + a_2 t + a_3 t^2,$$

where $a_1, a_2, a_3$ are the constant coefficients,

$t$ - time.

$$\xi_t = \xi_{t-1} + u_t = \xi_0 + \sum_{t=1}^{\infty} u_t,$$

where $\xi_0$ is some initial value,

$u_t$ - a random variable.

The selection $\xi_t$ and $\xi_{t-1}$ is the subject of the analysis of the time series in the forecasting task. The estimation of future members of the series is usually made using a predictive model. A predictive model is a model that approximates a trend. Forecasts are estimates of the future levels of the series, and the sequence of forecasts for different lead periods $\tau = 1, 2, ..., k$ is an estimate of the trend.

The time series of the NS DSS under study are generated not by one, but by several probabilistic models alternately (see Figure 1), that is, models with multiple states. Moreover, the transition from one state to another is a probabilistic process and corresponds to the appearance of increased random disturbances, then stepwise changes in the level of the series, then jumps in the dynamics of their growth [4] (see Figure 2).

![Figure 2. The main states of the process generating a series](image)

With this approach, events that are random in nature are clearly reflected in the model, and consistently incoming data is used to calculate a posteriori probabilities and analyze situations.

The methods of analysis and forecasting of an isolated series according to Figure 2 are flexible enough to model a wide class of one-dimensional processes or their individual sides to ensure safety for each class of ship states. The processes considered in the NS DSS are not isolated from each other, so it is necessary to consider the cumulative impact of all third-party factors (both internal and external) over time, then the methods of analyzing isolated series give way to multidimensional statistical analysis. This allows us to include valuable additional information in the model, take into account the structure of the NS DSS and get interrelated forecasts of several variables.

In the case of multidimensional statistical analysis, systems of linear equations and multiple regression models are usually constructed. In the procedure for constructing such models, five main stages can be distinguished: the selection of time series (factors) for inclusion in the model, the separation of all selected factors into exogenous (external) and endogenous (internal), the adoption of a hypothesis about the nature of the relationship between endogenous and exogenous variables (that is, the structure of the model), the evaluation of model parameters according to a given criterion, the analysis of the adequacy of the model.

Classical regression analysis is based on the hypothesis that the process under study can be approximated by a linear equation with constant coefficients. These coefficients reflect the degree of connection of various variables with the studied value. In the considered navigation safety system, the force of interaction of variables does not remain unchanged, just as the environment in which the process under study develops does not remain unchanged. The estimates of the coefficients reflect the
nature of the relationship of variables only on average in the sample, so it is difficult to expect that they will lead to good short-term forecasts.

In the work [4], a method for adapting the coefficients of multiple regression is proposed. This makes it possible to study the direction and nature of the evolution of the relationships of variables and to obtain forecasts using a model that better reflects the current state of the process. The task is to study a series with rows $x_1, x_2, \ldots, x_M$, where the estimate of the value of $y$ can be obtained as a weighted sum of the form:

$$\hat{y}_t(t) = \omega_{t,t}x_{1,t} + \cdots + \omega_{M,t}x_{M,t} = \sum_{i=1}^{M} \omega_{i,t}x_{i,t}, \tau \geq 0.$$  

This is a multiple regression equation. By comparing the estimate $\hat{y}_t(t)$ with the actual point of the series $y_{t+\tau}$, you can calculate the error:

$$e_{t+\tau} = y_{t+\tau} - \hat{y}_t(t) = y_{t+\tau} - \sum_{i=1}^{M} \omega_{i,t}x_{i,t},$$

and on the basis of the obtained result, make an adjustment of the coefficients $\omega_{i,t}$.

3. Forecasting methods.

Now let's go directly to forecasting. Forecasting characterizes the future development based on the hypothesis that the main factors and trends of the past period will remain for the forecast period or that it is possible to justify and take into account the direction of their changes in the considered perspective [4].

The presence of a predictive function is one of the essential characteristics of the NS DSS, which allows solving the following tasks:

- identification of undesirable trends in the development of the current situation;
- assessment of the consequences of the application of control actions developed by the decision-making block.

As it was shown above, the efficiency of the NS DSS forecasting block depends on the forecasting methods used [5]. Therefore, it is important to clearly distinguish the areas of application of different forecasting methods and models in order to obtain a forecast. It is known that among the forecasting methods, there are intuitive (expert) and formalized (mathematical) methods.

3.1 Intuitive forecasting is used when the object of forecasting is either too simple or so complex that it is almost impossible to take into account the influence of many factors analytically. The following expert methods are known:

1. The commission method;
2. The "Delphi" method;
3. The script method;
4. The goal tree method;
5. The method of collective generation of ideas, etc.

3.2 Formalized (objective) forecasting methods are methods of studying an object in order to obtain a judgment about its future state, which are based on the description and (or) modeling of the predicted process using mathematical methods. Among the formalized methods, there are:

1. Regression forecasting models
2. Autoregressive forecasting models (ARIMAX, GARCH, ARDLM)
3. Exponential Smoothing (ES) models
4. Model on the most similar pattern (MMSP)
5. A model based on neural networks (ANN)
6. The model on Markov chains (Markov chains)
7. A model based on classification and regression trees (CART)
8. A model based on a genetic algorithm (GA)
9. Support vector machine (SVM)
10. Transfer function-based model (TF)
11. A model based on fuzzy logic (FL), etc.

The advantages and disadvantages of models and methods are systematized in [6] and are shown in Table 1.

Table 1. Comparison of models and forecasting methods

| Model and method                          | Advantages                              | Disadvantages                                                                 |
|-------------------------------------------|-----------------------------------------|--------------------------------------------------------------------------------|
| **Regression models and methods**         | simplicity, flexibility, transparency   | the complexity of determining the functional dependence; the complexity of finding the coefficients of dependence; the lack of the possibility of modeling nonlinear processes (for nonlinear regression) |
|                                           | of modeling; uniformity of analysis and  |                                                                                |
|                                           | design                                   |                                                                                |
| **Autoregressive models and methods**     | simplicity, transparency of modeling;   | the complexity and resource intensity of model identification; the impossibility of modeling non-linearities; low adaptability |
|                                           | uniformity of analysis and design; many |                                                                                |
|                                           | application examples                     |                                                                                |
| **Exponential smoothing models and methods** | simplicity of modeling; uniformity of  | insufficient flexibility; narrow applicability of models                        |
|                                           | analysis and design                      |                                                                                |
| **Neural network models and methods**     | non-linearity of models; scalability;   | lack of transparency; complexity of the choice of architecture; strict requirements for the training sample; complexity of the choice of the learning algorithm; resource intensity of the learning process |
|                                           | high adaptability; uniformity of analysis and design; many application examples |                                                                                |
| **Models and methods based on Markov chains** | simplicity of modeling; uniformity of  | impossibility of modeling processes with long memory; narrow applicability of models |
|                                           | analysis and design                      |                                                                                |
| **Models and methods based on classification and regression trees** | scalability; speed and simplicity of the learning process; the ability to take into account categorical variables | ambiguity of the tree construction algorithm; complexity of the stop issue |

The above analysis shows that not all of these methods and models are suitable for the purposes of forecasting processes in the NS DSS. The considered methods and forecasting models (see Table 1) can be used only within the boundaries of a particular state of the ship, where they are effective, reliable and have high performance. Therefore, when applying specific models, it is necessary to take into account the most likely patterns of development of the real security process and correlate them with the capabilities of the models used. The main task of the forecasting model is that it must have such properties that are sufficient to track the real process during the transitions of the ship's state from one to another with a given accuracy.

3.3 Combined models and methods. One of the most popular modern trends in the field of creating forecasting models is the creation of combined models and methods. This approach makes it possible
to compensate for the disadvantages of some models with the help of others and is aimed at improving the accuracy of forecasting, as one of the main criteria for the effectiveness of the model. The use of combined models is a direction that, with the correct approach, allows you to increase the accuracy of forecasting.

4. Statement of the problem and tasks of choosing a forecasting method in the NS DSS.

The choice of the most effective method for solving the forecasting problem for a specific state of the ship from a set of states \( S_1, S_2, \ldots, S_i, \ldots, S_{n} \) consists in the formation of a set of methods that allow predicting the time series \( X(t) \) with the least error and the least time spent. With this approach, the number of forecasting models is significantly reduced and the effectiveness of the chosen method is significantly increased.

The choice of the forecasting method based on the state of the ship will primarily be influenced by the fact that the processes of ensuring safe navigation take place in a certain geographical space. Therefore, there is a need for modeling the environment using the technology of geoinformation systems (GIS), in which a ship or a group of ships operates [8,9].

In this case, to obtain forecast values, it is necessary to use not only the actual values of the desired series, but also the values of a set of external factors presented in the form of time series. In general, the time series of external factors may have a time resolution different from the resolution of the desired time series [4]. Such external factors include environmental parameters: the speed and direction of the current, waves, ambient temperature, atmospheric transparency, and many others, as well as seasonality, that is, the hour of the day, day of the week, month of the year.

In general, external factors can be discrete, that is, represented by time series, or categorical, that is, consisting of subsets, so the term "visibility" can be attributed to two categories: "in full view of each other" or "limited visibility". Only some forecasting models allow us to take into account categorical external factors, most models allow us to take into account only discrete ones. Among such models, we can distinguish classes of regression models, autoregressive models, etc.

4.1. Determination of the criterion of forecasting methods. Now let's define the criteria for the applicability of forecasting methods. The most important criteria are:
- a criterion for the accuracy of the forecast, which can be expressed by the error value – \( K_{E} \);
- the criterion of the speed of the forecasting method, which can be expressed by the amount of time spent on performing the forecasting procedure – \( K_{tm} \).

Thus, the set of criteria has the following form:

\[ K = \{ K_{E}, K_{tm} \}. \]

4.2 The task of choosing a forecasting method. Based on the above requirements and conditions of the NS DSS, it is possible to formulate the task of choosing a forecasting method and the proposed method of its solution:

Let \( X(t) \) be a time series, \( M = \{ m_1, m_2, \ldots, m_W \} \) – a set of applied forecasting methods, \( A = \{ a_1, a_2, \ldots, a_N \} \) - a set of characteristics of the problem and the object of forecasting (a time series \( X_c \)), \( K = \{ k_1, k_2, \ldots, k_M \} \) - a set of criteria for evaluating the optimality of methods \( M \). It is necessary to form a set:

\[ M_{optX_c} = \{ m_1, m_2, \ldots, m_W \}; m_j \in M_{optX_c} \rightarrow K_{M_j} = \arg \max f \left( K_{M_j} \right), \]

where \( M_{optX_c} \) is the set of \( m_j \) of optimal methods for predicting the time series \( X_c \);
\( K_{M_j} \) and \( K_{M_i} \) are the sets of values of the optimality criteria \( K \) for the methods \( m_j \) and \( m_k \in M \);
\( f \left( K_{M_j} \right) \) – a function for generating an overall score according to the criteria \( K \).
From this we can conclude that the task of determining the optimal methods and models of forecasting in the NS DSS is the task of determining the best alternative from the set of alternatives that denote the choice of a particular forecasting method (decision-making tasks) [7].

5. Solving the task of determining the optimal forecasting methods

The solution of the task of determining the optimal forecasting methods, as well as in the decision-making block of the NS DSS, can be carried out according to precedents [8]. Of interest is the work [7], which demonstrates the methodology for determining optimal methods and models using precedents for choosing a forecasting method.

5.1 A method for determining optimal forecasting methods and models using precedents. In general, a precedent may include the following components[8]:

- description of the task (problem situation);
- solving the problem (diagnosing the problem situation and recommendations of the LPR);
- the result (or forecast) of the application of the solution.

The result may include a list of completed actions, additional comments, and links to other precedents. A precedent (CBR) can have both a positive and a negative outcome of the application of the solution, and in some cases, a justification for the choice of the proposed solution and possible alternatives can be given.

Based on this representation of the precedent, you can write:

\[ C_k = (A_{C_k}, D_{C_k}, R_{C_k}) \]

where \( A_{C_k} = \{a_1, a_2, ..., a_N\} \) is the set of features that perform the description of the task, which can be presented both in quantitative and qualitative form;

\( D_{C_k} = \{d_1, d_2, ..., d_Q\} \) - solving the problem;

\( R_{C_k} = \{r_1, r_2, ..., r_W\} \) - the result of applying the solution of the problem (it can be either positive or negative), which can represent a set of both quantitative and qualitative characteristics.

To solve the problem of determining the optimal forecasting methods, we modify the type of precedent \( C_k \):

1. \( A_{C_k} = A \), where \( A \) is the set of characteristics of the problem and the object of forecasting, containing the statistical characteristics of the time series (variance, mathematical expectation, coefficient of variation, etc.), as well as the forecast horizon.
2. \( D_{C_k} = \{d_i\} \), where \( d_i \) is the forecasting method.
3. \( R_{C_k} = \{r_{d_i}\} \), where \( r_{d_i} \) is the average absolute error of forecasting the time series \( X(t) \) using the solution \( d_i \).

To implement reasoning based on precedents, it is necessary to ensure the correct extraction of precedents from the library of precedents (LP). The analysis of the methods performed in [7] showed that the disadvantage of the "k-nearest neighbors method" is its low efficiency when processing a large number of precedents; when using a method based on the use of genetic algorithms, there is a problem of extracting all similar precedents, which can have a negative impact on the result of solving the problem; the use of the knowledge-based method, as well as the method based on the use of decision trees, is effective with large volumes of the precedent base; the method based on artificial neural networks (ANN) allows you to get a more accurate result than the method based on the use of binary trees; the ANN, in addition to extracting precedents, also performs inference based on them, allowing you to get a final assessment of the applicability of certain solutions to the current problem situation; the time for setting up and training the ANN exceeds similar indicators for hierarchical trees;
the knowledge-based method, as well as the method based on the use of decision trees, extract precedents without performing inference based on them; the method of extracting use cases by assessing applicability can be applied at the stage of adapting the resulting solution in accordance with the current problem [8].

Thus, according to the results of the analysis, it is determined that the most promising method for solving the problem of determining optimal forecasting methods is the use of a method based on the use of decision trees, as well as a method based on the use of Artificial neural networks. To determine the optimal methods for predicting the time series $X$, the inputs of the ANN receive the values of the features $I_{j=1,2,...,N}$, while each output $r_{di} = 1,2,...,W$ corresponds to a solution $m_i = m_{li}$, therefore, a set of optimal methods for predicting the time series $X(M_{opt,X})$ can be formed according to the function:

$$f(r_{di}) = (r_{di} > \theta) \rightarrow (m_i \in M_{opt,X}).$$

where $\theta = \text{const}$. Thus, the most optimal forecasting methods will be chosen to predict the time series $X$. The time series of predicted values $X$ can be obtained by the formula:

$$X_f = \{X_{f,t} = \sum_{i=1}^N \zeta_{m_i} X_{m_i,t}\},$$

where $\zeta_{m_i} = \frac{r_i}{\sum_{i=1}^N r_i}$; $N$ is the number of elements of the set $M_{opt,X}$;

$$X_{m_i} = \{X_{m_i,t}\} - \text{a time series of } X \text{ values predicted using the method } m_i.$$

5.2 The method of extracting process precedents. Let’s consider another method of choosing a forecasting method $m_i$ by extracting process precedents [9,10]. Forecasting methods in the NS DSS largely depend on the state of the ship. The condition of the ship, as shown above (see figure 1) — this is the process of transferring a ship from a dangerous to a safe state. The process of ensuring the safety of the ship is based on general algorithms of actions (MPPSS-72, instructions, orders, etc.), and the options for selecting and executing individual procedures within the general sequence depend on the “circumstances and conditions of navigation”. This model contains knowledge about all possible options for choosing sequences of actions. Such a generalized model contains knowledge about typical approaches to solving the problem of process management and is a precedent, which can be used when organizing the output by analogy.

Intelligent process analysis (IPA) (processmining) is a methodology for building models of ship safety processes by analyzing sequences of events that are recorded by information systems. Therefore, it can be assumed that for each model of the security process precedent $C_{\text{safety}}$ that reflects the cause-and-effect relationships between events and actions (performed tasks) of the process, it is possible to choose a predictive model $C_{\text{prediction}}$ of the precedent in accordance with the inference rules:

$$C_{\text{safety}} \xrightarrow{\text{Rule}} C_{\text{prediction}}.$$

The permissible relationships between $C_{\text{safety}}$ and $C_{\text{prediction}}$ represent a set of declarative knowledge in the form of production rules, such as “if..., then...” and limit the selection of models $m_i$ for the current state of the ship. In other words, the rules define a limited set of possible models $m_i$ depending on the state of the ship.

The choice $m_i$ is determined by the values of the input variables (see section 5.1), as well as the criteria for evaluating the effectiveness and efficiency (see section 4.1). With this interpretation, the choice of the forecasting model method $m_i$ can be considered as an analog of the traditional logical inference in artificial intelligence, characterized by a combination of procedural and declarative knowledge. The log $M$, as well as a set of restrictions on the states of the ship, $C_{\text{prediction}}$ act as similar data when building a precedent.
The prediction models $m_i$ are displayed in the log as a finite sequence belonging to the complete set $M$. Between the models $m_i$ of this sequence, the ratio of transitions of the ship's states is set $\{S_1, ..., S_n, \ldots, S_k, S_1, \ldots, S_p\}$:

$$M = \{m_{s_1}, ..., m_{s_n}, m_{s_k} \rightarrow ..., m_{s_1} \rightarrow m_{s_p}\},$$

where $\{S_1, ..., S_n, \ldots, S_k, S_1, \ldots, S_p\}$ is the complete set of ship states, $\{m_{s_1} \rightarrow ..., m_{s_k}, m_{s_1} \rightarrow ..., m_{s_p}\}$ is a complete set of transitions of forecasting models.

The ratio $M$ compares each state of the ship, the forecasting model. Each state of the ship $\{S_1, ..., S_n, \ldots, S_k, S_1, \ldots, S_p\}$, as discussed above, is associated with the solution of one of the typical tasks implemented by the process of state transitions. Based on the selection of subsets of the log corresponding to a particular situation, it is possible to obtain a predictive model $m_i$ for the classes of three states according to Figure 1:

$$m_1 = \{m_{s_1} \rightarrow ..., m_{s_n}\},$$

$$m_2 = \{m_{s_1}, m_{s_2} \rightarrow ..., m_{s_k}\},$$

$$m_3 = \{m_{s_1} \rightarrow ..., m_{s_p}\}.$$

where $m_1, m_2, m_3$ — is the route reflecting the application of forecasting methods corresponding to the state of the ship.

The model obtained as a result of using the method (process mining) has the ability to adapt taking into account the limitations and expected results. The constraints are evaluated based on the interval representation of time. This assessment allows us to find out the possibility of improving the effectiveness of the forecasting model by parallelizing its actions. The adaptation is performed by removing tracks (or fragments of tracks) from the presented models that do not meet the time constraints, as well as shifting fragments of tracks on the security time line in the NS DSS. The selection of the deleted traces (or their fragments) is carried out on the basis of a qualitative description of the process.

6. Conclusion

Thus, the presented analysis of forecasting methods and models showed that uncertainty when choosing a forecasting method is a factor that has a negative impact on the reliability of the result of the forecasting unit and, as a result, on the reliability of the control system as a whole.

At the same time, the properties of the NS DSS, such as dynamism, uniqueness of the structure and algorithm of functioning, incompleteness of the description, impose increased requirements on the accuracy and time complexity of the applied forecasting methods. These circumstances make it very urgent to choose the optimal forecasting methods for use in the forecasting unit of the NS DSS being developed, where the forecasting method has "a certain field of application in which it is effective" [6]. Solving the problem of choosing the optimal method will guarantee obtaining a forecast with a certain level of accuracy, which will significantly increase the reliability of the forecast and, as a result, the effectiveness of the NS DSS, which allows us to assert the relevance of this problem and further research.

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