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Decision making in an intelligent health management system of the ship crew in maritime transport

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Abstract. This paper proposes a methodological approach for the decision making in a distributed intelligent health management system for ship crew in maritime transport. The decision-making methodology is based on the concept of a person-centered approach to managing the health and safety of ship personnel, which implies the inclusion of employees as the main component in the control loop. Develops a functional model of the health management system for workers employed on ship and implements it through three phased operations that is monitoring and assessing the health indicators of each employee and making decisions. These interacting operations combine the levels of a distributed intelligent health management system. It presents appropriate approaches to the implementation of decision support processes and describes one of the possible methods for evaluating the generated data and making decisions using fuzzy pattern recognition. The models of a fuzzy ideal image and fuzzy real images of the health status of an employee are developed and an algorithm is described for assessing the deviation of generated medical parameters from the norm. The paper also compiles the rules to form the knowledge bases of a distributed intelligent system for remote continuous monitoring. It is assumed that embedding this base into the intelligent system architecture will objectively assess the trends in the health status of the members of ship crew and make informed decisions to eliminate certain problems.

Keywords: *maritime transport; ship crew; human factor; Internet of things; distributed intelligent health management system; fuzzy pattern recognition; decision making*

1. INTRODUCTION

The development of maritime logistics is one of the main priorities of the giant countries. Maritime logistics refers to the organization and provision of cargo transportation by sea, i.e., a transport service that determines the activities of most customers. While there are options for road and rail transports in terrestrial shipping, maritime transport is the only way of transporting goods by sea over long distances. Maritime transportation is the main means of transporting large volumes of cargo and raw materials by water from one country to another, from one continent to another [1]. [2] shows that 90% of world trade is carried out by sea. Maritime cruises are estimated to be the fastest growing tourist field, with demand for cruises increasing by 20,5% in 2015-2019. The cruise industry is estimated to worth 150 billion USD in 2018. The specificity of the work of seafarers has led to a special emphasis on the “human factor” in maritime logic. This specificity is due to the long-term stay of sailors on board [3]. All the factors (noise, vibration, high-frequency electromagnetic radiation, harmful substances in air, etc.) accumulated in the integrated concept of “ship environment” affect the sailors’ organism, causing functional changes, psychological problems, and the development of pathological conditions. These lead to the reduction of sailors’ working ability, their health deterioration and, consequently, the loss of sailors’ working ability.

Such a situation has led to the emergence of concepts as “human factor” and “fatigue” in marine. Analysis of incidents in maritime transport shows that 80-85% of them are related to human activities [1]. The accidents chiefly occur due to errors and mistakes made by decision-makers during the operation of the ship, rather than due to any equipment failure. Psychological and psychophysiological stress of sailors, especially ship navigator officers and captains, is the main source of incidents at sea. [4] proposes a conceptual approach for the monitoring and evaluation of psychological condition of ship crew members before and after the shift to avoid the marine transport accidents.

At present, the Industry 4.0 characterized by the development of high technologies, the Internet of Things (IoT), nanotechnology, biotechnology, artificial intelligence, etc., has created innovative research trends to overcome these problems [5-7]. This article proposes a new innovative approach to focus on the human factor and IoT base to prevent shipwrecks. It offers a method for decision making of the intelligent system to monitor the health status of ship crew based on IoT.

2. MATERIALS AND METHODS

Acquiring and evaluating real time information on the health status of each employee and making automatic decisions according to the critical situation and providing prompt feedback will allow for more effective management of each employee’s health, as well as the prevention of accidents due to the human factor, and these are currently possible with the application of digital technologies, especially IoT technologies. However, it should be noted that the development and application of IoT solutions to eliminate possible representation of the human factor and to support the health and safety of ship workers has been poorly studied yet [6], although in a number of increased risk facilities, such studies are already being carried out. Thus, [7] highlights the possibilities of modern network platforms and applications for solving healthcare problems based on IoT. The approach to remote health monitoring proposed in [8] based on non-invasive and wearable sensors and modern information and communication technologies is an effective solution to support the elderly living in comfortable home conditions. These systems allow medical staff to monitor important physiological signs of their patients in real time, assess health status and provide feedback from remote facilities. The paper [9] shows the possibilities of using IoT applications in healthcare, in particular for the physiological monitoring of personnel involved in fire fighting. [10] reviews published research related to the implementation of IoT in high-risk industries focusing on various areas of healthcare, food logistics (FSC), mining and energy industries.

In [11], the authors highlight the problem of effective management of the health and safety of shift workers on an offshore oil platform (OOP) from the perspective of human factors. The specific aspects of the environment, dangers and risks, labor and professional activity conditions On the OOP are studied, and the possibilities of applying IoT to ensure the health and safety of employees are analyzed in detail. The possibilities of integrating IoTs with cloud, Big Data, artificial intelligence technologies for the systematic monitoring of the health status of employees, monitoring their safety, and making appropriate decisions if necessary are shown. In the following research of the authors, a new conceptual approach is proposed for the development of a continuous remote monitoring system of the health status of employees working on the OOP in the environmental context based on the Internet of Things ecosystem and smart medicine (e-medicine) solutions for the prevention of accidents caused by the human factor. According to this concept, the architecture-technological and functionalization principles of the geographically distributed multi-level intelligent system are developed for the management of the workers’ health and safety [12]. The main idea of the concept is to improve the safety of ship personnel members through the introduction of a person-centered approach to managing their health. This approach implies the inclusion of worker themselves in the management loop as the main component. “Placing” a person at the center of the personnel health and safety management system enables linking the vital health indicators of each employee with the context of the environment and reasonably assessing the criticality of current situation.

In this paper, based on informative parameters of health status of workers employed on ship, a decision-making technique is proposed to identify the current health status of workers using fuzzy pattern recognition methods.

3. THE ARCHITECTURE OF AN INTELLIGENT HEALTH MANAGEMENT SYSTEM FOR SHIP GROW

All the physical, psychological, medical, social, production and environmental factors inherent in the ship environment act as a potential source of sea voyages, affect the human activity system, and lead to dangerous actions of crew members [3-5]. Deviations in the employees' health status while performing their duty and living on ship can lead to “dangerous” behavior, actions, psychological disorders and, consequently, wrong decisions and accidents. Making wrong decisions by crew members directly depends on their health condition, which affects the crew members' behavior and performance in accordance with their professional activities. Therefore, the health status is an important aspect of the ship's human resources and the main component that directly affects their professional activities.

Taking measures to protect the employees' health allows them to successfully address the physiological, psychological and social situation, improve their functional capabilities, and most importantly, to make better decisions in non-standard situations.

In the given context, to prevent accidents at sea, it is proposed an architecture to systematically monitor system the crew members' health status in the working environment (before and after the shift).

Architecture of intelligent health management system for shift workers on ship has a hierarchical structure, in which each of the three geographically distributed layers is a target intelligent information system (IIS) with particular purpose and functions (Fig. 1). All three layers are integrated into a single decision support process and ensure the functioning of system as a whole.

Application of IoT-based platform is capable of simultaneously transmitting sensed data to various situational control centers (servers) located both horizontally (at the same layer) and vertically along the control hierarchy. In this case, each member of ship personnel acts as a biological object equipped with body-worn and/or wearable devices generating different information in accordance with the purpose. These devices (security gadgets) provide user interaction with the environment and are capable of recording, accumulating, processing and transmitting data. Smart sensors provide both local data processing (on ship) and reliable and safe real time transmission of this data to situation centers or emergency response services at different non-hierarchy control levels.

The IoT technological ecosystem, functioning in conjunction with physical devices, computing platforms and analytical tools, integrates entire work processes in the proposed architecture of the ship personnel health management system into hierarchically distributed computing levels: Dew computing, Fog computing and Cloud computing.

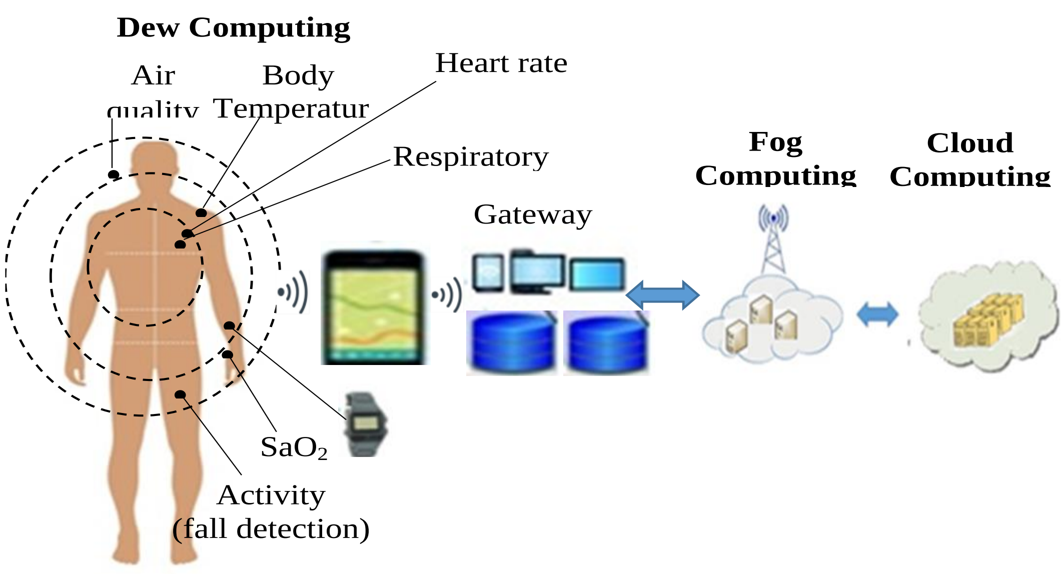

Fig. 1. The architecture of an intelligent health management system for workers employed on ship

First layer of Distributed Intelligent System (DIS) focuses on health and safety monitoring of workers on ship. This layer takes urgent measures to organize the rescue of an employee at scene of accident and provide first aid. Data collection, processing and analysis is implemented through Dew computing, which provides real-time decision making ensuring low latency in data processing. Targeted data of workers recorded by sensors and RFID through wearable device and smartphone used as a gateway is transmitted via wireless or wired communication to the Local Situation Center for Emergency Response (LSCER) on ship. LSCER is a computerized workplace of persons responsible for health and safety of workers on ship. Physically, this is a local computer (Dew data center) designed to receive and analyze incoming data streams on health and safety of workers during the shift. IoT continuously compares the normative (reference), initial (pre-shift) and current (real) values of monitored health indicators and parameters of the contextual environment of workers. As long as all data of workers and their environments is within acceptable limits, nothing is transferred to local computer (Dew data center). As soon as the values of any health indicators and/or coordinates and parameters recorded by sensors go beyond the typical range, these data are sent to local IoT application for processing, analysis and decision-making. IoT application (IIS), equipped with special analytical tools and intelligent algorithms, identifies changes in the health of each employee and deviations of environmental parameters from standards and offers solutions for their elimination.

Second layer in the network architecture of DIS is designed for remote health and safety monitoring of workers employed on ship from the nearest coastal situation center. Reception of data generated at sensor layer, their analytical processing, decision making and temporary storage are implemented in real time through Fog computing. The intelligent IoT platform DIS implements the following services in Fog environment: 1) accepting and processing actual data coming from Dew layer in the absence of direct communication between ship and Cloud; 2) based on Fog analytics results, making decision on each received situation and transfer the appropriate control action for execution to Dew layer; 3) sending data to Cloud DPC that are critically deviated from the standards.

Third layer of the network architecture of DIS, that is Cloud Computing is designed to manage the personal health trajectory of shift workers. Solution of this problem is based on the regular data collection and accumulation from various sources on the dynamics of health and safety of workers and the formation of representative data bases on the chronology of changes in the vital physiological indicators of each worker. These data bases are stored in Private Cloud and serve for decision-making at management level of shipping company.

4. RESULTS AND DISCUSSION

A person-centered approach to health and safety managing involves continuous remote monitoring of the ship workers' vital health indicators and, at the same time, the parameters of the context-sensitive environment of each of them. The current (actual) situation here refers to a model (image) of the real health status of a shift employee, which is shaped upon the fact of deviation of continuously sensed health indicators and relevant context-sensitive information from regulations, accepted restrictions, standards, safety rules, etc. Smart sensors, GPS trackers built into wearable devices and active RFID tags issued to each employee continuously monitor the physiological health indicators of workers on ship (temperature, pulse, blood pressure, etc.), parameters, geolocation characteristics and coordinates, activity, and employee's behavior through the prism of compliance with labor safety standards and rules.

In the course of continuous monitoring of the workers' health and safety, a large amount of data on the workers' health status is generated, which complicates analysis through traditional methods. This leads to the development of intelligent algorithms for automatic (without human intervention) data analysis and decision making.

Thus, the goal of this article is in development decision-making technique is proposed to identify the current health status of workers. To achieve this goal, the following problems are stated:

– to develop an algorithm for assessing the current situation on the health status of a ship employee;

– to make decisions on the health status of each employee.

4.1. Assessing the current situation on the health status of ship crew

IoT-based geographically distributed intelligent health management system for ship crew described above instantly analyzes the current situation, detects deviations of certain indicators from the norm and assesses the current situation. If the indicator values deviate from the norm, i.e., are beyond the normative range, the situation is assessed as critical and the monitoring system decides on the execution of specific actions depending on the criticity of situation (e.g., low critical, medium critical, high critical). In other cases, the monitoring system records the facts of deviation of certain indicators from the etalon value of the parameter within the standard range and sends this information to the system database. In this case, depending on the parameter value, the following situations are possible: ideal reference, average reference, reference at the criticity edge. Information systematically accumulated over a certain period of time will identify current changes in the health status of each employee and make informed decisions on managing their personal trajectories.

Fuzzy logic is an effective mathematical tool to identify the deviation rate of various health indicators from the norm (also from ideal) and determine the relationship between the deviation values and their expert estimates [13]. Depending on the task, various approaches, algorithms and methods for its solution are possible.

In this case, the task is reduced to the development of a methodology for determining the ideal and current (real) health status of workers and identifying the deviation degree between them. Depending on the compliance degree of indicators from the ideal value, the decision-making problem is reduced to the recognition of fuzzy images [14]. This necessitates:

– the development of models of a fuzzy ideal image and fuzzy real images of the health status of an employee located on ship;

– the development of an algorithm for assessing the deviation of generated medical parameters from the ideal.

A. Development of models of a fuzzy ideal image and fuzzy real images of the health status of a ship employee

Let: $A=\{A_1, A_2,..., A_k\}$ or $A=\{A_i, i=\overline{1,k}\}$ be a set of workers located on ship and k – total number employee located on ship and provided with IoT devices for measuring medical indicators;

$X=\{x_1, x_2,..., x_n\}$ or $X=\{x_j, j=\overline{1,n}\}$ be vital signs of the worker's health and n – total number vital signs of the ship worker's health.

The model *D=(X)* of the ideal image of the health of a worker employed on ship can be described by a matrix $D_X=\|x_j\|_n$, where the row D_x characterizes his ideal state.

The ideal state of health of an employee within the framework of reference and regulatory requirements, specified restrictions on specific medical indicators x_j is determined in the form of fuzzy sets with a membership function $\mu_{x_j}(D): D\times X \rightarrow [0.98, 1]$.

Let the model $B=(X)$ be a real image of the health status of an employee, which is formed based on medical data obtained from IoT applications. $B=(X)$ can be described by a matrix $B_X=\|x_{ij}\|_{kn}$, where each row B_i ($i=\overline{1,k}$) characterizes the current state of health of a particular employee x_{ij}, $j=\overline{1,n}$, located on ship and provided with IoT devices for measuring medical indicators.

The degree to provide the real state of health of an employee B_i with medical indicators x_{ij} is determined in the form of fuzzy sets with membership functions $\mu_{x_{ij}}(B_i): B\times X \rightarrow [0,1]$, expressing the current level of the health status of a particular employee *i*.

In fact, there are two sets of fuzzy situations describing the ideal health status of an employee $\tilde{D}$ and the actual health status of an individual employee $\tilde{B}_i$ during a shift on ship:

$$\tilde{D} = \{< \mu_{x_n}(D) >\} = \{\mu_D(x_j)/X\}$$
$$\tilde{B}_i = \{< \mu_{x_{kn}}(B_i) >\} = \{\mu_{B_i}(x_j)/X\}$$

Here, the set $\tilde{D} = \{\mu_D(x_j)/X\}$ $j=\overline{1,n}$ describes a fuzzy ideal situation, whereas the set $\tilde{B}_i = \{\mu_{B_i}(x_j)/X\}$ $i=\overline{1,k},\ j=\overline{1,n}$ describes fuzzy real situations.

B. Algorithm for assessing the deviation of generated medical parameters from the ideal condition

Data on health status received from IoT applications varies in its physical nature and is fuzzy. The fuzziness of health indicators is determined by the possibility of their change in various ranges, characterizing their representation intensity. These circumstances predetermine the need for *scaling* the input information, i.e., bringing all parameters of the health status to a generalized dimensionless indicator. The main scaling problems include the choice of an acceptable scale *X* and the choice of the affiliation function φ(x). The following requirements are applied to the choice of the scale:

1. Possibility of descrbing numerical and dimensionless information to ensure comparability of parameters of different physical nature.
2. Universality, applicability to parametric and non-parametric input information.
3. Possibility of descrbing the definition area for any values of all medical parameters of the health status.

When estimating the intensity of representation of signs by an expert, the followings are taken into account [13]:

1. Qualitative character of estimates.
2. Approximate estimates.
3. Symmetry of gradations of opposite estimates depending on the ideal value of the medical parameter.
4. The use of $5 \div 7$ gradation in parameter estimation.

Thus, assessment of the deviation of real images of the health status of an employee from a fuzzy ideal image necessitates the use of a universal fuzzy scale to determine the compliance of the current parameter value with the ideal one. The advantage of the fuzzy universal scale is the ability to assess the compliance of the current medical parameters' values with the ideal one in a single term-set of linguistic variables [13]. Below, we propose an approach to constructing a fuzzy universal scale for assessing the deviation of generated medical parameters from the norm, which covers the implementation of the following algorithm:

1) the ideal value of the parameter x_{id} is determined (for example, for the temperature parameter x_{id} =36.6°);

2) the minimum $x_{\min}$ values and maximum $x_{\max}$ values of the subject scale *X* are determined, which are corresponding to the lower and upper limits of the values of the medical parameter (this takes into account the symmetry of these values, i.e., $x_{id} = \frac{x_{\min} + x_{\max}}{2}$, e.g., for the temperature parameter $x_{\max}$=*42°*, it can be assumed $x_{\min}$= *31.2°*).

Taking into account the accepted limits for inclusion and equality of two situations, the lower limits (x_{ll}) and upper limits (x_{ul}) of the range of parameter changes [x_{ll}; x_{ul}] within the norm, a certain value is assigned from the interval [0, 1], for example, 0.7, and it is assumed $\varphi(x_{ll}) = \varphi(x_{ul}) = 0.7$ (for example, the range of temperature parameter change can be taken [35,2°; 38.0°]). In other cases, i.e., for parameter values from the range [$x_{\min}$; x_{ll}] (the parameter value is below the norm) and [x_{ul}; $x_{\max}$] (the parameter value is above the norm) correspond to the affiliation function with a value from the interval [0, 0.7], taking into account that $\varphi(x_{\min}) = \varphi(x_{\max}) = 0$.

4. Segments [$x_{\min}$; x_{id}] and [x_{id}; $x_{\max}$] are divided into several parts (for example, into 6 parts), depending on the choice of qualitative gradations of the linguistic variable "deviation of the real value of the medical parameter from the ideal one" and the corresponding change ranges of the value of the parameter and situation are determined (Tab. 1). Further, depending on the severity of the linguistic variable, each level is assigned a fuzzy area from the interval [0, 1], representing the change area of the

affiliation functions of fuzzy sets of verbal gradations of the linguistic variable (Tab. 1).

Tab. 1

Range of membership functions of fuzzy sets of verbal gradations
“deviations of the real values of medical parameters from the ideal”

Linguistic variable	Term sets of a linguistic variable	Situation	Change ranges of parameter value x	Range of terms on the scale
Deviation of real value of medical parameter from ideal	slight deviation	Ideal reference	$\left[x_{id}-\frac{x_{id}-x_{l.l.}}{3};\ x_{id})\right)$ *or* $\left(x_{id};x_{id}+\frac{x_{u.l.}-x_{id}}{3}\right]$	[0.90;1)
	very low deviation	Average reference	$\left[x_{id}-2\frac{x_{id}-x_{l.l.}}{3};\frac{x_{id}-x_{l.l.}}{3})\right)$ *or* $\left(x_{id}+\frac{x_{u.l.}-x_{id}}{3};2\frac{x_{u.l.}-x_{id}}{3}\right]$	[0.80; 0.90)
	low deviation	Reference at the egde of critical	$\left[x_{l.l.};x_{id}-2\frac{x_{id}-x_{l.l.}}{3})\right)$ *or* $\left(x_{id}+2\frac{x_{u.l.}-x_{id}}{3};x_{u.l.}\right]$	[0.70; 0.80)
	significant deviation	Low critical	$\left[x_{l.l.}-\frac{x_{ll}-x_{\min}}{3};x_{ll}\right)$ *or* $\left(x_{iul};x_{iul}+\frac{x_{\max}-x_{ul}}{3};\right]$	[0.50; 0.70)
	high deviation	Average critical	$\left[x_{l.l.}-2\frac{x_{ll}-x_{\min}}{3};x_{l.l.}-\frac{x_{ll}-x_{\min}}{3}\right)$ *or* $\left(x_{iul}+\frac{x_{\max}-x_{ul}}{3};\ x_{iul}+2\frac{x_{\max}-x_{ul}}{3};\right]$	[0.30; 0.50)
	very high deviation	High critical	$\left[x_{\min};\ x_{l.l.}-2\frac{x_{ll}-x_{\min}}{3}\right)$ *or* $\left(x_{iul}+2\frac{x_{\max}-x_{ul}}{3};x_{\max}\right]$	[0; 0.30)

Fig. 2 provides a visual description of the proposed universal scale.

For each situation, the affiliation function in a fuzzy set defined in the interval [0,1] can be selected based on the expert assessment. There are different approaches to the formation of a single collective value based on individual assessments of experts [15, 16]. According to [15], the sought collective value of the situation under consideration is perceived as the intersection of the individual values of individual experts in the same fuzzy set. [16] accepts the value occupying the “middle position” in relation to external values in the set of individual values as the collective single value of the individual values included in the same fuzzy set. Thus, according to the approach proposed in [16], the affiliation function value in fuzzy sets is determined. Based on these results, the rules for expressing the affiliation function representing the compliance of the current values of medical parameters with the ideal one, are as follows.

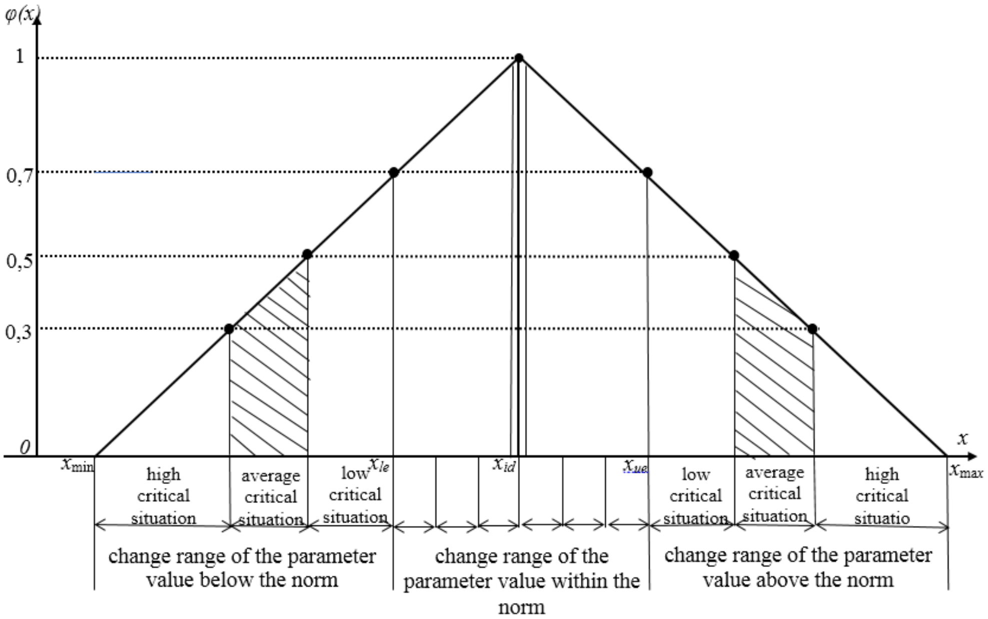

Fig. 2. Universal fuzzy scale showing the correspondence of the medical parameters' value with the ideal value

$$If\ ((x_{id} - \frac{x_{id} - x_{l.l.}}{3} \le x < x_{id}) \vee (x_{id} < x \le x_{id} + \frac{x_{u.l.} - x_{id}}{3}))\ then\ \varphi(x) = 0.94.$$

$$If\ ((x_{id} - 2\frac{x_{id} - x_{l.l.}}{3} \le x < x_{id} - \frac{x_{id} - x_{l.l.}}{3}) \vee (x_{id} + \frac{x_{u.l.} - x_{id}}{3} < x \le 2\frac{x_{u.l.} - x_{id}}{3}))\ then\ \varphi(x) = 0.83.$$

$$If\ ((x_{l.l.} \le x < x_{id} - 2\frac{x_{id} - x_{l.l.}}{3}) \vee (x_{id} + 2\frac{x_{u.l.} - x_{id}}{3} < x \le x_{u.l.}))\ then\ \varphi(x) = 0.72.$$

$$If\ \ ((x_{l.l.} - \frac{x_{ll} - x_{\min}}{3} \le x < x_{ll}) \vee (x_{iul} < x \le x_{iul} + \frac{x_{\max} - x_{ul}}{3}))\ then\ \varphi(x) = 0.62$$

$$If\ \ ((x_{l.l.} - 2\frac{x_{ll} - x_{\min}}{3} \le x < x_{l.l.} - \frac{x_{ll} - x_{\min}}{3}) \vee (x_{iul} + \frac{x_{\max} - x_{ul}}{3} < x \le x_{iul} + 2\frac{x_{\max} - x_{ul}}{3}))\ \ then\ \varphi(x) = 0.45.$$

$$If\ \ ((x_{\min} \le x < x_{l.l.} - 2\frac{x_{ll} - x_{\min}}{3}) \vee (x_{iul} + 2\frac{x_{\max} - x_{ul}}{3} < x \le x_{\max}))\ then\ \varphi(x) = 0.18.$$

4.2. Decision-making on the health status of a ship employee

As noted above, depending on the deviation degree of certain medical indicators from the ideal value, the task of decision-making on the health status of an employee is reduced to the fuzzy image recognition. The search and decision-making in this case is reduced to comparing the fuzzy real image of the health status of each employee with the fuzzy ideal image and to identifying the compliance degree. In this setting, decision-making (logical inference) about the health status of an employee is based on the situational management using the measures to determine the proximity degree of two fuzzy situations. Various measures for determining the degree of similarity between two fuzzy situations including one-step or multi-step estimation procedures are discussed in [14]. In the present work, the degree of fuzzy inclusion of situation $\tilde{B}_i$ into situation $\tilde{D}$ and the degree of fuzzy equality $\tilde{B}_i$ and $\tilde{D}$ were used as the measures of estimation of the degree of proximity of fuzzy real and ideal situations.

1. According to [14], the degree of fuzzy inclusion of situation $\tilde{B}_i$ into situation $\tilde{D}$ is defined as follows:

$$\varphi(\tilde{B}_i, \tilde{D}) = \& \varphi(\mu_{B_i}(x_j), \mu_D(x_j)) = \underset{x_j \in X}{\&} (\max(1-\mu_{B_i}(x_j), \mu_D(x_j))) = \min(\max(1-\mu_{B_i}(x_j), \mu_D(x_j))) \quad (1)$$

The situation $\tilde{B}_i$ is considered fuzzily included into situation $\tilde{D}$ ($\tilde{B}_i \subsetneqq \tilde{D}$) if the degree of inclusion of $\tilde{B}_i$ into $\tilde{D}$ is not less than some threshold of inclusion $\psi \in [0,7;\ 1]$ defined by the management conditions, i.e. $\varphi(\tilde{B}_i, \tilde{D}) \geq \psi$.

In other words, the situation $\tilde{B}_i$ is fuzzy included in the situation $\tilde{D}$ if the fuzzy values of the indicators $\tilde{B}_i$ (fuzzy real values of the medical indicators of a particular employee *i*) are fuzzy included in the indicators' values of the situation $\tilde{D}$ (fuzzy ideal values of the employee's medical indicators).

2. The degree of fuzzy equality (equivalence) as a measure for determination of proximity of any two fuzzy situations is based on the following reasoning. Let the threshold of equality of two situations (e.g., $\psi \in [0,7;\ 1]$) is set and there are situations which mutually include each other, i.e. $\tilde{B}_i \subsetneqq \tilde{D}$ и $\tilde{D} \subsetneqq \tilde{B}_i$, $i = \overline{1, k}$, ($\subsetneqq$ – is the sign of a fuzzy inclusion), then situations $\tilde{B}_i$ and $\tilde{D}$ are considered approximately equal. Such similarity of situations called fuzzy equality is determined from the expression:

$$\mu(\tilde{B}_i, \tilde{D}) = \vee(\tilde{B}_i, \tilde{D}) \& \vee(\tilde{D}, \tilde{B}_i) = \& \mu(\mu_{B_i}(x_j), \mu_D(x_j)) =$$
$$= \min_{x_j \in X}\left[\min(\max(1-\mu_{B_i}(x_j), \mu_D(x_j)),\ \max(1-\mu_D(x_j), \mu_{B_i}(x_j)))\right]. \quad (2)$$

The situations $\tilde{B}_i$ and $\tilde{D}$ are considered fuzzily equal $\tilde{B}_i \approx \tilde{D}$ if $\mu(\tilde{B}_i, \tilde{D}) \geq \psi,\ \psi \in [0,7;\ 1]$, where ψ is some threshold of fuzzy equality of situations.

Following the determination of the degree of fuzzy equality (equivalence) of the fuzzy ideal image and fuzzy real images of the employee's health status, decisions are made. In this regard the following rules are introduced in advance into the knowledge base of the intelligent system for continuous remote monitoring of the workers' health status:

IF ($\mu(\tilde{B}_i, \tilde{D}) \rightarrow [0{,}90;1]$ *) then "employee's health status is very good';*

IF ($\mu(\tilde{B}_i, \tilde{D}) \rightarrow [0{,}80;0.90)$ *) then "employee's health status is good";*

IF ($\mu(\tilde{B}_i, \tilde{D}) \rightarrow [0{,}70;0.80)$ *) then "employee's health status is approaching a critical point";*

IF ($\mu(\tilde{B}_i, \tilde{D}) \rightarrow [0{,}50;0.70)$ *) then "employee's health status is somewhat critical";*

IF ($\mu(\tilde{B}_i, \tilde{D}) \rightarrow [0{,}30;0{,}50)$ *) then "employee's health status very critical";*

IF ($\mu(\tilde{B}_i, \tilde{D}) \rightarrow [0;0.30)$ *) then "employee's health status is extremely critical".*

The systematic collection and accumulation of such information will make it possible to assess trends in the health status of workers.

5. CONCLUSION

The possibility of making erroneous decisions by an individual worker directly depends on his health status and determines the behavior and actions of the latter during the shift on ship. To identify the current health status of workers, a technique based on fuzzy pattern recognition methods was proposed, which allowed automatically analyzing the generated data and synthesizing a diagnostic solution.

Implementation of such a technique allows to:

- assess the health status of each employee in real time;
- automatically make decision in real time according to the critical situation;
- determine the level of health risk in accordance with the critical situation;

- acquire information about the health status of each employee in real time;
- systematically collect individual health data of each employee and form a dynamic database.

Embedding this base in the architecture of an intelligent personnel health management system as a dynamic database module and joint analytical processing of current and retrospective data will allow:

– to objectively assess the changes' tendency in the health status of each employee;

- make informed and objective decisions to eliminate problems negatively affecting the personnel's health in the short, medium and long term.

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