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METHOD OF AUTOMATED IDENTIFICATION OF HAZARDOUS FATIGUE FACTORS IN NAVIGATORS BASED ON SLEEP INDICATORS

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The issue of fatigue among navigators during the performance of their duties poses a significant risk to maritime safety, with human factors being the primary cause of marine accidents. The aim of this study is to develop and test an automated method for identifying hazardous fatigue factors in navigators based on sleep indicators. This study addresses the challenge of accurately diagnosing fatigue, which is often underestimated or misinterpreted by the navigators themselves. The research involved long-term monitoring of the psychophysiological state of navigators during their duties and rest periods on the vessels "Alexander" IMO 9433353, "Brigitte M" IMO 9155913, and "LONGWOOD" IMO 9504138. Various statistical and dynamic analysis methods were used in the study, including regression analysis, time series analysis, and Student's t-test.

The experiments demonstrated a significant correlation between the duration of deep sleep and the reduction in wakefulness periods, indicating that longer periods of deep sleep mitigate the effects of fatigue. It was established that an increase in deep sleep time by 1% leads to a decrease in wakefulness time by an average of 0.736% to 0.98%. The correlation coefficient between deep sleep duration and stress level ranged from 0.73 to 0.98, confirming a high degree of correlation. The approximation error values ranged from 0.34% to 12.44%, indicating satisfactory model quality.

The developed automated system for fatigue detection showed promising results in enhancing navigational safety by providing real-time analysis and adaptive watch scheduling based on crew condition. The system is capable of automatically adjusting watch schedules and rest periods, ensuring an optimal balance between workload and rest. The practical significance of the system lies in its potential to reduce the impact of the human factor on maritime safety by 18-28% and optimize voyage time, contributing to fuel and energy savings. The system can also automatically intervene in cases of critical decreases in navigator performance, for example, by automatically switching to auxiliary control systems (autopilot) or sending alarm signals to other crew members or the control center.

The theoretical significance of the obtained results lies in the experimental proof of the effectiveness of using sleep indicators for real-time monitoring and analysis of navigator fatigue. The practical significance of the results lies in the development of a system that ensures timely detection of hazardous navigator states, reduces the risk of accidents, and enhances overall navigational safety.

Key words: *automation of fatigue detection; sleep indicators; maritime safety; psychophysiological monitoring; automated control system; method.*

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Introduction. According to the latest EMSA Annual Overview of Marine Casualties and Incidents 2023, the trend of marine accidents has not decreased from 2014 to 2022. The total number of accidents during this period amounted to 23,814 cases, with an average of 2,646 accidents per year. In 2022 only were 2,510 cases. 59% of accidents were caused due to influence of the Humans factors. The second most common cause was system failures, accounting for 25.3%, which is more than twice lower then human factor's impact, once again proving that while humans are the key link in ensuring the safe operation of a vessel, they are also the least reliable [1].

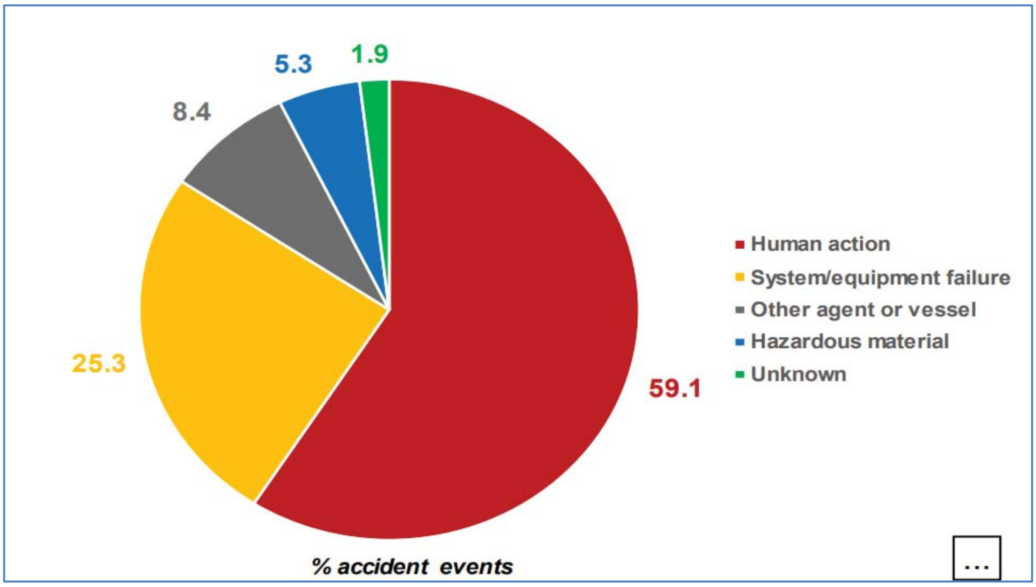


Figure 1 – EMSA Annual Overview of Marine Casualties and Incidents 2023 – Percentage distribution of incidents by type from 2014 to 2022

Currently, there are several intelligent tools aimed at improving maritime navigation safety that consider the human factor [2–4]. The human factor of a navigator is a complex phenomenon that requires a multifaceted approach to analysis [5]. An important aspect in this context is using the various testing methods to assess an individual's psychological state. For example, using the Minnesota Multiphasic Personality Inventory (MMPI) allows for obtaining a specific psychological profile of an individual [6]. It is also important to perform tests that check reaction, attention, and movement skills, using, for example, Task Attention Control software (TAC) to assess the psychophysiological characteristics of a person.

Fatigue and stress manifestations significantly impact navigators during their duties, especially during watchkeeping, which is critical for ensuring navigational safety. Global practices in the application of intelligent systems are predominantly focused on navigation safety and do not focus on ship operators [7]. Fatigue is defined as a temporary decrease in performance caused by prolonged or intense physical or intellectual activity, manifested as a decrease in qualitative and quantitative work indicators, as well as a deterioration in the navigator's working functions. The initial stages of fatigue can have symptoms similar to stress (distress); however, recovery from stress occurs almost immediately after the stressor is removed, while fatigue requires a time for recovery [8].

Despite the significant contributions of researchers worldwide in analyzing the physiological indicators of fatigue on the navigator's actions and decision-making accuracy and timeliness, there is a need for automation of these processes. The creation of an automated system for studying navigator fatigue in real-time will significantly increase the process of identifying dangerous trends in the navigator's actions. Considering that the ship's crew does not include psychologists, there is a need to create an artificial automated system that can replace a specialist in this field.

Problem Statement. To build a specialized automated system that identifies fatigue of navigators during watchkeeping, it is necessary to thoroughly investigate the relevant physiological manifestations, especially those that cannot be determined through visual observations. One of the physiological indicators of fatigue is a decrease in blood oxygen levels, which is a characteristic sign for a healthy person. Drowsiness is also a typical symptom of fatigue. In cases of severe fatigue, there may be a decrease in heart rate and body temperature, which can indicate the approach to sleep [9].

In the current context of cargo transportation, which never ceases, crews often work overtime, enduring significant physical and psychological stress. This includes nighttime maneuvers in ports, handling cargo, and keeping the vessel in working condition [10]. Over the past 30 years, numerous studies have been conducted on the impact of fatigue and stress on navigational safety. These studies have led to the development of optimal watch schedules, necessary rest hours, and the creation of codes, instructions, company policies, and fatigue management plans. Additionally, compliance with these measures is monitored by port authorities and the flag state control. Despite this, the effectiveness of these measures often remains insufficient.

A significant compensatory factor in counteracting the negative effects of stress and fatigue is adequate quantity and quality of sleep. According to the "IMO guidelines on fatigue," the normal sleep duration should be 7–8 hours per day, with the presence of deep sleep phase being crucial for effective recovery. Breaking sleep into several shorter periods does not have the same restorative effect as continuous sleep. According to the MLC Code, the minimum rest time per day should be at least 10 hours, and in a seven-day period – at least 77 hours, with daily rest divided into no more than two periods, one of which should be at least 6 hours of continuous sleep [11].

Studies have shown that the human body's recirculation time is around 16 hours, after which the brain begins to lose its efficiency. It is important to note that the brain often cannot adequately assess its own level of fatigue, especially under stress. Experiments with students who slept 4 to 6 hours a day for a month showed that they assessed their condition as normal. However, they experienced a 400% increase in periods of micro-sleep (spontaneous falling asleep) compared to those who slept 8 hours [12].

Sleep has a complex structure that includes different phases – the deep sleep phase and the rapid eye movement (REM) sleep phase. It is often believed that the deep sleep phase is the most restorative, but this is an oversimplification. In reality, both phases are important. They are closely linked to external stimuli, but circadian rhythms have an endogenous nature and function as an "internal biological clock."

In the context of work on water transport, the influence of circadian rhythms is complex. During daytime watches, circadian rhythms usually promote increased activity, which is positive. However, during night watches, they can induce sleepness, even after sufficient rest. Thus, this factor is important to consider when planning crew watch and rest schedules. For this reason, it is necessary to develop an intelligent system for identifying and controlling watchkeeping in the context of processing navigators' physiological data.

There are not many publications dedicated to solving this problem to improve navigational safety, but there are related issues in other fields of human activity. A comprehensive analysis of the literature in these areas will allow for a more detailed and effective approach to solving the problem.

In particular, in the article [13], devices are described that include systems for collecting, processing, and analyzing data to monitor patient conditions. Image processing technologies were also used to detect and analyze health conditions, which can be adapted to monitor their psychophysiological state. The use of specialized robots will allow performing routine tasks, collecting data, and providing support. However, it is difficult to imagine how robots, which require stable surfaces in rooms, can be used to support watchkeeping.

Joint approaches to solving the problem are described in the article [14], which involve the use of intelligent agents. This can be used to monitor the psychophysiological state of the crew, collecting data in real time and adapting working conditions according to the collected information. Additionally, the development of intelligent rules or algorithms that automatically adapt watch schedules based on the current state of the crew is of interest, similar to minimizing errors in GSM networks as mentioned in the article.

In the study [15], the focus is on optimizing the monitoring of logistics systems using the FIFO (First-In First-Out) method with the application of intelligent systems. Key aspects that can be adapted to development include real-time data collection and analysis, which can be applied to monitor crew conditions. Additionally, adapting FIFO for crew shift planning, taking into account their physiological state and needs, is of interest. However, potential difficulties in integrating intelligent monitoring systems into existing maritime operational systems must be considered due to differences in technologies and interfaces. The proposed technology also requires laboratory testing in stormy weather to ensure the accuracy of data collection and analysis quality.

A new approach to patient monitoring [16] uses hybrid adaptive machine learning methods, elements of which can be applied in the research. In particular, the use of convolutional neural networks (CNN) can be employed for automatic detection of important features in large datasets, and support vector machines (SVM) can ensure reliable classification in complex informational spaces. However, optimizing parameters in such complex models can be challenging, considering their integration into a real ship. Additionally, many factors and variables must be taken into account, which can complicate the process of model tuning and testing, considering the computational limitations on a ship.

The problem of feedback with navigators as watch members can be partially solved using the approaches described in the article [17]. This work uses chat dialogue subsystems adapted for integrated crew condition monitoring, where the system can conduct dialogues to collect information, for example, about the psychophysiological state of the members of the watch. Task-oriented multi-turn dialogue modules can also be used for analysis and adaptive watch planning, where the system recognizes the intentions and needs of the crew and accordingly adapts the work schedule. The application of Seq2Seq (Sequence-to-Sequence) models and task-oriented multi-turn dialogue modules may be useful for developing warning systems and automated interventions of the captain, where a quick response to requests or critical watch conditions is expected. However, there may be challenges in ensuring the accuracy and reliability of data interpretation, as automated data interpretation from navigators can be complicated due to the ambiguity of statements or unpredictability of their psychophysiological states.

For visualization, the application of media in intelligent service systems, which include personalization and multimodal interactions [18], can significantly improve the monitoring and management processes of navigators' watchkeeping, ensuring more accurate perception and response to the crew's psychophysiological state.

In the article [19], robotic monitoring systems are also used, which can be adapted to collect data on the psychophysiological state of navigators, providing the opportunity for more accurate and continuous monitoring through digital pulse signal processing and data filtering. The usage of machine learning algorithms for data analysis, including the development of predictive models for early detection of changes in the watch crew's condition, can also be effective. However, there is a difficulty in integrating these systems with existing ship safety management systems to create a comprehensive system that takes into account both technical and human aspects.

Reliable data transmission is also important, considering the confined spaces of merchant fleet ship rooms. In the work [20], the use of Data Distribution Service (DDS) technology is proposed, which can ensure reliable and flexible data exchange in a distributed system. This technology can be adapted for monitoring and managing watchkeeping on board of the ships. DDS can provide efficient data exchange between system components, and digital twins can be used for modeling and analyzing navigators' psychophysiological state.

In turn, there is a need for the use of mobile devices to identify the physiological data of navigators. In the study [21], a CNN-LSTM model, which is a combination of convolutional neural networks (CNN) and long short-term memory (LSTM), is used for ECG signal classification. This model is integrated into the STM32F429 microcontroller for real-time ECG signal identification at the network edge. Such an approach can be used for monitoring and analyzing the psychophysiological state of navigators.

Beyond data processing within a single ship, it is extremely important to have the capability of modern intelligent networks in the macrostructure, analyzing the conditions of ship navigators within a specific water area who are interacting, i.e., involved in a common maneuvering scheme. In this case, scaling the computer network using intelligent means [22] is appropriate, allowing for: adapting network parameters; optimizing router settings; detecting trends and anomalies in the network; automatically detecting and correcting errors; managing virtual networks and services; adjusting traffic using SDN (Software-Defined Networking), etc.

One of the important aspects is the analysis of behavior, movements, and reactions of watch team members, which would allow determining the level of fatigue and reaction speed in emergency situations, conducting an analysis of the logicality and systematization of navigators' actions. The work [23] discusses the application of intelligent systems for such tasks as: implementing synchronous video recording for rapid detection of potential dangers; monitoring internal traffic in real-time; developing a geographical spatial model for efficient query and modeling of transport situations, etc.

The analysis of modern research highlights the importance of integrating contemporary technological approaches for comprehensive monitoring and intelligent management of watchkeeping on board of the ships. Particularly effective are the applications of systems from other fields of knowledge, such as medical monitoring and intelligent transport systems, which include data collection and analysis, process optimization, and adaptation of working conditions depending on the crew's state. Machine learning methods, algorithms, and Internet of Things technologies can play a key role in improving navigational safety, reducing the impact of the human factor, and enhancing the efficiency of monitoring and managing navigational watchkeeping on ships.

The described problem requires comprehensive automated monitoring and intelligent management of watchkeeping time, capable of adapting to the psychophysiological state of navigators, to reduce the impact of the human factor on navigational safety.

Research Purpose and Objectives. The purpose of the research is to develop an automated method for diagnosing navigator's states of fatigue to manage the composition of the navigational watch using an intelligent safety module.

To ensure effectiveness and achieve the research goal, it is necessary to accomplish the following tasks:

1. Develop and implement methods for controlling and analyzing the psychophysiological parameters of navigation officers. To do this, long-term monitoring of the psychophysiological parameters of officers during their duties and rest periods should be conducted using Student's t-test, time series analysis methods, regression methods, and dynamic research methods. The experiments should involve navigation officers who have undergone a medical professional examination.

2. Analyze the sleep and wakefulness parameters of officers using regression analysis. This requires analyzing the deep sleep time and the total wakefulness time of navigation officers. Regression analysis should be used to establish relationships between these parameters, determining the impact of increased deep sleep time on reducing wakefulness time.

3. Investigate the impact of circadian rhythm on the physiological indicators of officers using time series. This involves analyzing the impact of circadian rhythm on the cardiovascular system indicators of officers, constructing time series, and analyzing them as multiplicative and additive models to understand the dynamics of physiological changes. It is important to establish how circadian rhythm and time spent on the ship affect the navigator's condition.

4. Identify factors of cumulative fatigue and develop methods to prevent hazardous situations. This involves conducting multiple regression calculations to identify the impact of cumulative fatigue on the state of navigators, constructing planes of rest and wakefulness states to identify dangerous conditions such as drowsiness or excessive excitement. Methods should be developed to control the quality and quantity of sleep for officers to improve their ability to perform duties and reduce the risk of accidents.

Solving these tasks will ensure:

1. Integrated crew condition monitoring: Using biometric sensors for continuous monitoring of the physiological indicators of navigators, such as blood oxygen level, heart rate, body temperature, and sleep patterns, for early detection of signs of fatigue and stress.

2. Psychophysiological state analysis: Implementing machine learning algorithms to analyze collected data and assess the degree of fatigue, stress, and overall psychophysiological state of crew members.

3. Adaptive watch planning: Developing algorithms that automatically adjust watch schedules and rest periods based on crew condition data, ensuring an optimal balance of workload and rest.

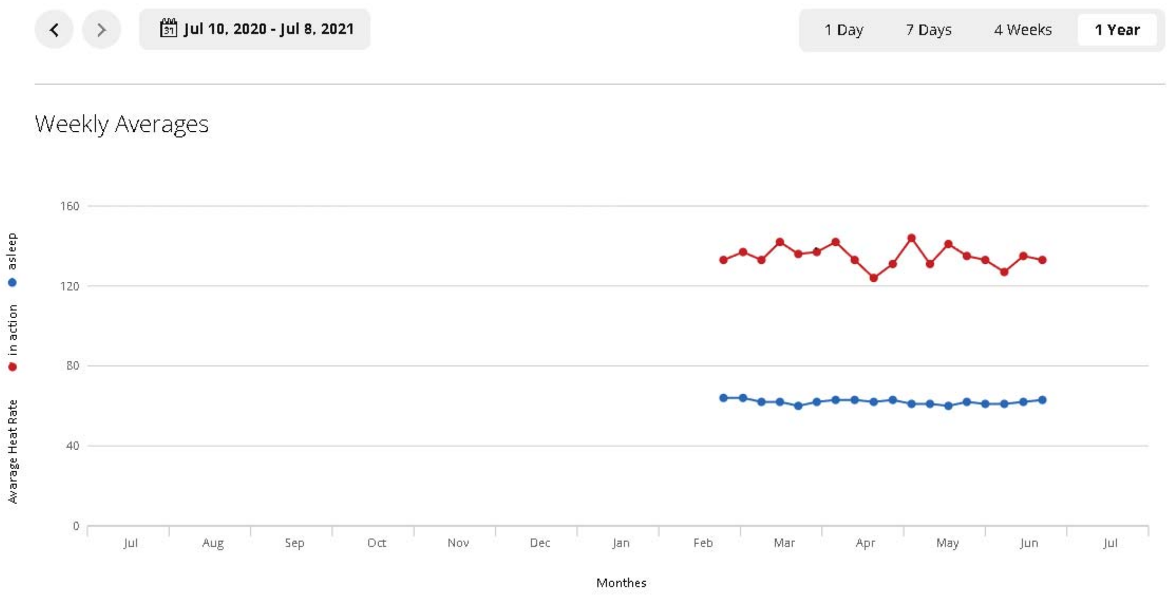
4. Warning and automated intervention system: Implementing a system that can intervene in case of a critical decrease in the navigator's performance, for example, by automatically switching to auxiliary control systems or sending an alarm signal to other crew members or the control center.

5. Ergonomic solutions development: Improving the ergonomics of workplaces based on collected data to minimize physical and psychological strain on navigators.

Thus, this research is indeed relevant and requires solutions through intelligent systems and automation.

Primary Research Material. Considering the research goal and tasks, we will conduct a detailed analysis and a series of necessary studies in real-time during the ship's movement and watchkeeping by the navigator team.

From 2020 to 2023, a number of experiments were conducted on board of the merchant ships in real time to monitor the long-term control and monitoring of the psychophysiological parameters of navigational officers during their duties and during time of rest, followed by analysis of these data. GARMIN Vivo Active 3 and Fossil Gen6 sports smartwatches, BEURER BC58 portable tonometer, BEURER PO80 pulse oximeter, and Xintai HT-101 portable infrared camera for remote body temperature measurements were used. The patented GARMIN time system, which includes a heart rate variability sensor and an accelerometer, allows to detect the time of falling asleep, the time of waking up and the stage of sleep in which the respondent is in.The total number of observations was 397 days, the observation time for one respondent ranged from 36 to 92 days.The experiments involved 3 senior officers, 2 second officers, 1 third officer and 1 captain. All were conditionally healthy according to the results of medical professional examinations. They were aged 32 to 39 years old [Figure. 2] [Figure. 3]. For the analysis, the statistical method of Student's t-test, time series methods, regression methods, and dynamic research methods were used. The following parameters were analyzed: time of deep sleep, total arousal time (the time when the heart rate, as the best indicator of arousal, was above normal), dependence of arousal time on deep sleep. Unfortunately, today there are no methods that would allow to stimulate the deep sleep phase, and in shipboard conditions external negative factors affect the body so much that the body rarely enters this phase naturally. Therefore, only days when this sleep phase was present at least minimally were chosen for the regression study [Figure. 4].



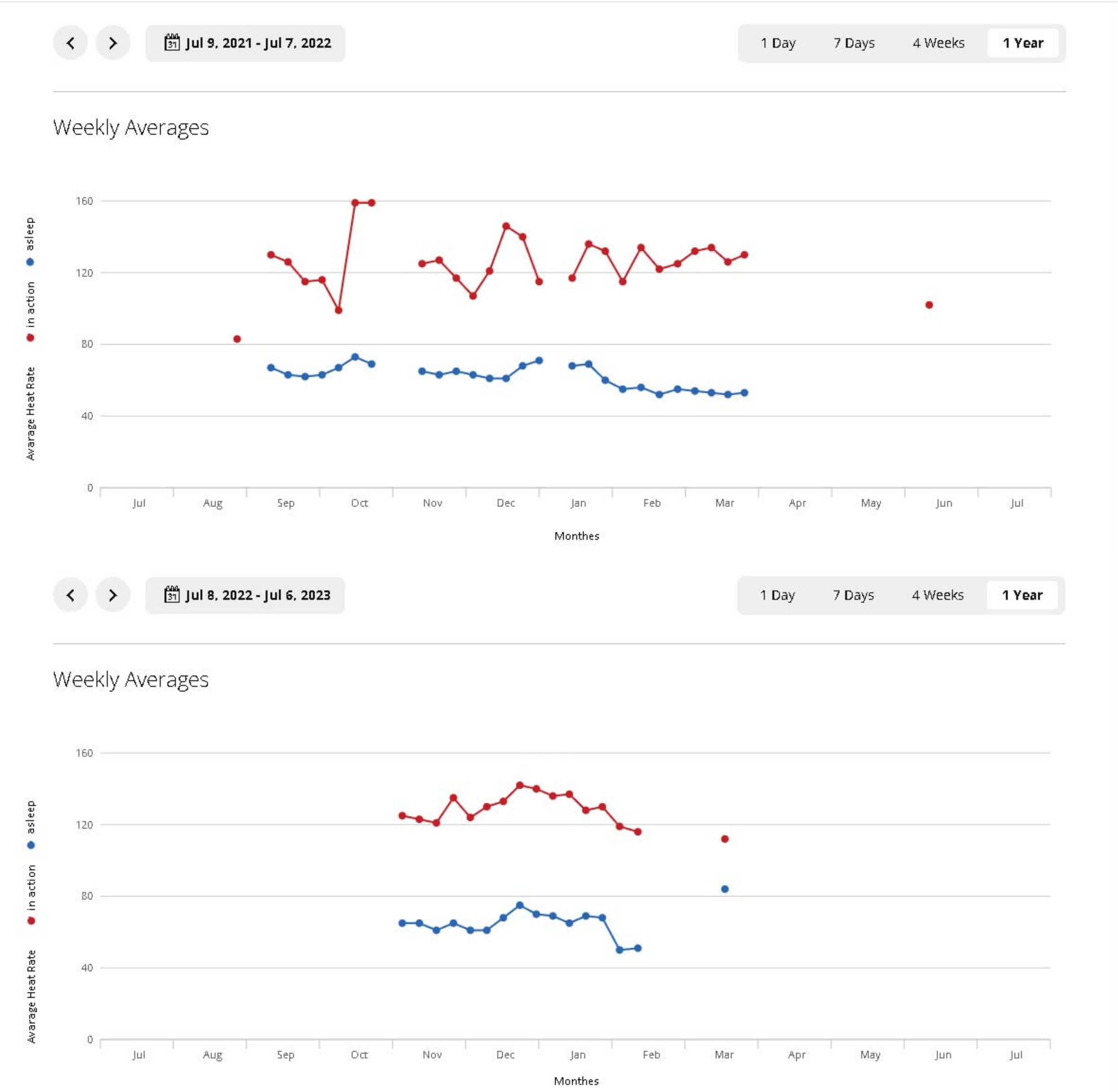


Figure 2 – Weekly average heat rate during the year

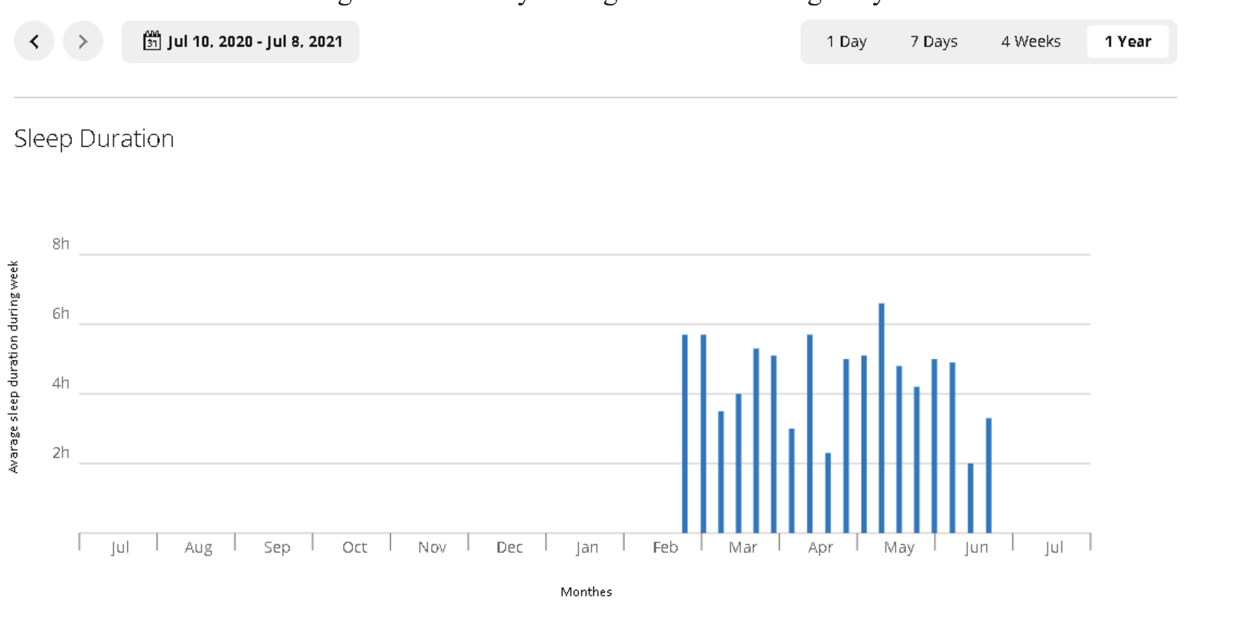
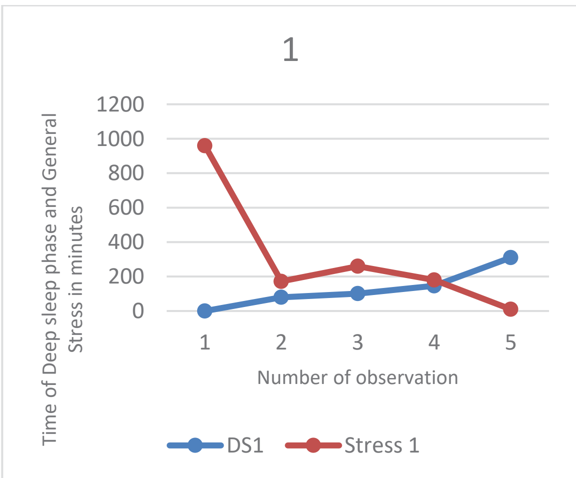


Figure 3 – Weekly average sleeping time during the year



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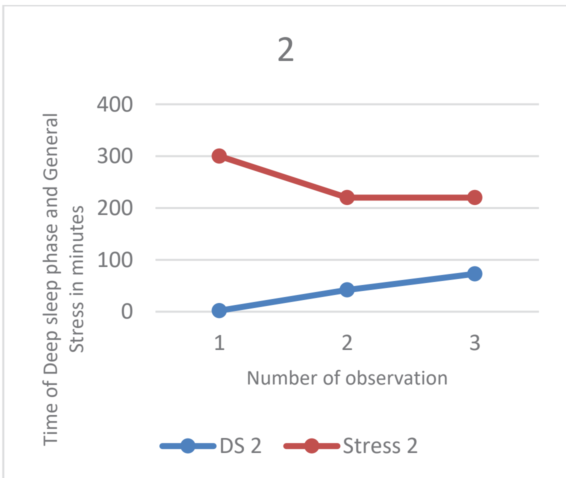

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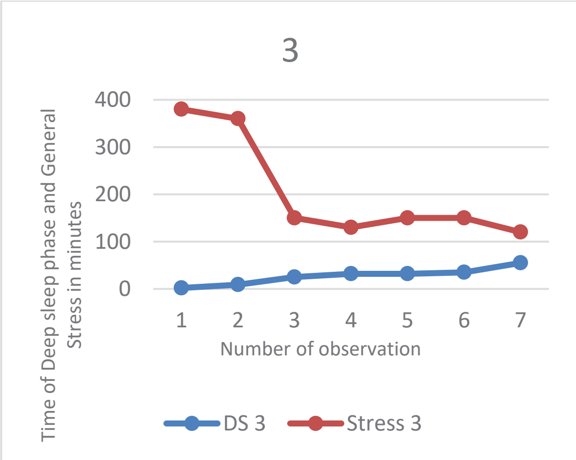

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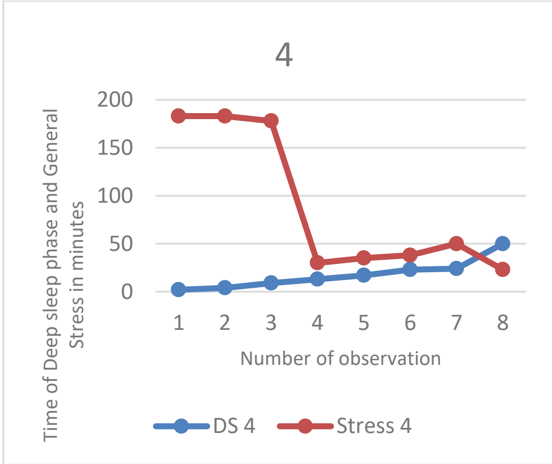
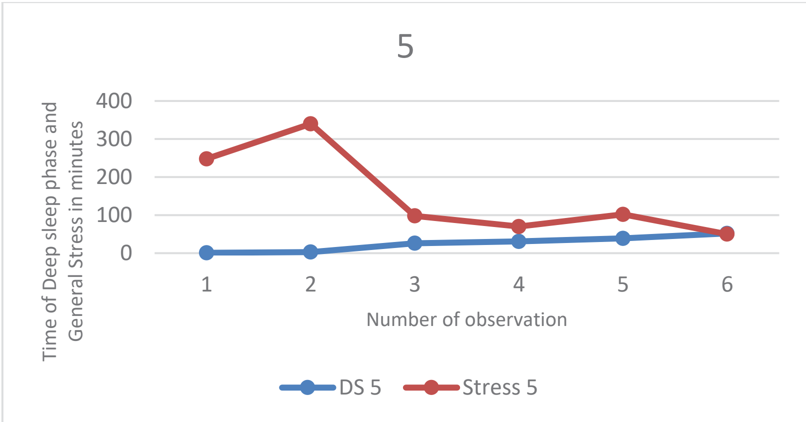


2nd officer



2nd Officer

Figure 4 – Graphs of the dependency of wakefulness time on deep sleep time

What can be seen from the graphs immediately, without additional analysis, is that as longer the deep sleep time, as less the body perceives situations as stressful.

To understand the difference between the deep sleep graphs, we will apply Student's t-test. Given that the sample sizes vary significantly, a more complex and accurate formula was chosen [24]:

$$t = \frac{\left|M_1 - M_2\right|}{\sqrt{\frac{(N_1-1)\sigma_1^2 + (N_2-1)\sigma_2^2}{N_1+N_2-2}\left(\frac{1}{N_1}+\frac{1}{N_2}\right)}} \tag{1}$$

Where M_1 and M_2 are the sample means, N_1 and N_2 are the sample sizes, σ_1 and σ_2 are the standard deviations.

$$\sigma = \sqrt{\frac{\sum (x_i - \mu)^2}{N}} \tag{2}$$

Where N- is the sample size, x_i – is the value of each indicator in the sample, and, μ – is the sample mean.

The calculation of degrees of freedom for entering the tables is calculated by the formula:

$$df = N_1 + N_2 - 2 \tag{3}$$

In our case, the criterion values for each pair ranged from 0.9 to 1.3, which is within the non-significance zone. Therefore, the hypothesis that the values differ is not supported, which in turn may confirm that deep sleep has the same positive effect on all people.

Regression analysis is a statistical analytical method used to calculate the relationships between a dependent variable and one or more independent variables.

For assessing dependencies, a power regression equation was chosen, which has the form [25]:

$$y = a \cdot x^b \tag{4}$$

For linearization, we chose logarithmic linearization with base 10.

The regression equation (constructed from sample data) will have the form:

$$y = a \cdot x^b + \varepsilon \tag{5}$$

Where ε_i – are the observed values (estimates) of errors ε, and b_i are the estimates of the parameters α and β of the regression model, which need to be found.

The deviations ε_i for each specific observation i – i are random, and their values in the sample are unknown, so only x_i and y_i the estimates of the parameters α and β of the regression model, which are respectively a and b can be obtained from the observations, and these estimates have a random nature since they correspond to a random sample.

After linearization, we obtain the following: $\ln(y) = \ln(a) + b \cdot \ln(x)$.

To estimate the parameters α and β – we use the least squares method, which provides the best estimates of the regression equation parameters. Formally, it can be written as:

$$S = \sum (y_i - y \cdot i)^2 \to \min \tag{6}$$

And the system of normal equations will have the form:

$$a - n + b - \sum x = \sum y - x \tag{7}$$

For the calculations, we constructed Table 1:

Table 1 – Calculation table of parameters for the least squares method (LSM)

$\ln(x)$	$\ln(y)$	$\ln(x)^2$	$\ln(y)^2$	$\ln(x) \cdot \ln(y)$
$\ln(x_1)$	$\ln(y_1)$	$\ln(x_1)^2$	$\ln(y_1)^2$	$\ln(x_1) \cdot \ln(y_1)$
$\ln(x_n)$	$\ln(y_n)$	$\ln(x_n)^2$	$\ln(y_n)^2$	$\ln(x_n) \cdot \ln(y_n)$

Equate equation (1) to equation (2) for the indicator a by multiplying it by the coefficient $-\sum \frac{x}{n}$ and solving the system of equations, we get the coefficient b, after substituting it into the first equation, we get the value of the coefficient a. The empirical equation will have the form

$$y = 10^a \cdot x^b \tag{8}$$

Calculate the parameters of the regression equation for each sample:

1) Sample means

$$\overline{x} = \frac{\sum x_i}{n},\ \overline{y} = \frac{\sum y_i}{n},\ \overline{xy} = \frac{\sum x_i y_i}{n} \tag{9}$$

2) Selective variances

$$S(x)^2 = \frac{\sum x_i^2}{n} - \overline{x}^2,\ S(y)^2 = \frac{\sum y_i^2}{n} - \overline{y}^2 \tag{10}$$

3) Standard deviation

$$S(x) = \sqrt{S^2(x)},\ S(y) = \sqrt{S^2(y)} \tag{11}$$

Now the correlation coefficient b can be calculated by the formula:

$$b = \frac{\overline{xy} - \overline{x} \cdot \overline{y}}{s_x^2}, \tag{12}$$

and the coefficient a accordingly:

$$a = \overline{y} - b\overline{x} \tag{13}$$

To understand how much the value of the resultant feature changes on average by a part of its standard deviation when the factor feature changes by the amount of its standard deviation while keeping the values of the other independent variables constant, we calculate the coefficient β_j by the formula:

$$\beta_j = b_j \cdot \frac{S_{(x)}}{S_{(y)}} \tag{14}$$

We will assess the quality of the equation by calculating the approximation error using the following formula:

$$\bar{A} = \frac{\sum_{i=1}^{n} \frac{|y_i - y_x|}{y_i}}{n} \cdot 100\% \tag{15}$$

The results are shown in Calculation Table 1.

To understand how close the relationship between the considered features is and how reliable the regression equation is, we calculate the value of the correlation index R. The boundaries of this index range from 0 to 1, and the closer to one, the stronger the relationship:

$$R = \sqrt{1 - \frac{\sum (y_i - y_x)^2}{\sum (y_i - y)^2}} \tag{16}$$

In our case, the factor x significantly affects y (see Calculation Table 2).

Unlike the linear correlation coefficient, R characterizes the tightness of the nonlinear relationship and does not characterize its direction. This coefficient is universal as it reflects the tightness of the relationship and the accuracy of the model and can be used for any form of variable relationship.

The statistical measure of agreement, which can determine how well the linear regression model fits the data on which it is built, is the coefficient of determination R^2.

$$R^2 = 1 - \frac{\sum (y_i - y_x)^2}{\sum (y_i - y)^2} \tag{17}$$

In our case, the criterion accuracy ranges from 0.73 to 0.98 for all cases, high in all cases (see Calculation Table 2).

The coefficient of determination R^2 is also used to test the significance of the nonlinear regression equation in general using the Fisher F-criterion, the calculated value of which is found as the ratio of the variance of the original series of observations of the studied indicator and the unbiased estimate of the variance of the residual sequence for this model.

The statistical significance assessment of the paired linear regression is conducted according to the following algorithm: The null hypothesis is put forward that the equation is generally statistically insignificant: H_0: $R^2 = 0$ at the significance level α. Then the actual value of the Fisher criterion is determined by the formula:

$$F = \frac{R^2}{1 - R^2} \cdot \frac{n - m - 1}{m} \tag{18}$$

Where m – is the number of factors in the model

If the calculated value with $k_1 = (m), k_2 = (n - m - 1)$, degrees of freedom is greater than the tabular value for a given level of significance, the model is considered significant.

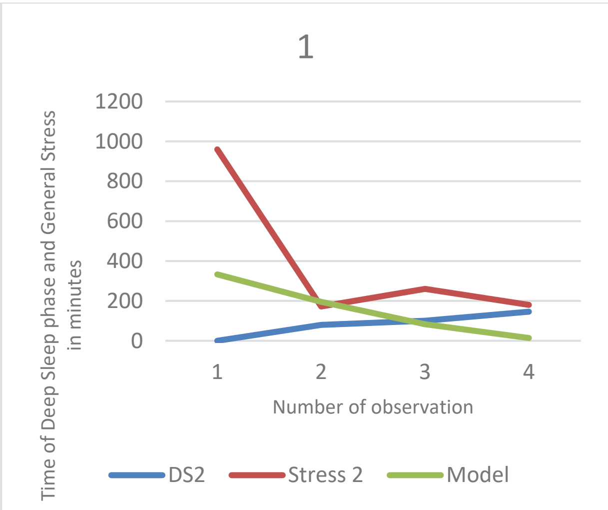
Table 2 – Estimated coefficients of the regression equation

No	a	b	x	y	xy	S(x)^2	S(y)^2	S(x)	S(y)	β	A	R	R^2	F
1	2,503	-0,0915	1,263	2,387	2,971	0,47	0,00403	0,687	0,0635	-0,99	0,34%	0,99	0,98	48,121
2	6,905	-2,3022	2,141	1,967	4,117	0,0496	0,32	0,223	0,568	-0,903	12,44%	0,903	0,8155	8,84
3	2,537	-0,4117	1,115	2,078	2,148	0,41	0,086	0,642	0,239	-0,901	5,60%	0,901	0,811	17,164
4	2,77	-0,3945	1,278	2,262	2,813	0,21	0,0379	0,45	0,195	-0,927	2,13%	0,927	0,858	30,314
5	2,6	-0,7363	1,08	1,805	1,818	0,18	0,13	0,422	0,362	-0,858	8,06%	0,858	0,736	16,754

The coefficients a and b and the values of x from the experimental data were substituted into the obtained formula, and the following data were obtained, on the basis of which graphs were constructed. These graphs also clearly show the adequacy of the model, especially with the increase in sleep quality (Figure 5) (Table 3).

Table 3 – Linearized dependencies of wakefulness time on deep sleep time

Model1	296	224	213					
Model2	333	195	83	14				
Model3	346	220	91	84	77	68		
Model4	447	247	165	149	149	144	120	
Model5	238	142	78	59	48	39	37	22



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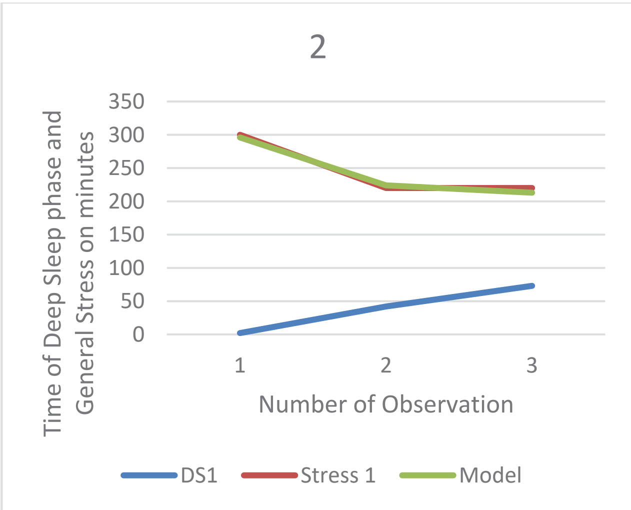

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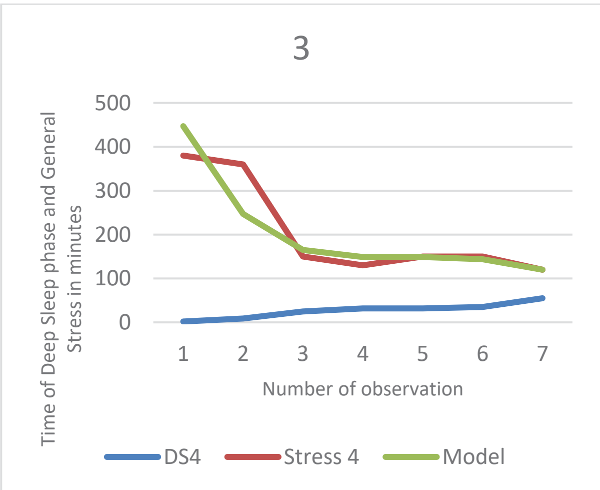
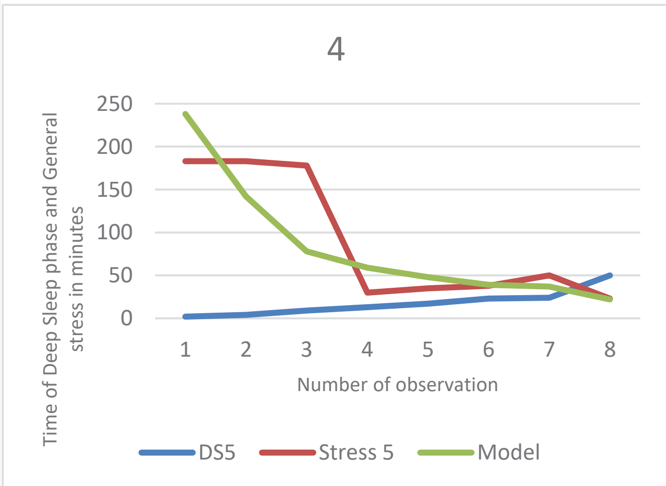
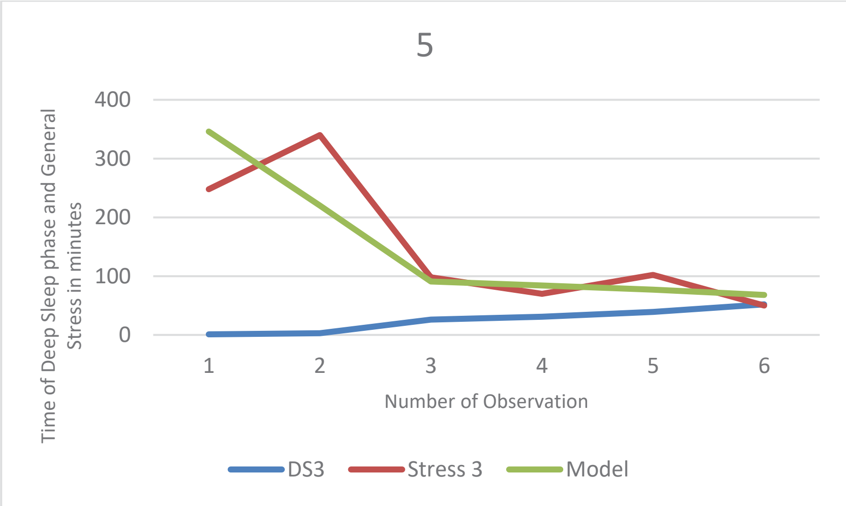


Master



2nd Officer



2nd Officer

Figure 5 – Graph of the linearized model of the dependency of wakefulness time on deep sleep time

The dependencies of Y on X (the dependency of human wakefulness on deep sleep) were studied. At the specification stage, a paired power regression was chosen, linearized by a logarithm with base 10, and its parameters were estimated using the least squares method (8).

The statistical significance of the equation was tested using the coefficient of determination and the Fisher criterion. It was found that in the studied situations, from 73.63% to 98% of the total variability of Y is explained by the change in X. It was also found that the model parameters are statistically significant. The interpretation of the model parameters is that an increase in deep sleep time by 1% leads to a decrease in wakefulness time on average from 0.736% to 0.98%.

The approximation error values from 0.34% to 12.44% indicate satisfactory quality of the found model. The Fisher criterion value confirms the statistical significance of the model.

Thus, considering all the above, this model allows for fairly accurate calculation of the minimum necessary quality sleep indicator before starting a watch for a navigation officer.

Also, during the experiment, the average total sleep time of navigators during the experiment period who working on the 8hours rest 4hours watch schedule as the most acceptable for work was measured using smartwatches with a patented sleep monitoring system The average sleep time was from 4.5 to 6 hours.

According to the MLC 2006 and IMO Guidance of Fatigue, normal sleep should be at least 8 hours and should include a deep sleep stage of 30% of the total time. And according to the experiments conducted by various researchers, partial sleep deprivation disrupts the normal functioning of all psychophysiological systems of the body, including memory. Complete wakefulness for 10 days can cause of death [18].

Today, most of the methods of identification of the fatigue and sleep deprivation are the questionnaires, such as the Karolinska Sleepness Scale or Fatigue Assessment Scale based on subjective assessments of their condition by respondents. During our experiments, we did not find any significant correlation between the actual sleep time and the respondent's assessment. Thus, the navigation assistant could report feeling normal after 3 hours of sleep, and at the same time could report a very strong feeling of fatigue after 12 hours of a good quality sleep, which in turn once again confirms that the brain is not able to perceive the body's state adequately, and therefore it is necessary to develop new methods for monitoring and evaluating states

Conclusion. Thus, during the study, an automated method for detecting dangerous factors of fatigue based on sleep indicators was developed and successfully tested During the experiments, a relationship between the quantitative phase of deep sleep and the impact of the perception of negative factors was found. Today, sleep is the one factor that can compensate for these effects, and this relationship makes it possible to calculate its required quantity and quality after exposure to these factors and already understand whether the assistant is able to perform his duties

The analysis, which included statistical analysis, regression methods and dynamic studies, showed that the developed system significantly reduces the risk of fatigue-related errors and increases the safety of navigation. The practical significance of the study is to develop a system that ensures timely detection of dangerous conditions of navigators, reduces the risk of accidents and increases overall safety of navigation. It is expected that the implementation of this system will reduce the impact of the human factor on safety of navigation by 18–28% and increase the efficiency of ship management. In addition, the system will save fuel and energy on board the vessel by optimizing the time spent on the voyage.

Prospects for further research. Prospects for further research include the improvement of the developed method and monitoring system for navigator fatigue by increasing the accuracy and reliability of physiological data analysis algorithms, using advanced machine learning methods and hybrid models. Integrating the system with existing ship navigation systems will ensure a comprehensive approach to navigation safety, including automated data transmission and real-time route adjustments. Further expansion of the system's functionality will include the development of modules for adaptive watch planning and automatic work schedule adjustments based on navigators' conditions, promoting optimal load distribution on the crew and reducing the risk of fatigue. Implementing the system in real ship operation conditions will provide additional data for further analysis and improvement of monitoring methods. Overall, further research aims to increase the effectiveness and reliability of the monitoring system, ensuring improved navigation safety and reduced risk of accidents at sea.

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Корецький О. А., Носов П. С., Зінченко С. М., Погорлецький Д. С. МЕТОД АВТОМАТИЗОВАНОГО ВИЯВЛЕННЯ НЕБЕЗПЕЧНИХ ФАКТОРІВ ВТОМИ У НАВІГАТОРІВ НА ОСНОВІ ПОКАЗНИКІВ СНУ

Проблема втоми серед навігаторів під час виконання їх обов'язків становить значний ризик для безпеки мореплавства, причому людський фактор є основною причиною морських аварій. Метою цього дослідження є розробка та тестування автоматизованого методу виявлення небезпечних факторів втоми у навігаторів на основі показників сну. Це дослідження вирішує проблему точної діагностики втоми, яка часто недооцінюється або неправильно інтерпретується самими навігаторами. Дослідження включало довгостроковий моніторинг психофізіологічного стану навігаторів під час виконання своїх обов'язків та періодів відпочинку на суднах: "Олександр" IMO 9433353, "Brigitte M" IMO 9155913 та "LONGWOOD" IMO 9504138. У дослідженні використовувалися різні статистичні та динамічні методи аналізу, зокрема регресійний аналіз, аналіз часових рядів та критерій Стьюдента.

Експерименти показали значний зв'язок між тривалістю глибокого сну та зменшенням періодів неспання, що свідчить про те, що триваліші періоди глибокого сну зменшують вплив втоми. Було встановлено, що збільшення часу глибокого сну на 1% призводить до зменшення часу неспання в середньому на 0,736% до 0,98%. Коефіцієнт кореляції між тривалістю глибокого сну та рівнем стресу

склав від 0,73 до 0,98, що підтверджує високий ступінь зв'язку. Значення похибки апроксимації становило від 0,34% до 12,44%, що свідчить про задовільну якість моделі.
Розроблена автоматизована система для виявлення втоми показала перспективні результати у підвищенні безпеки навігації, забезпечуючи аналіз у реальному часі та адаптивне планування вахт на основі стану екіпажу. Система здатна автоматично коригувати графіки вахт та періодів відпочинку, забезпечуючи оптимальний баланс між робочим навантаженням та відпочинком. Практична значущість системи полягає у її потенціалі знизити вплив людського фактора на безпеку мореплавства на 18–28% та оптимізувати час плавання, сприяючи економії палива та енергії. Система також може автоматично втручатися у випадку критичного зниження продуктивності навігатора, наприклад, шляхом автоматичного переключення на допоміжні системи управління (автопілот) або надсилання сигналу тривоги іншим членам екіпажу або до центру управління.
Теоретичне значення отриманих результатів полягає у експериментальному доведенні ефективності використання показників сну для моніторингу та аналізу стану втоми навігаторів у реальному часі. Практичне значення результатів полягає у розробці системи, яка забезпечує своєчасне виявлення небезпечних станів навігаторів, знижує ризик аварій та підвищує загальну безпеку навігації.
Ключові слова: *автоматизація виявлення втоми; показники сну; безпека мореплавства; психофізіологічний моніторинг; автоматизована система управління; метод.*

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