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Improving safety of navigation by constructing a dynamic model of the navigator's actions in the conditions of navigation risks

This study tackles the complex task of constructing a dynamic model of a navigator, planning their experience trajectory, and making decisions under navigational risks in the maritime industry using automated control systems. the proposed mathematical model accounts for individual skills, experiences, and personalities, while considering unpredictable industry dynamics. the study asserts the importance of adaptable automated control systems capable of simulating navigation risk situations and determining suitable career and development paths. in addition, it discusses the importance of assessing external factors such as economic, technological, and regulatory changes and ensuring compliance with industry standards, data security, and privacy. the paper further emphasizes the necessity for scalability and flexibility, as well as the seamless integration of automated systems with existing organizational infrastructures. the study concludes that the proposed model, optimized for the "safety of navigation" parameter using the Pontryagin maximum principle, enhances recruitment processes, creates comprehensive professional profiles for seafarers, and supports career development. the paper suggests the potential of this model's application in other maritime and related professions, ultimately enhancing individualized training and operational efficiency.

Keywords: *safety of navigation, automated system, maritime industry, human factor, navigation risks, training, dynamic model.*

Introduction. Constructing a dynamic model of the navigator and planning his trajectory of experience, regarding decision-making in the conditions of navigational risks before becoming a specialist in the marine industry with the help of automated control systems is a multifaceted task. It must account for individual differences in navigators' skills, experiences, education, and personalities, making the creation of a universal model a complex task [1-3]. The dynamics in the maritime industry are often unpredictable and subject to change, which means that automated control systems must have adaptive capabilities to meet the changing needs of a navigator's career and training, especially in the simulation of navigation risk situations.

Moreover, assessing a navigator's competencies and skills necessitates the collection and analysis of vast amounts of data. The automated management systems in place should be efficient in evaluating this data and determining the most suitable career opportunities and development paths. The automated systems should also be integrated with training and development plans tailored to the navigator's needs and the requirements of the maritime industry.

External factors such as economic, technological, and regulatory changes in the maritime industry must be considered. The automated control systems should be adept at analyzing these factors and proposing appropriate strategies for the navigator's development. It is also essential for these systems to facilitate effective collaboration between navigators and other professionals or organizations, ensuring coordinated learning, experience and knowledge sharing, as well as collaborative project and task management.

In addition to these considerations, automated control systems should ensure transparency and quality control in the assessment, planning, and development of the navigator. They should also incorporate quality control mechanisms to ensure compliance with maritime industry standards and requirements. Data security and privacy are critical, with personal data and confidential information needing to be protected according to current security and data privacy standards.

Analysis of recent research and problem statement. Furthermore, these automated control systems should be scalable and flexible to adapt to various organizations in the maritime industry and changes in the recruitment, training, and development of navigators. The systems must also be able to integrate seamlessly with existing organizational systems and infrastructure, such as HR systems, training and development programs, accounting, and reporting systems.

Addressing these issues creating an effective automated control system for the development of a dynamic model of the navigator and planning the trajectory of improving his qualifications in decision-making under conditions of uncertainty requires a multidisciplinary approach. Experts from fields like information technology, human resource management, training and development, and the maritime industry must collaborate to create the latest automated systems [4].

In the context of a crewing company's seafarer selection process, several stages ensure the selection of qualified, reliable, and experienced seafarers for ship work. These stages include the preparation of candidate requirements, analysis of CVs, contract signing, paperwork, and employee support and development. However, despite its advantages, this approach presents certain disadvantages, such as the labor-intensive and time-consuming process, human factor potential, limited access to candidate information, lack of standardization, challenges in employee training and development, and weaknesses in the motivation system [5].

Implementing automated system of selection and process management systems can address these shortcomings by streamlining selection processes, enhancing the standardization of assessment criteria and methods, reducing human factor probability, and providing more effective employee training and development [6].

The purpose and tasks of the study. The goal of this research is to develop an integrated, dynamic model of the navigator within automated control systems, thereby improving recruitment, facilitating personalized career development, and enhancing decision-making skills under navigational risks in the maritime industry.

Main research material. There are automated management systems for the employment of seafarers. These systems, also known as "Maritime Recruitment Agencies" or "Crew Management Systems", offer platforms that connect seafarers with employers, facilitating the job search and recruitment process for ships.

Some examples of automated management systems for the employment of seafarers and their references:

- Martide: Crew Management and Recruitment Platform
- CrewInspector: Crew Management Software
- Hanseatic soft: Cloud Crewing
- CrewSmart: Crewing and Compliance Management Software
- SDSD: Matrix Crew Management Software
- Navatom: Crew Management System
- Adonis HR: Maritime HR and Crew Management Software

They may include features such as:

Registration and creation of profiles of seafarers, including uploading CVs, certificates and other documents.

Search for vacancies corresponding to the qualifications and experience of a seafarer.

Sending applications for vacancies and tracking the status of applications.

Automatic notification of seafarers about new vacancies that match their profile and preferences.

Selection systems for employers based on criteria such as experience, qualifications, language skills and other parameters.

Online interview features that allow employers and seafarers to communicate and conduct interviews from a distance.

Document management, including verification and storage of certificates, licenses and other necessary documents.

Organization and coordination of training, internships and certification for seafarers.

Management of contracts and employment contracts between seafarers and employers.

Reporting and analytics systems that allow employers to monitor the effectiveness of the recruitment process and develop strategies to improve the personnel policy.

Ensuring compliance with legislation and international standards in the field of employment of seafarers, including the MLK (Marine Labor Convention) and STCW (Convention for the Training, Certification and Watchkeeping of Seafarers) agreements.

Features to ensure the security and privacy of seafarers' and employers' data, including data encryption and measures to prevent unauthorized access.

Support for communication and feedback between seafarers and employers, including feedback, evaluation and recommendation functions.

Schedule management and scheduling systems that allow employers to optimize the allocation of seafarers to ships and control the availability of the required number of crew on board at different times.

Integration with other maritime systems and services, such as port authorities, insurance companies and medical institutions, to facilitate administrative processes and speed up the exchange of information.

Functions for managing salaries and payments, including automatic calculation of salaries, taxes, insurance premiums and other payments, taking into account the laws of different countries and the terms of contracts.

Modules for managing social and domestic issues such as onboard morale, holidays, social security and medical insurance.

Career and development support for seafarers, including career planning, mentoring and training functions, as well as providing opportunities for professional development and promotion to higher positions within the company or industry.

Creation of communities and networks for seafarers, allowing them to exchange experience, knowledge and information about work, as well as maintain social connections and mutual assistance in a professional environment.

Providing information about the maritime industry and news that may affect the employment and working conditions of seafarers, such as legislative changes, technological innovations and economic trends.

Integration with mobile applications and devices to provide access to the functions of the crew management system at any time and from anywhere in the world.

Providing support services and advice to seafarers and employers, helping to resolve emerging issues and problems related to employment, legislation and compliance with industry norms and standards.

Collaboration with professional associations and organizations such as the International Maritime Organization (IMO), the International Chamber of Shipping (ICS) and seafarers' unions to improve the quality of services and promote the development of the maritime industry.

Ensuring environmental sustainability and social responsibility by applying environmental and ethical standards in the recruitment, training and crew management processes.

In general, maritime recruitment agencies and automated crew management systems contribute to a more efficient and safe employment of seafarers, streamline work processes on ships and improve the quality of work in the maritime industry. They provide rich platforms for seafarers and employers that streamline job search, recruitment, training, document and contract management, and ensure transparency and compliance with international regulations and laws.

These automated systems are constantly evolving and adapting to changes in the maritime industry, technological innovations and regulatory requirements. As a result, they contribute to raising the level of professionalism of seafarers, improving their working and living conditions, as well as increasing the efficiency and competitiveness of maritime companies and the industry as a whole [7,8]. An important aspect of these systems is to keep information up to date and to innovate quickly, ensuring their long-term relevance and value to seafarers and employers.

As can be seen from the analysis, with the development of digital technologies and their integration into the maritime industry, maritime recruitment agencies and automated crew management systems can introduce additional functions and capabilities, such as the use of artificial intelligence and machine learning to analyze data, predict staffing needs and determine the optimal personnel management strategies.

Thus, maritime recruitment agencies and automated crew management systems play an important role in today's maritime industry, providing convenient and reliable solutions for the employment of seafarers and crew management on ships. Their further development and integration with other industrial and digital technologies will further improve the quality of work, increase efficiency and create new opportunities for seafarers and shipowners. Possible directions for development include the improvement of analytical tools, the expansion of cooperation with international organizations and the standardization of processes within the global maritime industry.

However, there are certain aspects of seafarer employment that automated crew management systems may not fully address:

Personal Communication and Interpersonal Skills: Online platforms may not always convey the full range of interpersonal interactions that are important in assessing seafarers. Employers may have difficulty assessing the personality and communication skills of candidates based solely on online profiles and interviews.

Cultural and Diversity: Automated systems may not always accommodate cultural differences and crew diversity, which can affect the consistency and efficiency of ship operations.

Unforeseen Circumstances: Automated systems may not be able to handle unforeseen situations such as urgent crew changes or shipboard emergencies. In such situations, human involvement and decisions remain critical.

Morale and well-being of seafarers: Maintaining the morale and well-being of seafarers on board ship is an important factor that can affect their productivity and safety. Automated systems may not always be able to effectively assess and manage this aspect of seafarer employment.

Incomplete understanding of ship operating conditions: Automated systems may not always provide a complete picture of actual ship operating conditions. This can create a gap between the expectations of seafarers and the actual conditions they face on board.

Recognizing the gaps in current automated maritime recruitment and crew management systems, the next step in our research aims to further refine the selection process for seafarers, particularly for the position of an operator-navigator. While existing platforms already offer a range of features to aid the recruitment process, they may fall short in accurately assessing factors such as interpersonal skills, cultural differences, morale, and the ability to handle unforeseen circumstances. Additionally, these systems may not have a complete understanding of ship operating conditions, which can lead to a mismatch between seafarer expectations and actual shipboard life.

To address these shortcomings, we are proposing the development of a generalized mathematical modeling to enhance the assessment of potential operator-navigators. This model takes into account five key criteria and characteristics: Skills (S), Experience (E), Education (Ed), Personality Qualities (PQ), and Additional Certifications (C). These criteria are carefully selected to provide a holistic view of a candidate's suitability for the role of operator-navigator, going beyond the current capabilities of automated systems.

The proposed mathematical modeling will not only be able to evaluate a candidate based on their professional abilities but also their interpersonal skills and adaptability to various situations, thereby bridging the gaps identified in existing automated systems. This model seeks to bolster the efficiency and accuracy of the recruitment process, ultimately leading to a more productive and harmonious maritime working environment.

Based on the specified criteria and characteristics, the following mathematical modeling can be proposed for evaluating a candidate for the position of operator-navigator:

$$\text{Candidate Evaluation} = w_1 \cdot S + w_2 \cdot E + w_3 \cdot Ed + w_4 \cdot PQ + w_5 \cdot C$$

where: Candidate Evaluation - a numerical value representing the overall assessment of the candidate for the position of operator-navigator;
w_i - weight coefficients for each criterion (their values can be determined on the basis of expert knowledge or statistical analysis of the source data);
S, E, Ed, PQ, C - values of criteria and characteristics for each candidate.

To determine the weighting factors, you can use multi-criteria optimization methods, such as the analytical hierarchy of processes (AHP) or the weighted sum method [9,10].

These coefficients will determine the relative importance of each criterion in the candidate's overall assessment.

After determining the weighting factors, you can apply this model to evaluate candidates for the position of operator-navigator. First, for each candidate, it is necessary to collect data for each of the criteria (*S, E, Ed, PQ, C*). Then, using the obtained weight coefficients, you can calculate the numerical value " Candidate Evaluation " and compare the candidates with each other.

Based on the collected data, it is necessary to train a model that will predict the performance of the operator-navigator based on his characteristics and qualities. You can use various machine learning methods such as linear regression, support vector machine (SVM), random forest, or neural networks. The choice of method depends on the characteristics of the data, the sample size, and the complexity of the model required.

Also, to assess the accuracy of the model, cross-validation should be carried out using a test set. This will help determine how well the model generalizes the information and is able to predict the performance of navigators.

If the results of the model evaluation are satisfactory, it can be used to predict the performance of potential navigator candidates based on their characteristics and qualities.

The next step is to split the data into training and test sets. The training set will be used to train the model, and the test set will be used to evaluate its performance.

As an example, let’s consider training a model using the random forest algorithm. The convergence of random trees plays an important role in machine learning and optimization. For example, random search algorithms in the navigator model formation space, like random forests, use stochastic processes to build decision trees and can be analyzed in terms of convergence and performance, which is important for obtaining a competitiveness criterion in the maritime industry.

In our case, this approach will work according to the following principle[11,12]:

1. Definition of hyper parameters for the random forest algorithm, such as:

`n_estimators`: number of decision trees in the forest; `max_depth`: maximum depth of trees; `min_samples_split`: the minimum number of observations required to split a node; `min_samples_leaf`: the minimum number of observations required for a leaf node; `max_features`: number of features considered when splitting a node; `random_state`: random value for model training reproducibility

2. Training the model on the training set (X_train, y_train) using the selected

hyperparameters: `RF_model = RandomForestClassifier(n_estimators, max_depth, min_samples_split, min_samples_leaf, max_features, random_state); RF_model.fit(X_train, y_train).`

3. Model performance evaluation: model performance on the test set (metrics: accuracy, recall, F1-measure or correlation coefficient). This will determine how well the model predicts the success of navigator-operators based on their characteristics.

3.1. Accuracy: Proportion of correctly classified objects among all objects (`accuracy = (TP + TN) / (TP + TN + FP + FN)`).

3.2. Recall: Share of objects among positive objects (`recall = TP / (TP + FN)`) or Clarity: (`precision = (TP / (TP + FP)`)).

3.3. F1-score: Harmonic mean between clarity and recall, used to account for the balance between the two (`F1-score = 2 * (precision * recall) / (precision + recall)`).

3.4. Test use of the trained model to predict the target variable on the test set (X_test):`y_pred = RF_model.predict(X_test)`.

3.5. Compute model performance metrics based on true values of targetvariable `(y_test)` and predicted values `(y_pred):accuracy = accuracy_score(y_test, y_pred); recall = recall_score(y_test, y_pred); precision = precision_score(y_test, y_pred); F1-score = f1_score(y_test, y_pred).`

4. Construction a computer program in Python for automated calculation ofmodel performance metrics [13,14]:

```
Import Libraries
├── pandas as pd
├── numpy as np
├── sklearn.model_selection as model_selection
├── sklearn.metrics as metrics
├── sklearn.ensemble as ensemble
└── matplotlib.pyplot as plt
Generate and Save Sample Data
├── Create random dataset using np.random and pd.DataFrame
└── Save dataset to CSV file with .to_csv()
Load and Prepare Data
├── Load data from CSV file with pd.read_csv()
├── Divide the data into feature matrix X and label vector y
using.drop() and slicing
Setup Cross-Validation
├── Define the number of folds k
└── Initialize KFold with k splits
Initialize Variables for Metrics
├── Accuracy
├── Recall
├── Precision
└── F1 Score
Choose Machine Learning Model
└── RandomForestClassifier from ensemble
Training and Evaluation in K-Fold Cross-Validation Loop
├── Loop over each fold in kf.split(X)
│   ├── Split data into training and validation sets
│   ├── Train model on training set with.fit()
│   ├── Make predictions on validation set with.predict()
│   └── Calculate and store performance metrics (accuracy, recall,
precision, F1 score)
Compute Average Performance Metrics
├── Calculate average accuracy, recall, precision, and F1 score using
np.mean()
└── Print average metrics
Visualize Parameter Values Over Time
├── Define decay function
```

```
├── Loop over each parameter
│   ├── Calculate initial value using.mean()
│   ├── Set decay rate
│   ├── Compute parameter values over time using decay function
│   └── Plot parameter values over time with plt.plot()
└── Show plot with plt.show()
```

The simulation data amounted to:

Averageaccuracy: 0.79; Averagefullness: 0.7824;

Average (precision): 0.812; Average F1-measure: 0.7854.

The data obtained are the average values of the model performance metrics obtained as a result of cross-validation:

1. Average accuracy:The model has an average accuracy of 0.79, which means that it correctly classifies approximately 79% of the observations. This indicates a fairly good performance of the model, although it all depends on the context of the study.

2. Average fullness / recall: A value of 0.7824 means that the model correctly identifies about 78.24% of positive cases.

3. Precision: A value of 0.8120 means that about 81.20% of the predicted cases are actually positive.

4. Average F1-measure: The value of 0.7854 means that the F1-measure is about 78.54%, which is a fairly high figure at the stage of simulation and multifactorial.

We will conduct a simulation modeling of the decay of the safety parameter in maritime transport for ship navigators, if the following three models and observable circumstances are applied:

Exponential decay: This can be an appropriate option if the safety level quickly decreases without regular training or practice. For example, if a ship navigator has not been practicing his profession for some time, his crisis management skills may rapidly deteriorate, especially in the first months or years.

Power law decay (2): This might be suitable for situations where the safety level decreases over time, but at a more moderate pace. This can pertain to parameters that require regular practice but are not as critical to safety, such as communication skills and coordination with other crew members and shore services.

Logarithmic decay (3): This model might be appropriate for situations where the safety level gradually decreases but then remains stable. This could be associated with parameters that, once they reach a certain level, can remain stable even without continuous learning, for example, knowledge and compliance with maritime rules and regulations.

We have five parameters:

$P_1(t)$ - Knowledge of maritime rules and regulations

$P_2(t)$ - Crisis management skills

$P_3(t)$ - Level of safety training and simulations

$P_4(t)$ - Experience in difficult maritime conditions

$P_5(t)$ - Communication and coordination skills with other crew members and onshore services

Each of these parameters' decays over time according to one of three decay functions:

Exponential decay: $P_i(t) = P_{i0} e^{(-r_i t)}$;

Power law decay: $P_i(t) = P_{i0} / (t+1)^r$;

Logarithmic decay: $P_i(t) = P_{i0} - r_i \log(t+1)$,

where:

$P_i(t)$ - the value of the *i*-th parameter at time *t;*

P_{i0} - the initial value of the *i*-th parameter;

r_i - the decay rate for the *i*-th parameter;

t – time.

This model assumes that each parameter independently decays over time according to its decay function.

Let us give an example of software modeling of the predicted level of navigation safety in general terms (Fig. 1).

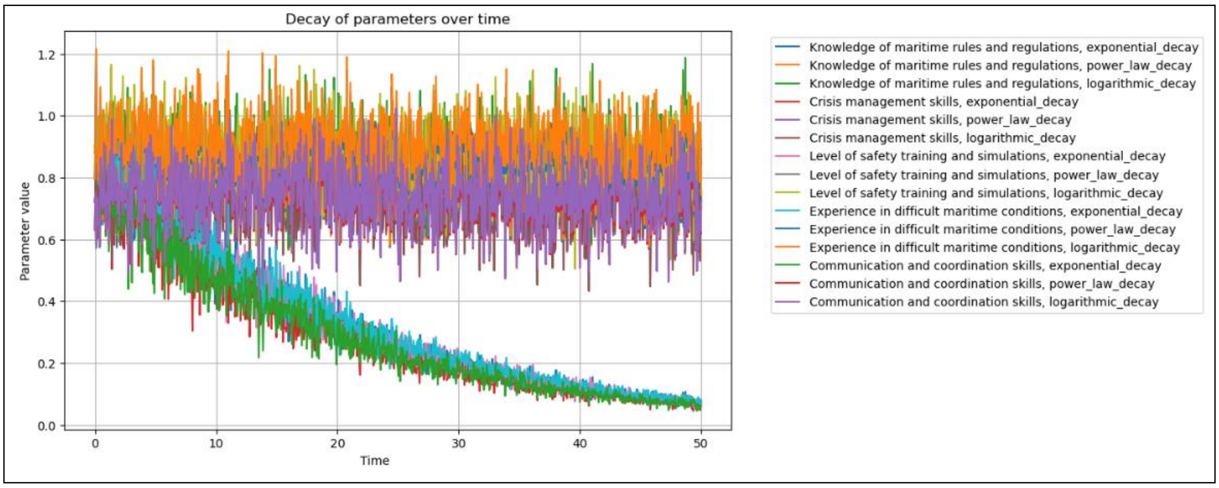

Fig. 1. Modeling the safety of navigation in general

Let's carry out a simulation for the parameter "Safety of navigation" based on the real data of four officers - navigators with similar initial data, but different circumstances that affect the degree of attenuation of the parameter under study (Fig. 2).

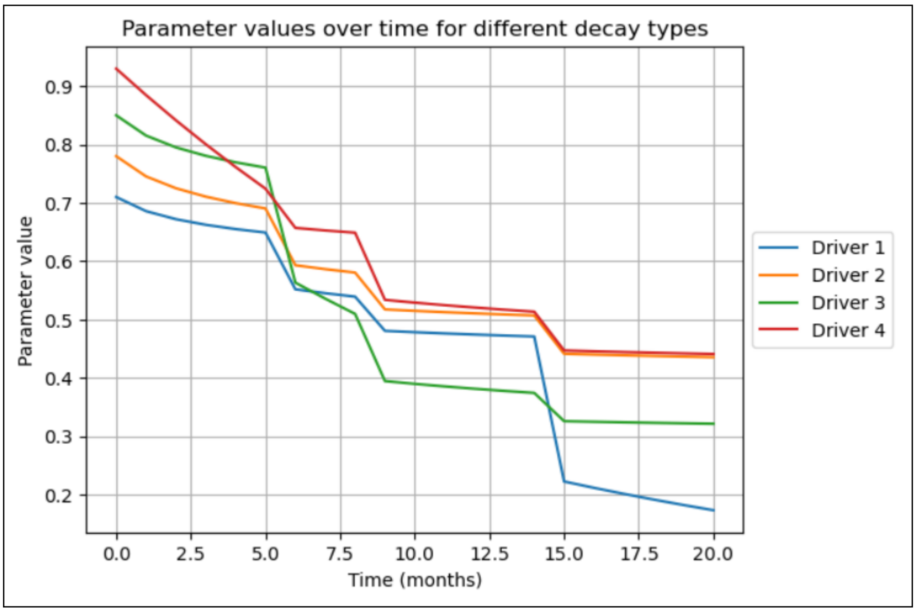

Fig. 2. Simulation graph for the navigation watch safety parameter

This chart and the methodology on which it is based have several strong points when applied to the monitoring of maritime safety (Fig. 3):

Clarity: The chart is easy to interpret and provides a visual representation of how the levels of various safety parameters change over time under different decay conditions. This can help assess the overall trend and track potential problem areas.

Flexibility: The use of different decay functions allows for the modeling of various scenarios, assuming different rates of skill decay. This can be useful when it is necessary to take into account various factors, such as the frequency of training or the occurrence of certain maritime conditions.

Predictive ability: The chart can be used to predict future safety levels based on current data and assumed decay rates. This can be a useful tool for planning training, simulations, and other safety measures.

Personalization: The model parameters can be tailored to a specific navigator or group of navigators, allowing for more accurate and relevant results. For example, various initial skill levels, experience, and individual characteristics can be considered.

Objectivity: The use of quantitative methods and mathematical models in the assessment of safety levels helps reduce subjectivity and the possibility of errors in the evaluation process.

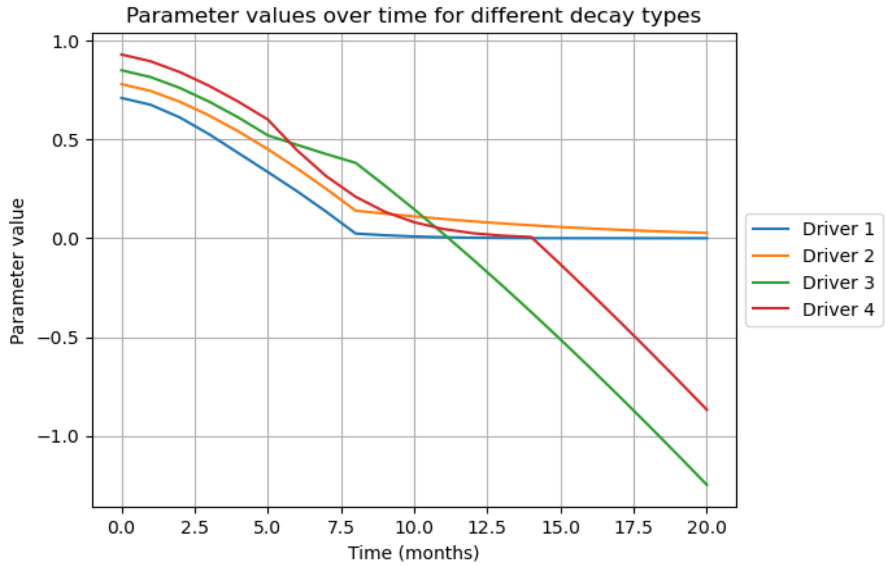

Fig. 3. Modeling based on feedback - parameter recovery

Based on the current task, let's assume that we want to optimize a maritime crew set in order to maximize the average skill level of navigator operators across the entire crew over a given period of time (e.g., 2 years). Let's suppose that the skills of the navigator operators can change over time using decay functions, but we have the ability to influence this process (e.g., through additional training or other support measures), and this influence can be modeled as a control effect in our system.

In this case, our objective function could simply be the sum of the average skill levels of the navigator operators across the entire crew over 2 years. Our task here would be to find the optimal control interventions (in the form of additional training programs, for example). Pontryagin's maximum principle can now be used to find the optimal control that maximizes the objective function [15].

From the perspective of mathematical modeling, numerical methods (specifically, Euler's method) were employed to simulate the dynamics of parameters over time, taking into account different types of damping (exponential, step, and logarithmic). Several parameters ("navigators") are modeled independently from each other with randomly selected types of damping.

This is expressed in the form of a system of differential equations (1):

$$\frac{dy_i}{dt} = -u \cdot k \cdot f\left(t, y_i, k\right) \tag{1}$$

where:

y_i - is the value of the i-th parameter (navigator);

t - is the time

u - is the initial control (constant)
k - is the damping coefficient
$f(t, y_i, k)$ - is the damping function, which could be exponential, step, or logarithmic.

Moving towards optimal control, it is advisable to apply the Pontryagin maximum principle, which serves as a tool for finding the optimal safety level trajectory based on navigator data in a dynamic system.

This criterion usually requires defining constraints and a target function. Suppose our target function is to minimize the overall damping of all navigators over a certain period of time (for instance, 20 months, as in the program's algorithm) (Fig. 4). Therefore, we should minimize (2):

$$J = \int_0^{20} \left(y_1(t) + y_2(t) + y_3(t) + y_4(t)\right) dt, \qquad (2)$$

where $y_i(t)$ are the solutions to our system of differential equations, and t from 0 to 20 months.

According to the Pontryagin maximum principle, the unique optimal control u(t) is the one that maximizes the Hamiltonian (3):

$$H = L + \lambda'(t)\, f\left(t, y(t), u(t)\right) \qquad (3)$$

where $L = y_1(t) + y_2(t) + y_3(t) + y_4(t)$ - is our target function;

$\lambda(t)$ - is the vector of Pontryagin multipliers, and $f\left(t, y(t), u(t)\right) = \frac{dy}{dt}$.

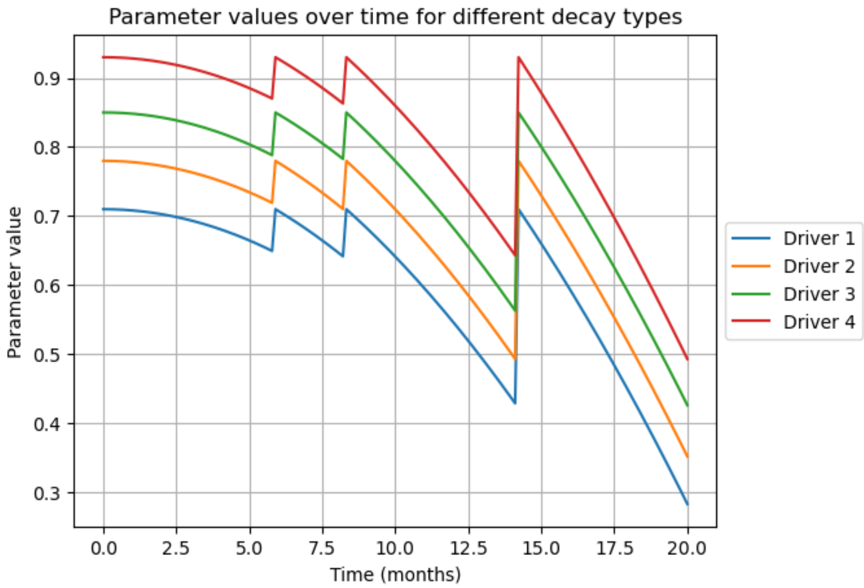

Fig. 4. Graph of the indicator "Safety of navigation" based on optimal control according to the criterion of Pontryagin's maximum

$\frac{\partial H}{\partial u} = 0$ (necessary condition for maximizing the Hamiltonian concerning control),

$\frac{dy}{dt} = \frac{\partial H}{\partial \lambda}$ (Pontryagin's equation),

$\frac{d\lambda}{dt} = -\frac{\partial H}{\partial y}$ (Pontryagin's coprime).

These conditions will help us define the optimal control $u(t)$, which minimizes the overall damping of navigator parameters. The results of the modeling are presented in the chart based on the calculations of a computer program written in Python.

Step-by-step counteraction to damping allows for reaching a safe level without significant time loss. However, we see that the next wave has a larger damping angle, and already on the fourth stage, the safety level drops sharply. This requires a change in methods of maintaining the safety level at the 3rd and 4th stages.

Thus, the functionality was optimized for the "Safety of navigation" parameter associated with the parameters of the system, to which a step was added that calculates the optimal control at each time step using the Pontryagin maximum principle.

Conclusion. The simulation data exhibits a well-performing model with balanced metrics across various indices. On average, the model correctly classifies 79% of observations, identifies about 78.24% of actual positive instances, and approximately 81.20% of predicted positive results are accurate. The overall F1 score, which balances precision and recall, stands at around 78.54%, signifying a promising multifactorial model at this stage of simulation.

Based on this model, a forecast was made on the extent to which unneeded professional qualities directly influencing navigational safety are diminishing. The forecast indicates that with a mixed type of professional team's expertise fading (Fig. 1), there is a noticeable drop to 54% annually without recovery (Fig. 2). The presence of feedback only slightly reduces the decline of these indices, to 38% (Fig. 3). It is only under constant control based on Pontryagin's maximum principle in an integrated software product's online mode that allows safety levels to be restored synchronously during downtime.

However, it should be considered that the minimum decline is observed during the first two cycles, dropping to 6...8% over six months. Subsequent downtime in the third and fourth cycles leads to a more significant drop and may be catastrophic in the most critical navigation zones, dropping to 32% over six months. The most effective approach was the second cycle within 2.5 months, with full recovery of indices, which can be used as a foundation for application in maritime transport to ensure a sufficient level of navigational safety.

Assessment of the model's long-term effects on career progression and employer satisfaction will yield critical insights for further refinement of the system. Thereby, we can enhance the efficiency of the automated selection and recruitment process, which ultimately contributes to enriched career growth opportunities for operator-navigators and strengthens navigational safety.

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Покращення безпеки навігації шляхом створення динамічної моделі дій навігатора в умовах навігаційних ризиків

Це дослідження вирішує складне завдання створення динамічної моделі навігатора, планування його траєкторії досвіду та прийняття рішень в умовах навігаційних ризиків в морській промисловості з використанням автоматизованих систем управління. Запропонована математична модель враховує індивідуальні навички, досвід та особистісні риси, враховуючи непередбачувану динаміку галузі. Дослідження підкреслює важливість адаптивних автоматизованих систем управління, здатних моделювати ситуації навігаційного ризику та визначати відповідні кар'єрні та розвиткові шляхи. Крім того, обговорюється важливість оцінки зовнішніх факторів, таких як економічні, технологічні та регулятивні зміни, а також забезпечення відповідності стандартам галузі, захисту даних і приватності. В роботі також підкреслюється необхідність масштабування і гнучкості, а також інтеграції автоматизованих систем з існуючою організаційною інфраструктурою. У дослідженні робиться висновок, що запропонована модель, оптимізована за параметром "безпека навігації" за допомогою принципу максимуму Понтрягіна, покращує процеси набору, створює всеосяжні професійні профілі для моряків і сприяє розвитку кар'єри. У роботі наводиться припущення про потенціал застосування цієї моделі в інших морських та суміжних професіях, що в кінцевому результаті покращує індивідуальне навчання та оперативну ефективність.

Ключові слова: *безпека навігації, автоматизована система, морська галузь, людський фактор, навігаційні ризики, підготовка, динамічна модель.*