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SYNTHESIS OF DECISION MAKING IN A DISTRIBUTED INTELLIGENT PERSONNEL HEALTH MANAGEMENT SYSTEM ON OFFSHORE OIL PLATFORM

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Abstract

This paper proposes a methodological approach for the decision synthesis in a geographically distributed intelligent health management system for oil workers working in offshore industry. The decision-making methodology is based on the concept of a person-centered approach to managing the health and safety of personnel, which implies the inclusion of employees as the main component in the control loop. This paper develops a functional model of the health management system for workers employed on offshore oil platforms and implements it through three phased operations that is monitoring and assessing the health indicators and environmental parameters of each employee, and making decisions. These interacting operations combine the levels of a distributed intelligent health management system. The paper offers the general principles of functioning of a distributed intelligent system for managing the health of workers in the context of structural components and computing platforms. 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 workers and make informed decisions to eliminate certain problems.

Keywords: offshore oil platforms, Internet of things, distributed intelligent health management system, decision making.

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1. Introduction

Currently, there is a trend towards the digitalization of oil and gas industry. The digital transformation of the industry is motivated by technological innovations such as Machine-to-Machine communication networks (M2M) [1], Wireless Sensor Networks (WSN), IoT technologies and smart sensors for data acquisition, processing and transmission [2], as well as a large number of IoT applications and services for industrial operations (Industrial IoT, IIoT) [3, 4]. Many tools in the oil and gas industry are already supplied with smart sensors for various purposes, which sense large amounts of previously unavailable information online at various stages of the development of oil and gas fields, share sensed data and transmit them for further processing [4, 5]. Analysis of electronic sources demonstrates a significant increase in the interest of almost all oil and gas companies, researchers and developers in solving industrial safety problems in the oil and gas industry benefitting from the potential of IoT [6–8]. The portfolio of many leading oil and gas corporations includes not only strategies or programs, but has already created and implemented specific digital services to solve some production and operational problems [6, 7]. Furthermore, more and more companies have recently begun to develop strategies and programs for the digital development of the industry, covering all links of the value chain (exploration and production, transportation and storage, processing and marketing [8].

However, achieving production efficiency only on the basis of digitalization of various operational processes does not seem realistic. Today, a significant number of skilled employees and specialists (oil workers) are involved in various operations and production processes implemented at geographically distributed offshore facilities and structures, offshore oil platforms (OOPs), whose functional duties and work activities are associated with potential hazards and health risks. Thus, according to the statistics, workers in the oil and gas industry are 8 times more likely to get injured [9, 10]. Thus, the US Bureau of Labor Statistics reports about 300 fatal and more than 410 thousand non-fatal industrial injuries registered in the private sector of the oil refining industry in 2016 [11]. According to the statistics of the UK Health and Safety Executive (HSE), in 2016–2017, 19 fatal accidents and 60 thousand non-fatal accidents were registered. According to the statistics provided by the Centers for Disease Control and Prevention (CDC), between January 2015 and January 2017, oil and gas workers were involved in 602 incidents, 481 hospitalizations and 166 amputations [12]. According to the statistics of the State Oil Company of the Azerbaijan Republic (SOCAR) [13], 32 accidents were registered in 2016–2018, 12 of which were fatal. The above statistics on accidents prove the need to develop an effective system for managing the health of human resources in oil and gas industry, particularly, in offshore industry [9, 10, 14], which refers to the high-risk segment. Therefore, oil and gas companies are interested in developing technologies and tools to monitor the health status and environment of employees during their work. 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 workers in oil and gas industry and, particularly, the offshore industry has been poorly studied yet [15, 16], although in a number of increased risk facilities, such studies are already being carried out. Thus, [17] highlights the possibilities of modern network platforms and applications for solving healthcare problems based on IoT. The approach to remote health monitoring proposed in [18] 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 [19] shows the possibilities of using IoT applications in healthcare, in particular for the physiological monitoring of personnel involved in fire fighting. [20] 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 [21], 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 [22, 23]. The main idea of the concept is to improve the safety of oil workers 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 in OOP, a decision-making technique is proposed to identify the current health status of workers using fuzzy pattern recognition methods.

2. Materials and methods

An analysis of the professional activities of workers involved in the offshore development and operation of oil and gas fields, through the prism of the impact of working conditions, everyday life and external factors on their health, shows that offshore development and operation of oil and gas fields take place in difficult and often extreme working and living conditions [15–17]. An analysis of the causes of accidents shows that many of them are associated with an unforeseen health deterioration of workers [21, 24]. Available rules and standards of labor safety fixed in regulatory documents mainly include the requirements for the safety of workplaces, the environment, and equipment. However, despite the constant improvement of regulatory documents considering technological innovations, the number of incidents caused by the human factor remains quite high (more than 70 % of accidents and incidents in the oil and gas industry) [9, 10].

Human factor on OOP refers to the possibility of person committing erroneous actions under certain conditions or making wrong decisions caused an incident. In such situations, the subjectivity of nature and the psychophysiological characteristics of a person are manifested [22]. Therefore, the human factor in hazardous production begins to pose danger rather than the production itself. Based on this, let's assume that the likelihood of making erroneous decisions by any employees directly depends on the state of health affects his/her behavior, as well as on the nature of his/her actions and activity during the shift on platform. This actualizes the need for systematic remote monitoring of health and safety of workers in their working and living environment.

Basing on IoT and e-health solutions, the works [22, 23] develop architecture of a distributed intelligent system (DIS) for managing the health and safety of workers employed in OOPs. Architecture of intelligent health management system for shift workers in OOS 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.

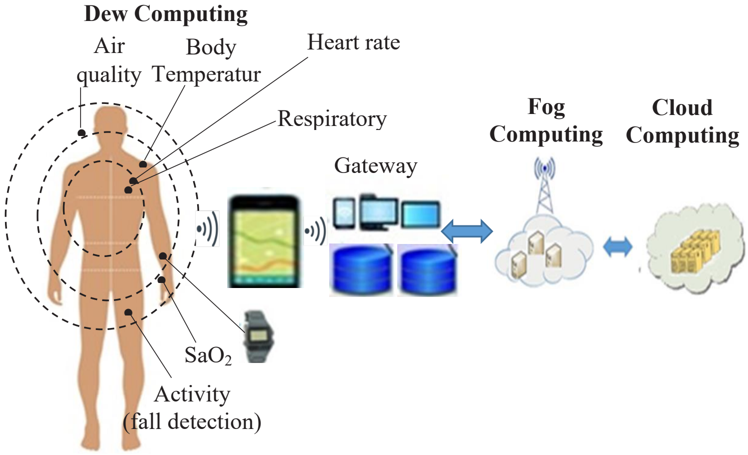

Fig. 1. The architecture of an intelligent health management system for workers employed on OOP

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, the OOP 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 the OOP) 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 OOP personnel health management system into hierarchically distributed computing levels: Dew computing, Fog computing and Cloud computing.

First layer of DIS focuses on health and safety monitoring of workers on OOP. 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 OOP. LSCER is a computerized workplace of persons responsible for health and safety of workers on OOP. 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 OOP 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 OOP 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 offshore oil and gas company.

At previous stages of research, the mechanism for remote monitoring of the health and safety of OOP personnel at the methodological and architectural and technological levels was reviewed.

A person-centered approach to health and safety managing involves continuous remote monitoring of the 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 an 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 OOP (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 synthesis of diagnostic decision.

Thus, the goal of this research 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 the principles of functioning of distributed intelligent system determining the approaches to the implementation of decision-making processes;

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

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

This article proposes one of the possible options for the analytical implementation of the functioning of the DIS for managing the health and safety of workers employed on OOPs, including tools for assessing and analyzing data and making decisions.

3. Results and discussion

3. 1. Principles of functioning of distributed intelligent system determining approaches to the implementation of decision-making processes

The functional model of the health management system of OOP personnel is implemented by tracking vital indicators of the physiological state and parameters of the environment of the following stages:

– tracking, i.e., continuous remote monitoring of vital health status indicators of the personnel and environment settings;

– monitoring and evaluation, i.e., comparison of monitored health indicators for compliance with standards in terms of medical requirements and specified restrictions;

– decision making, i.e., data processing and analytics to support decision making.

These interacting operations distributed across the DIS levels, are the links in decision-making process. The prinsips functioning of DIS in the context of structural layers are as follows:

1. All three layers of DIS along with many specific applications are equipped with a unique IoT application (software) for each of them. This application is an intelligent information system (IIS) based on a functional model of health management of personnel employed on OOP (**Fig. 1**).

2. Modules of IIS database include digitized ranges of changes in normative, edge and critical values of each health indicator (temperature, pulse, pressure, heart rate, etc.), information on standards (reference images) of activity and behavior within the framework of technological requirements and restrictions, authorized and prohibited formats and coordinates of access to hazardous geo-zones (in accordance with the map of drilling rig, working and residential sites, explosive zones on OOP, etc.), permissible limits and level of excess environmental toxicity.

3. IIS knowledge base contains cognitive information linking the expert assessments and decisions with granules of possible values of various indicators and parameters, including critical ones, provoking the emergency situations on OOP.

4. The process of continuous health and safety monitoring of workers employed on OOP generates a huge amount of data, which is problematic to analyze through traditional methods. Therefore, it is assumed that the analytical block of DIS computing platforms based on IoT solutions includes high-performance algorithms and intelligent analytical tools (Decision support tools, Softcomputing, Big Data, Machine Learning).

5. IoT monitors in parallel the streams of sensed data of all workers on OOP, compares them with the normative (reference) health status templates, behavioral patterns, geolocation and environmental parameters pre-recorded in IIS databases and knowledge bases, and identifies the deviation rate of a particular indicator and parameter in real time.

6. IoT, instantly analyzing the current situation, reveals the deviation of certain indicators and parameters from the norm and analyzes the current situation. Depending on the criticality of the situation, the degree of its compliance with already known (typical) models, or the identification of new patterns, decision can be made according to two scenarios:

1) automatic formation of a control action by the system;
2) real time data redirecting to emergency response services to make an operational decision.

3. 2. Assessing the current situation on the health status of employees

IoT-based geographically distributed intelligent health management system 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 [25]. 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 [26]. This necessitates:

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

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

3. 2. 1. Development of models of a fuzzy ideal image and fuzzy real images of the health status of an employee

Let:

$$A = \{A_1, A_2, ..., A_k\},$$

or

$$A = \{A_i, i = \overline{1,k}\},$$

be a set of workers located on the OOP and k – total number employee located on the OOP 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 worker's health.

The model $D = (X)$ of the ideal image of the health of a worker employed in the OOP can be described by a matrix $D_X = \|x_j\|_n$, where the row D_X characterizes his/her 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:

$$\mu_{x_j}(D) : D \times X \to [0.98, 1].$$

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 the OOP 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 $\mu_{x_{ij}}(B_i): B \times X \to [0,1]$, 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 the OOP:

$$\tilde{D} = \{< \mu_{x_n}(D) >\} = \{\mu_D(x_j)/X\},$$

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

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.

3. 2. 2. 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 $\varphi(x)$. The following requirements are applied to the choice of the scale:

1. Possibility of describing 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 describing 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 [25]:

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÷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 [25]. Below, let's 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 $x_{\min} = 31.2°$);

3) 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 (**Table 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 (**Table 1**).

Table 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 [27, 28]. According to [27], 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. [28] 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 [28], 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:

$$\text{If}\left(\left(x_{id}-\frac{x_{id}-x_{l.l.}}{3}\le x<x_{id}\right)\vee\left(x_{id}<x\le x_{id}+\frac{x_{u.l.}-x_{id}}{3}\right)\right)\text{ then }\varphi(x)=0.91.$$

$$\text{If}\left(\left(x_{l.l.}\le x<x_{id}-2\frac{x_{id}-x_{l.l.}}{3}\right)\vee\left(x_{id}+2\frac{x_{u.l.}-x_{id}}{3}<x\le x_{u.l.}\right)\right)\text{ then }\varphi(x)=0.71.$$

$$\text{If}\left(\left(x_{l.l.}-\frac{x_{ll}-x_{\min}}{3}\le x<x_{ll}\right)\vee\left(x_{iul}<x\le x_{iul}+\frac{x_{\max}-x_{ul}}{3}\right)\right)\text{ then }\varphi(x)=0.6.$$

$$\text{If}\left(\begin{array}{l}\left(x_{l.l.}-2\frac{x_{ll}-x_{\min}}{3}\le x<x_{l.l.}-\frac{x_{ll}-x_{\min}}{3}\right)\vee\\ \vee\left(x_{iul}+\frac{x_{\max}-x_{ul}}{3}<x\le x_{iul}+2\frac{x_{\max}-x_{ul}}{3}\right)\end{array}\right)\text{ then }\varphi(x)=0.4.$$

$$\text{If}\left(\left(x_{\min}\le x<x_{l.l.}-2\frac{x_{ll}-x_{\min}}{3}\right)\vee\left(x_{iul}+2\frac{x_{\max}-x_{ul}}{3}<x\le x_{\max}\right)\right)\text{ then }\varphi(x)=0.15.$$

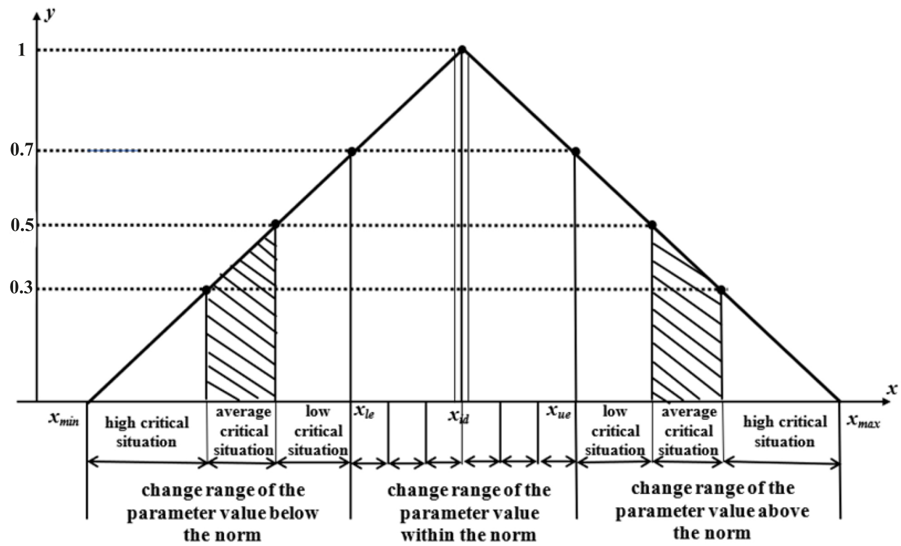

Fig. 2. Universal fuzzy scale showing the correspondence of the medical parameters' value with the ideal value

3. 3. Decision-making on the health status of an 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 [26]. 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 [26], 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 $\tilde{D}$ ($\tilde{B}_i \underset{\sim}{\subseteq} \tilde{D}$) 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. $\tilde{B}_i \underset{\sim}{\subseteq} \tilde{D}$ and $\tilde{D} \underset{\sim}{\subseteq} \tilde{B}_i$, $i=\overline{1,k}$ ($\underset{\sim}{\subseteq}$ 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, according to **Table 1**, 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 critical»;

IF $(\mu(\tilde{B}_i,\tilde{D}) \rightarrow [0.75;0.80[)$ then «employee's health status very critical»;

IF $(\mu(\tilde{B}_i,\tilde{D}) \rightarrow [0.70;0.75))$ 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.

3. 4. Discussion

The possibility of making erroneous decisions by an individual worker directly depends on his/her health status and determines the behavior and actions of the latter during the shift on the OOP. 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.

The issue of health data analysis was solved by comparing the currently generated data value with the ideal value. In this regard, a fuzzy universal scale was used, which allowed to evaluate various medical data in a single measure, and their fuzzification was performed according to the ideal conformity of the values of the medical parameters.

A fuzzy image of ideal health based on parameters characterizing the health of employees and fuzzy images of current health conditions based on parameters characterizing the current state of the employee were modeled [26]. For fuzzy images recognition, the method of assessing the health status of the worker by applying the formula (1) or (2) was given. The If-Then model of knowledge description was used to make decisions according to the obtained results [25].

The proposed technique can be implemented in accordance with two scenarios. The proposed IoT platform-based algorithm automatically analyzed the data and synthesized a diagnostic decision in typical situations that can be implemented in accordance with two scenarios:

1. Decision automatically made by the IoT application, as a response to the critical situation, instantly acts as a control action both for the wearable devices of workers (as an alarm) and for the emergency response service at HRFs. In this case, the IoT platform of the intelligent system for continuous remote monitoring is actually transformed into a cyber-physical system (CPS), which ensures the integration of the real physical world with the virtual world of computing processes without human interference in the human out of loop.

2. Decision automatically synthesized by the IoT platform is sent to the responsible clinician for confirmation (CPS human in the loop). The clinician evaluates the results of the data analysis, involving, if necessary, the relevant specialists, and makes the final decision, which is transferred to the HPF for execution within a specified period of time.

In non-standard situations, all relevant information and IoT solutions automatically proposed by intelligent decision system in real time are provided to interested coastal services and their authorized persons (supervisors, doctors, occupational safety specialists, heads of relevant departments, experts). This enables the latter to find out the reasons for deviations of indicators from the standard values and make informed decisions to eliminate hazards to health and possible incidents, thereby minimizing the impact of the human factor. In this case, the task of decision-making can be addressed by reducing it to the decision-making methods, taking into account the different types of functional and distributed knowledge (for example, each employee's electronic health records (EHR)) in the individual cloud of the employee's health.

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.

The proposed technique aims at assessing the health status of employees and making decisions with the reference to only medical parameters generated by IoT-applications, and fuzzy image recognition as artificial intelligence methods, and the If-Then model of knowledge representation. At present, due to the lack of possibility to obtain real data, it is impossible to experimentally implement the proposed technique.

In the distributed system of remote intelligent monitoring of the health and safety of employees, the concept of situation assessment and decision-making is put forward, taking into account the parameters related to geolocation, behavior, and the environment of the employee, along with health data. The solution of this problem requires the application of big data, deep learning methods, and machine learning methods, in addition to the methods of artificial intelligence used above.

4. Conclusions

The study proposes a technique for the decision synthesis in the remote continuous intelligent monitoring system of the health status of the OOP personnel, designed to timely eliminate incidents related to the human factor. The technique provides an opportunity to:

a) collect and evaluate real-time information about the health status of each worker employed on the OOP;

b) identification of the criticality rate of the values of vital health indicators;

c) automated decision-making appropriate to the current situation. These interacting operations, as links in the decision-making process, combine the levels of a distributed intelligent system for managing the health of workers and ensure its functioning as a whole.

The number, heterogeneity and uncertainty of medical parameters characterizing the health status of an employee, the variation of each parameter within different limits determine the multivariance of possible situations related to the health status of an employee. In this regard, let's introduce the concepts of «fuzzy image of the current health status of an employee» and «fuzzy image of the ideal health status of an employee» and propose their formal models. Based on these models, let's offer a method for making decisions on the health status of an employee based on fuzzy image recognition using similarity (identity) measures of two fuzzy situations, i.e., the current and ideal health status of an employee. As the similarity measures of two situations, fuzzy equality and fuzzy inclusion of the ideal image and fuzzy real images of the health status of an employee are chosen with the establishment of a certain inclusion threshold, the introduction of which enhances the interpretability at the fuzzy control system level.

To interpret the recognition results, i.e., to transform the data into knowledge at the level of the knowledge representation model, the «if-then» model is chosen. The use of this model will allow further introduction of new rules into the knowledge base, including other context-dependent parameters (geolocation, environmental toxicity, etc.), without causing problems for existing rules.

A fuzzy universal scale is developed for the identification of medical parameters, taking into account the diversity and fuzziness of these parameters. When constructing the scale, the following requirements are taken into account: the possibility of describing numerical and dimensionless information to ensure comparability of parameters of different physical nature; universality, applicability to parametric and non-parametric input information; the possibility of describing the definition domain for any values of the considered medical parameters of the health status. When evaluating the intensity of manifestation of signs by an expert, the qualitative and quantitative nature of medical indicators, the inaccuracy of estimates, the symmetry of the gradations of opposite estimates depending on the ideal value of the medical parameter and its acceptable threshold are taken into account.

The method for constructing a fuzzy universal scale, its visualization and a stepwise algorithm provide an increase in interpretability at the level of fuzzy term sets of linguistic variables.

A technique proposed for decision synthesis in the remote continuous intelligent monitoring system of the health status of personnel on the OOP can be used in modeling semi-structured processes at other objects with a high health risk, occurring under other uncertainty conditions.

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