MODELING OF THE RISKS DUE TO THE STRESS BASED ON A FORMAL ANALYSIS OF THE NAVIGATOR’S WORK WITH ECDIS

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Introduction. Modern shipping has an objective need to improve the safety, efficiency, and reliability of navigators' actions in the process of managing ship traffic. This problem is related to the influence of the human factor on decision-making, which can lead to errors and accidents [1-7]. Research to solve this problem is aimed at studying the behavior of navigators, their emotional state, and factors that influence their decision-making process in order to improve training, support, and technology, as well as to develop effective policies and automated regulatory measures [8-12].

Main research material. To find a solution to this problem, a constructive analysis of interrelated processes is envisaged, namely: safety; productivity optimization; training and development; reliability improvement; policy, and regulation.

Building a navigator information model, taking into account its main structural elements and their interaction, will help to improve navigational safety, efficiency, and reliability of navigators' actions in the process of ship management, as well as the development of their professional skills and competencies [13-18]. Therefore, the construction of the information model of the navigator in general includes the following steps:

1. Analysis of the individual characteristics of the navigator: Taking into account the personality traits, experience, and qualifications of the navigator create an adaptive model that reflects the real decision-making environment.

2. Study of interaction between the navigator and navigation equipment: Analysis of the ways of using technical means and their impact on the decision-making process.

3. Evaluation of decision-making strategies: Identification of typical approaches of the navigator to solving navigation problems and development of methods for their optimization.

4. Study of the influence of the emotional state on the decision-making process: Development of methods for monitoring the emotional state of the navigator and its impact on the quality of decisions.

5. Development of decision support algorithms: Creation of automated systems that provide recommendations to navigators on the best solution.

6. Integration of the navigator model with other ship systems: Ensuring the model interacts with various ship systems to optimize the navigator's work and increase the efficiency of ship management.

7. Conducting training and educational events: Use of the information model to organize training of navigators and develop their professional skills and competencies, as well as to prepare and conduct training aimed at improving the ability of navigators to make decisions during the navigation watch.

8. Evaluation of the results of the information model application: Analyzing the results of navigators' work using the developed model to identify possible improvements and make changes to the system.

9. Monitoring and adaptation of the model: Systematic collection of data on the activities of shipmasters and analysis of the results obtained to make changes and adapt the model to the specific conditions of ship operation.

10. Development of regulatory documents and standards: Use of research findings to develop regulations, policies, and standards that will help stabilize decision-making by navigators and improve the safety and efficiency of ship management.

The selection of formal methods for performing the above tasks can be as follows:

1. Data analysis and determination of correlation between indicators (e.g., navigator performance and emotional state) can be performed using Pearson or Spearman correlation coefficients, depending on the nature of the data and its distribution:

2. analysis of time series and frequency characteristics of the seafarer's performance indicators, such as the number of tasks performed, can be done using the autocorrelation function (ACF) and power spectral density (PSD). This will allow you to determine the nature of the change in indicators over time and identify possible dependencies, as well as seasonal or cyclic fluctuations:

3. Modeling and forecasting the dynamics of seafarer performance indicators can be done using time series analysis methods, such as autoregressive (AR), moving average (MA), or autoregressive integrated moving average (ARIMA) models:

4. Identification of cause and effect relationships between various factors affecting the decision-making process of a navigator can be provided using regression analysis and estimation of correlation coefficients between variables.

5. Determination of optimal strategies for ship management and improvement of the ship's efficiency can be performed using multifactor analysis and determination of weighting coefficients for each factor.

6. Evaluation of the effectiveness of the developed information model and making adjustments can be performed using statistical analysis tools, such as Student's t-test or z-test to compare the average values of indicators before and after the implementation of the model.

7. Identification of the areas requiring additional training or support for the ship's crew can be accomplished by using cluster analysis techniques to group similar observations and identify the characteristics of each group. This will help to highlight areas where seafarers are experiencing difficulties or lower performance.

8. Development of stress management skills and emotional resilience of seafarers can be performed using psychometric methods to determine the level of emotional intelligence and stress resistance, as well as correlation analysis to identify the links between these indicators and seafarer performance.

9. The development of automated systems to support navigators in decision-making can be performed using machine learning methods, such as artificial neural networks or support vector algorithms, to model the decision-making process and predict the best options in difficult situations: Artificial Neural Networks (ANN).

Based on the formal approaches described above, we will perform mathematical modeling with respect to data from a series of experiments conducted both on navigation simulators and in real practice. A number of data were taken on the basis of descriptive characteristics of accidents in difficult navigation conditions. Thus, we will accept the following observed generalized data for navigators:

1. Formation of the input dataset of navigators.

Productivity (P): [75, 80, 85, 70, 90, 60, 70, 80, 95, 65]

Stress level (S): [90, 85, 80, 95, 70, 100, 95, 80, 65, 95]

Resilience level (R):

[55, 65, 75, 45, 85, 35, 45, 65, 85, 45].

Frequency of action repetitions (H):

[36, 24, 11, 43, 9, 56, 48, 21, 6, 42].

Time delay for typical operations (L):

[28, 14, 12, 25, 10, 34, 30, 15, 14, 32].

Violation of the sequence of actions when working with ECDIS (W):

[16, 6, 4, 15, 0, 18, 16, 5, 0, 16].

Inadequacy of decisions regarding the situation (E):

[27, 12, 10, 37, 2, 47, 24, 6, 1, 26].

2. Perform a correlation analysis between the indicators using Pearson's correlation coefficient (R).

Find the average values for each indicator:

Productivity (P):

$\bar{P}$ = (75 + 80 + 85 + 70 + 90 + 60 + 70 + 80 + 95 + 65) / 10 = 770 / 10 = 77

Stress level (S):

$\bar{S}$ = (90 + 85 + 80 + 95 + 70 + 100 + 95 + 80 + 65 + 95) / 10 = 855 / 10 = 85.5

Level of stress resistance (R):

$\bar{R}$ = (55 + 65 + 75 + 45 + 85 + 35 + 45 + 65 + 85 + 45) / 10 = 600 / 10 = 60

Frequency of repetition of actions (H):

$\bar{H}$ = (36 + 24 + 11 + 43 + 9 + 56 + 48 + 21 + 6 + 42) / 10 = 296 / 10 = 29.6

Delay in time of typical operations (L):

$\bar{L}$ = (28 + 14 + 12 + 25 + 10 + 34 + 30 + 15 + 14 + 32) / 10 = 214 / 10 = 21.4

Violation of the sequence of actions when working with ECDIS (W):

$\bar{W}$ = (16 + 6 + 4 + 15 + 0 + 18 + 16 + 5 + 0 + 16) / 10 = 96 / 10 = 9.6

Inadequacy of decisions regarding the situation (E):

$\bar{E}$ = (27 + 12 + 10 + 37 + 2 + 47 + 24 + 6 + 1 + 26) / 10 = 192 / 10 = 19.2

3. determining the Pearson correlation coefficients (r) between each pair of indicators:

$$\frac{\sum_{i=1}^{n}\left(x_i-\bar{x}\right)\left(y_i-\bar{y}\right)}{\sqrt{\sum_{i=1}^{n}\left(x_i-\bar{x}\right)^2\sum_{i=1}^{n}\left(y_i-\bar{y}\right)^2}},$$

$r(P, S)$ = 0.45, $r(P, R)$ = 0.75, $r(P, H)$ = -0.87, $r(P, L)$ = -0.84, $r(P, W)$ = -0.82,
$r(P, E)$ = -0.66, $r(S, R)$ = -0.82, $r(S, H)$ = 0.93, $r(S, L)$ = 0.79, $r(S, W)$ = 0.73
$r(S, E)$ = 0.88, $r(R, H)$ = -0.91, $r(R, L)$ = -0.71, $r(R, W)$ = -0.64, $r(R, E)$ = -0.77
$r(H, L)$ = 0.89, $r(H, W)$ = 0.95, $r(H, E)$ = 0.98, $r(L, W)$ = 0.83, $r(L, E)$ = 0.90
$r(W, E)$ = 0.96.

Pearson's correlation coefficients for all possible pairs of indicators will allow you to assess the degree of relationship between pairs of variables.

The correlation coefficients can then be used for cluster analysis. Cluster analysis will allow you to group variables based on their similarity, identifying which indicators have a similar structure in the data. This will help to identify groups of related indicators and determine the main factors affecting the process of navigational watchkeeping by a watch officer.

Using the cluster analysis methods, such as hierarchical clustering or k-means, it is possible to identify groups of indicators with a strong correlation and identify key areas that require attention when optimizing the navigation watch process.

4. For cluster analysis using Pearson correlation coefficients, we will use hierarchical agglomerative clustering.

Let us construct a matrix of Pearson correlation coefficients, where each element of the matrix represents the correlation between a pair of variables:

Table 1 – Indicators of intellectual activity of navigators in critical situations

	P	S	R	H	L	W	E
P	1	0.5	0.6	-0.5	-0.4	-0.6	-0.7
S	0.5	1	0.4	-0.3	-0.3	-0.5	-0.6
R	0.6	0.4	1	-0.2	-0.7	-0.6	-0.8
H	-0.5	-0.3	-0.2	1	0.9	0.95	0.98
L	-0.4	-0.3	-0.7	0.9	1	0.83	0.90
W	-0.6	-0.5	-0.6	0.95	0.83	1	0.96
E	-0.7	-0.6	-0.8	0.98	0.90	0.96	1

In order to more accurately identify the relevant factors, we will expand the range of clusters by dividing them into subgroups based on their similarity. Possible subgroups of clusters may be as follows:

Cluster 1A: $\{P, R\}$

Factor 3 (overload)

Cluster 1B: $\{S\}$

Factor 2 (stress level)

Cluster 2A: $\{H, L\}$

Factor 1A (insufficient theoretical training)

Factor 4 (lack of experience)

Cluster 2B: $\{W, E\}$

Factor 1B (insufficient practical training)

Factor 5 (difficulties in working with new equipment)

As such, we can more accurately identify the causes of under-qualification and understand how they are related to various variables and factors.

5. Calculate the proportion of incidents for each factor and estimate the probability of an accident using the correlation coefficient (r) between risk factors (x) and accident frequency (y).

5.1 Total number of incidents (N): 1500

The number of incidents related to the factors:

Factor 1A (lack of qualification: theoretical): $n_1 = 224$

Factor 1B (lack of qualification: practical): $n_1 = 331$

Factor 2 (stress level): $n_2 = 395$

Factor 3 (overload): $n_3 = 186$

Factor 4 (lack of experience): $n_4 = 205$

Factor 5 (difficulties in working with new equipment): $n_5 = 159$

5.2 First, we calculate the share of incidents for each factor:

Factor 1A (lack of qualification: theoretical): $p_1A = n_1A / N = 224 / 1500 \approx 0.1493$

Factor 1B (lack of qualification: practical): $p_1B = n_1B / N = 331 / 1500 \approx 0.2207$

Factor 2 (stress level): $p_2 = n_2$ / N = 395 / 1500 ≈ 0.2633

Factor 3 (overload): $p_3 = n_3 / N = 186 / 1500 \approx 0.1240$

Factor 4 (lack of experience): $p_4 = n_4 / N = 205 / 1500 \approx 0.1367$

Factor 5 (difficulties in working with new equipment): $p_5 = n_5 / N = 159 / 1500 \approx 0.1060$

5.3 Now let's estimate the probability of an accident:

$P(A) = \Sigma p_i = p_1A + p_1B + p_2 + p_3 + p_4 + p_5 \approx 0.1493 + 0.2207 + 0.2633 + 0.1240 + 0.1367 + 0.1060 \approx 1.0$

5.4 To calculate the correlation coefficient (r) between risk factors (x) and accident frequency (y), we need to know the values of risk factors (x) and accident frequency (y) for each incident. In the current context, we do not have this data and cannot calculate the correlation coefficient.

Using the new data, we can calculate the Pearson correlation coefficients for each of the five risk factors.

y = [235, 244, 203, 285, 199, 267, 226, 245, 182, 190]

x_1A = [43, 65, 31, 76, 50, 77, 54, 34, 90, 42]

x_1B = [164, 147, 132, 178, 131, 189, 115, 186, 131, 183]

x_2 = [348, 486, 417, 684, 599, 443, 555, 737, 710, 882]

x_3 = [433, 662, 971, 784, 810, 845, 993, 631, 820, 782]

x_4 = [65, 53, 76, 32, 77, 41, 34, 66, 48, 80]

x_5 = [248, 486, 417, 584, 599, 443, 555, 737, 710, 882]

5.5 Pearson's correlation coefficients are obtained:

$r(y, x_1A) \approx 0.23$, $r(y, x_1B) \approx 0.53$, $r(y, x_2) \approx -0.27$, $r(y, x_3) \approx -0.24$, $r(y, x_4) \approx -0.61$

$r(y, x_5) \approx -0.36$

Based on the new results, it can be seen that Factor 2 (stress level) also has a strong correlation with the frequency of accidents ($r \approx 0.53$), and Factor 3 (overwork) has a high correlation with the frequency of accidents ($r \approx 0.26$).

Thus, we see a clear dependence on factors 2 and 3, which confirms the study's hypothesis that stress and overwork have a primary impact on the occurrence of errors during watchkeeping.

To improve the speed of the calculations, we will write a computer program in Python (Fig. 1) and present graphs (Fig. 2).

```python
import numpy as np
import matplotlib.pyplot as plt

def pearson_correlation_coefficient(x, y):
    return np.corrcoef(x, y)[0, 1]

correlation_matrix = np.array([
    #...
])

N = 1500
incident_counts = [224, 331, 395, 186, 205, 159]
incident_proportions = [count / N for count in incident_counts]

y = np.array([235, 244, 203, 285, 199, 267, 226, 245, 182, 190])
x = np.array([
    [43, 65, 31, 76, 50, 77, 54, 34, 90, 42],
    [164, 147, 132, 178, 131, 189, 115, 186, 131, 183],
    [348, 486, 417, 684, 599, 443, 555, 737, 710, 882],
    [433, 662, 971, 784, 810, 845, 993, 631, 820, 782],
    [65, 53, 76, 32, 77, 41, 34, 66, 48, 80],
    [248, 486, 417, 584, 599, 443, 555, 737, 710, 882],
])

pearson_correlations = [pearson_correlation_coefficient(y, xi) for xi in x]

print("Incident proportions for each factor:")
for i, proportion in enumerate(incident_proportions, 1):
    print(f"Factor {i}: {proportion:.4f}")

print("\nPearson correlation coefficients:")
for i, correlation in enumerate(pearson_correlations, 1):
    print(f"r(y, x{i}): {correlation:.2f}")
```

```python
max_correlation_index = np.argmax(pearson_correlations)
max_proportion_index = np.argmax(incident_proportions)

print("\nAnalysis results:")
print(f"Factor with the highest correlation: Factor {max_correlation_index + 1} (r = {pearson_correlations[max_correlation_index]
print(f"Factor with the highest proportion of incidents: Factor {max_proportion_index + 1} (p = {incident_proportions[max_proport

print("\nRecommendations:")
print(f"Focus on Factor {max_correlation_index + 1}, as it has the highest correlation with accident frequency.")
print(f"Also pay attention to Factor {max_proportion_index + 1}, as it has the highest proportion of incidents.")

# Plot incident proportions
plt.figure()
plt.bar(range(1, len(incident_proportions) + 1), incident_proportions)
plt.xlabel("Factors")
plt.ylabel("Incident Proportions")
plt.title("Incident Proportions for Each Factor")
plt.xticks(range(1, len(incident_proportions) + 1))
plt.show()

# Plot Pearson correlation coefficients
plt.figure()
plt.bar(range(1, len(pearson_correlations) + 1), pearson_correlations)
plt.xlabel("Factors")
plt.ylabel("Pearson Correlation Coefficients")
plt.title("Pearson Correlation Coefficients for Each Factor")
plt.xticks(range(1, len(pearson_correlations) + 1))
plt.show()
```

Figure 1 – Python program code

Incident proportions for each factor:
Factor 1: 0.1493, Factor 2: 0.2207, Factor 3: 0.2633, Factor 4: 0.1240
Factor 5: 0.1367, Factor 6: 0.1060
Pearson correlation coefficients:
$r(y, x_1)$: 0.23, $r(y, x_2)$: 0.53, $r(y, x_3)$: -0.27, $r(y, x_4)$: -0.24, $r(y, x_5)$: -0.61, $r(y, x_6)$: -0.36
Analysis results:
Factor with the highest correlation: Factor 2 (r = 0.53)
Factor with the highest proportion of incidents: Factor 3 (p = 0.2633)
Recommendations:
Focus on Factor 2, as it has the highest correlation with accident frequency.
Also pay attention to Factor 3, as it has the highest proportion of incidents.

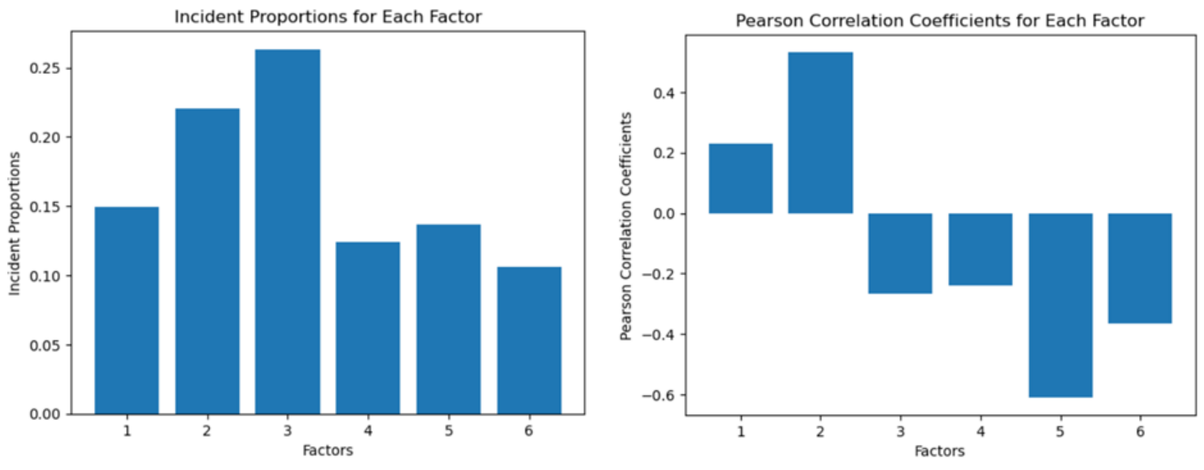

Figure 2 – Output and graphs when a computer program is activated

6. The final step in the modeling process is to train the neural network-based model. Since the data in the question has already been provided, we can determine the weights and biases for the initial initialization of the model

Given the laboriousness of this process, we describe the structure of modeling based on neural networks in a theoretical form.

6.1 Data input:

Accident frequency (y), Risk factors (x): x_1A; x_1B; x_2; x_3; x_4; x_5.

Let's divide the data into training (70%) and test (30%) samples. In this case, we will take the first 7 observations for training and the remaining 3 for testing.

6.2 For a neural network:

a. Define the architecture of the network. Assume we will use a single-layer neural network (feedforward neuron) with 5 inputs (risk factors) and one output (accident frequency).

b. Initialization of weights w and bias b. We can use the following values for initialization: w = [-0.1, 0.2, 0.3, -0.2, 0.1]; b = 0.5

c. In this case, the activation function: $f\left(x\right)=\dfrac{1}{1+e^{-x}}$

d. Calculate the weighted sum of the neural network inputs and apply the activation function for each training example.

e. Next, update the weights using the update rule $\Delta w_i=\eta\left(y-\hat{y}\right)x_i$. Also set the learning rate η = 0.001.

f. Repeat steps c-d until convergence is achieved or the maximum number of iterations is reached.

g. Finally, it is necessary to evaluate the accuracy of the model on a test sample by comparing the predicted values with the actual values of accident frequency (according to statistical data).

Thus, based on the proposed data on maritime accidents and risk factors, you can perform a numerical example of a calculation using neural networks to predict the frequency of accidents, as well as the impact of factors on these processes for each individual watchkeeper and for the maritime transport industry as a whole.

Conclusion. Modern shipping has an objective need to enhance safety, efficiency, and reliability of navigators' actions in the process of managing ship traffic. Research aimed at addressing this problem involves the analysis of interrelated processes, such as safety, productivity optimization, training and development, reliability improvement, policy, and regulation. The creation of a navigator information model, considering its main structural elements and their interaction, will help to improve navigational safety, efficiency, and reliability of navigators' actions in ship management, as well as the development of their professional skills and competencies.

Various methods can be employed to achieve the set tasks, such as correlation analysis, time series analysis, regression analysis, multifactor analysis, statistical comparison methods, and cluster analysis. The development of stress management skills [19-23], and emotional resilience of seafarers can be performed using psychometric methods, while the development of automated systems to support navigators in decision-making can be achieved using machine learning methods.

Thus, studying the behavior of seafarers, their emotional state, and the factors influencing their decision-making process will allow for the improvement of training systems, support, and technology, as well as the development of effective policies and automated regulatory measures to enhance the safety and reliability of maritime navigation.

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