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ARCHITECTURAL SOLUTION FOR THE DISTRIBUTION OF SOFTWARE AND HARDWARE SYSTEMS FOR MONITORING POTENTIALLY UNSAFE OBJECTS

*Vladyslav Sokolovskyi[1] and Eduard Zharikov[2]

[1,2]Department of Computer Science and Software Engineering, National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute", Kyiv, Ukraine

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ABSTRACT: The relevance of the scientific research topic is determined by the constant increase of accidents and technological disasters on modern industrial objects, especially those events, that developed further accidents. The basis of the scientific research methodological approach is a combination of the artificial intelligence-based (AI-based) software-hardware system development key principles systemic analysis method and complex research of AI-based software-hardware basic system employment to prognosis potential accidents during the organization of potentially unsafe object monitoring. The results acquired in the scientific research, state, that it is necessary to develop and implement new, improved architectural solutions, which will be used as a base for the creation of software-hardware automated potentially unsafe object monitoring systems, which will predict possible accidents in real-time and prevent the development of severe accidents, that may grow into major disasters. Moreover, the creation of a hierarchic, interbranch, potentially unsafe object monitoring system to prevent technological disasters, accidents, and events will save life and health of workers and the civilian population.

Keywords: Neural network, Prediction of possible accidents, Disaster, Automated accident risk control, Industrial hazard

1. INTRODUCTION

The constant economic development of modern countries is caused by reliable and accident-free production of the industrial sector. Most of Ukraine's industrial sector is the production of metallurgic, chemical, oil, and gas industries as well as energetic complex organizations. A guarantee of accident-free production of the industrial complex is the timely detection of a possible accident during the working process. It is especially important for productions, marked as potentially unsafe objects [1]. Absolute safety cannot be guaranteed on any industrial object. As such, the safe work of industrial objects depends on the external condition of the environment and the manufacturing state and training of the personnel. Therefore, there is always a possibility of accidents that pose a threat to the existence of an industrial object, human health, and the possibility of environmental damage.

The worst-case scenario is usually a major disaster, a prerequisite for such events is substantial instability of natural, technical, and social-economic processes. To include the possibility of danger and to respond to such threats immediately, there is a need to predict and assess the possibility of accidents. One of the main methods of technical and natural accident prevention is the implementation of monitoring systems, which will preventively warn the operators on the possibility of an accident or major disaster on the industrial object [2-4]. Monitoring systems in this context refer to technological tools or software-hardware systems that are implemented in high-risk industrial facilities to track and analyze data in real-time. The purpose of these systems is to detect and identify any potential hazards or anomalies in the operation of the facility which could lead to an accident or major disaster. The system sends warning signals or alerts to operators, allowing them to take prompt action and prevent such incidents [4].

In turn, Shaw et al. [5] emphasize that the likelihood of developing and implementing a system whose principle of operation is based on the use of artificial neural networks is a significant progress towards the formation of recommendations for decision-making in the direction of managing the quality monitoring of high-risk facilities. The quality of monitoring the state of high-risk objects will be of great importance in this context.

This research aims to develop and evaluate the possibility of practical implementation of information technology for prediction and early detection of the possibility of accidents at high-risk facilities based on information obtained during the monitoring of such facilities in real-time. The gap in the existing literature is the lack of practical implementation of information technology for early detection and prediction of accidents at high-risk facilities based on real-time monitoring. The study plans to address the existing gap by creating and testing AI-powered software-hardware systems to monitor potentially unsafe objects. The systems are expected to help prevent accidents and major disasters, leading to safer industrial production.

2. RESEARCH SIGNIFICANCE

The research on architectural solutions for the distribution of software and hardware systems for monitoring potentially unsafe objects is significant due to the increasing number of accidents and technological disasters that occur in modern industrial objects. The scientific research approach combines the use of AI-based software-hardware systems with systemic analysis and complex research to improve the prognosis of potential accidents during the monitoring of potentially unsafe objects. The practical value of this research lies in the possibility of creating hierarchic, interbranch monitoring systems that can prevent technological disasters, accidents, and events, ultimately saving the lives and health of workers and the civilian population. The results of this research can be used in the development of software-hardware automated potentially unsafe object monitoring systems that can predict possible accidents and disasters that may grow into major disasters.

3. MATERIALS AND METHODS

The basis of the scientific work methodological approach is a combination of methods of system analysis of the main aspects of the modern artificial intelligence-based (AI-based) prediction method development and implementation with a comprehensive study of the principles of the practical application of monitoring systems for potentially unsafe objects. The method of comparative analysis of its results with the results and conclusions of several scientific studies of the joint, and several other topics was applied. The main scientific research was preceded by the creation of a qualitative theoretical framework, which contained an analysis of the results of scientific research in the field.

The use of the system analysis method, key aspects of development, and practical implementation of the forecasting subsystem with the use of artificial intelligence in the widespread architecture of software and hardware systems for monitoring the state of potentially hazardous objects [1] gave grounds to state that the current state of development of industrial facilities tends to create a large number of risks of accidents. It was deducted that the implementation of a set of measures to modernize civil protection systems is a priority.

The employment of the complex research basis of the AI systems for the high-risk object state monitoring allowed us to determine key factors that cause the inefficiency of countering the probability of emergencies in industrial organizations with further risk of escalation. All results were presented in a form of tables and graphics. A comparison of acquired results with the results of another scientific research was conducted.

4. RESULTS

4.1 Artificial Intelligence Implementation into Potentially Unsafe Object State Monitoring Systems

The imperfection of the civil protection system in Ukraine requires the introduction of new ways to modernize both the civil protection system and technical monitoring systems for potentially unsafe objects [6, 7]. Monitoring the state of potentially unsafe objects and predicting the probability of an emergency is currently implemented in Ukraine only fragmentarily [4]. The situation that has developed in Ukraine regarding the implementation of possible emergency probability monitoring systems for early detection can be considered as corresponding to the initial stages of construction. And this is despite the existence of State Building Standards of Ukraine [1], a large number of methodological materials, publications by various authors, and the real need for such systems [8]. It is possible to create systems based on artificial neural networks that will make management decisions and form recommendations. Depending on the input signals, the artificial neural network output should generate a sign of the decision it made in the form of appropriate output signals.

Typically, the training process of an artificial neural network is performed by successively adjusting synaptic weights and thresholds [9]. This is an iterative process. Ideally, the artificial neural network establishes relationships at each iteration using a database. The choice of artificial neural network architecture is always performed experimentally.

The selection of the characteristics of the artificial neural network and the selection of training parameters are also performed experimentally (Figure 1). The key problem of the artificial neural network in the proposed system is the creation of predictions. In this case, the inputs of the artificial neural network are the previous values of the indicators. The output is the predicted values. The number of hidden layers of associative elements is selected experimentally [10].

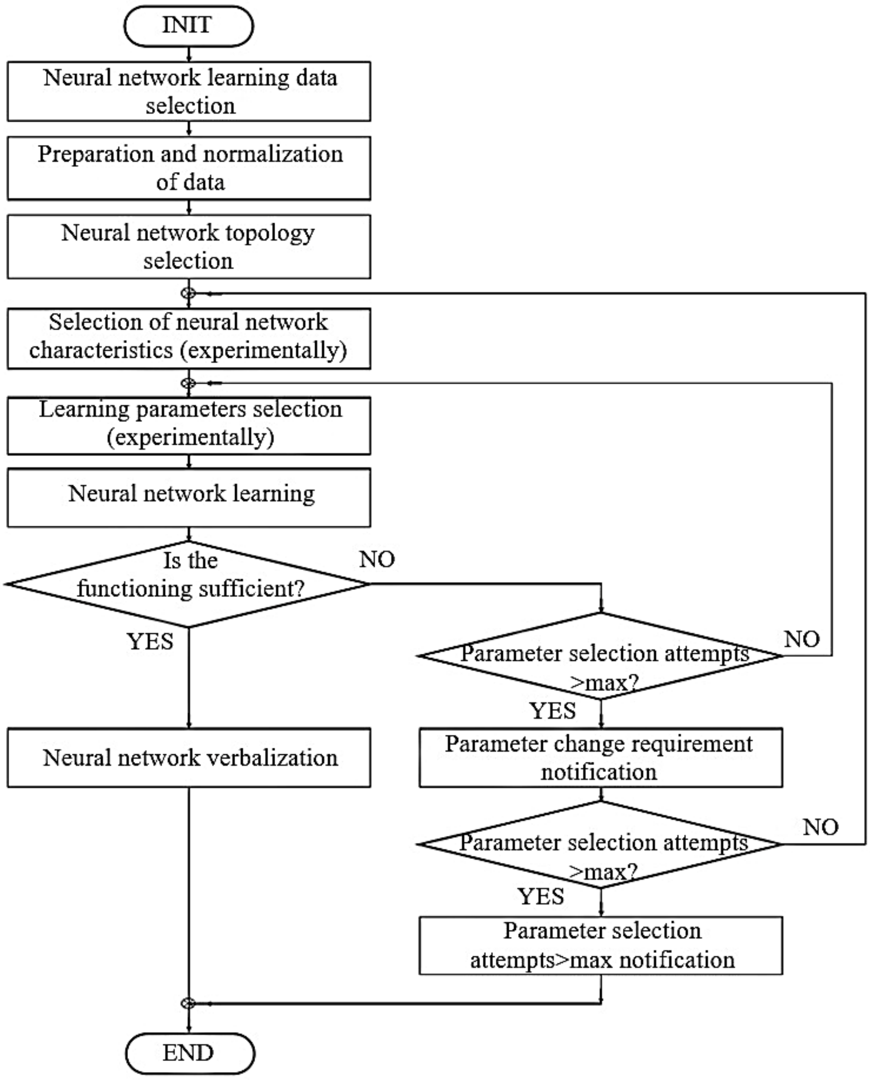

Fig. 1 The sequence of actions during the selection of architecture, topology, and characteristics of artificial neural network

The system adapts its parameters constantly. Therefore, this learning process is also constant. The algorithm of such continuous learning is shown in Figure 2. These artificial neural networks are usually used for prognosis: multilayer perceptron (MLP); radial-basis framework (RBF); generalized-regressive neural network (GRNN); Volterra network; Elman network (Table 1). The procedure for processing the comparison results based on expert surveys was as follows: The number of pairwise comparisons for the results "less than", "equal to", and "greater than" was calculated separately. The sum of the results of m1 pairwise comparisons that gave a result of "less than" was multiplied by "-1". The sum of the results of m2 pairwise comparisons that gave a result of "equals" was multiplied by "0". The sum of the results of m3 pairwise comparisons that gave a result of "greater than" was multiplied by "1". Then, a sum of the abovementioned variables was calculated. The result was considered "less" if the sum per item 5 was negative, "equal" if the sum was zero, and "more" if the sum was positive.

Then, the benefit coefficients were determined by the following procedure:

$$\mathbf{a_{ij}} = \begin{cases} \mathbf{1.5 \text{ on } x_i > x_j}; \\ \mathbf{1.0 \text{ on } x_i = x_j}\ ; \\ \mathbf{0.5 \text{ on } x_i < x_j}. \end{cases} \quad (1)$$

Table 1 Selection of artificial neural network prediction quality criteria

No.	Criteria name	Value
1	Prediction accuracy	x_1
2	Simplicity	x_2
3	Ergonomics	x_3
4	Reliability	x_4
5	Neural network learning implementation	x_5
6	Cost	x_6

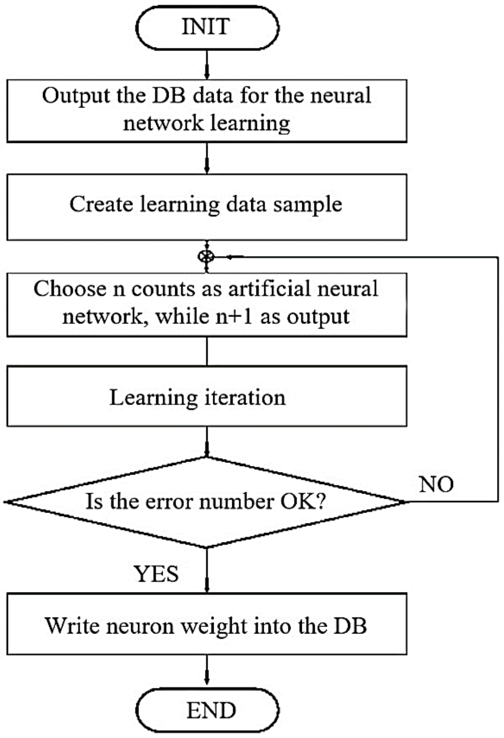

Fig. 2 The general artificial neural network learning algorithm

Table 2 Results of the criteria ranging based on an expert survey

n_i	Criteria ri of neural network prediction quality value complex evaluation	Criteria r_{ij} rank per expert rating (N = 5)					Ri =Σ rij	T= Σri /n	Δi= Ri-T	$Δi^2$
		Expert 1	Expert 2	Expert 3	Expert 4	Expert 5				
1	Prediction accuracy	6	6	6	6	6	30	21.0	9.00	81.00
2	Simplicity	5	4	4	3	2	18	21.0	-3.00	9.00
3	Ergonomics	4	4	3	2	5	18	21.0	-3.00	9.00
4	Reliability	5	5	5	5	5	25	21.0	4.00	16.00
5	Installation simplicity	2	2	1	5	3	13	21.0	-8.00	64.00
6	Implementation cost	4	5	5	4	4	22	21.0	1.00	1.00
n = 6	Sum	26	26	24	25	25	126	21.00		S= 180.0

Based on the numerical data a_{ij} of Table 2, a square matrix is compiled:

$$\mathbf{A} = \begin{Vmatrix} a_{11} \dots & a_{1j} \\ a_{i1} \dots & a_{ij} \end{Vmatrix} \quad (2)$$

The next step is a calculation of the neural prediction quality criteria value coefficient. As such: *bi* – the value of the i criteria, determined under full evaluation of experts:

$$\boldsymbol{b_i} = \sum\nolimits_{j=1}^{N} \boldsymbol{a_{ij}} \quad (3)$$

In the second and further stages of value coefficient $\boldsymbol{K_i}'\boldsymbol{K_i}''$ and others were calculated by the formula:

$$\boldsymbol{K_i}' = \frac{\boldsymbol{b'_i}}{\sum_{i=1}^{n} \boldsymbol{b'_i}}, \quad (4)$$

$$b'_i = a_{i1}b_1 + a_{i2}b_2 + \ldots + a_{in}b_n. \quad (5)$$

Several condition fulfillments were checked:

$$\begin{cases} \sum_{i=1}^{n} \boldsymbol{K_i} = \mathbf{1}; \\ \sum_{i=1}^{n} \boldsymbol{K'_i} = \mathbf{1}. \end{cases} \quad (6)$$

As demonstrated in Table 4, it was possible to achieve such results, when the next values of the relative weighting coefficients K''_i differ negligibly (ε<2%) from the previous K'_i, only after the second step (iteration). The quality of the system and its behavior are characterized not only by the fact of achieving the goal, but also by the degree of achievement, and is determined by the objective function. The next step was to select the objective functions and determine their numerical values for each variant of the implementation of the forecasting subsystem using neural networks. The results of the calculations are summarized in Table 5, where the values of S1, S2, and S3 are the objective functions for each variant of the system implementation. The values of the objective functions were calculated by the formulas:

$$\boldsymbol{S_1} = \sum_{j=1}^{6}\left(\boldsymbol{K_j} \cdot \boldsymbol{B_{1j}}\right) = \mathbf{0.219} \quad (7)$$

$$\boldsymbol{S_2} = \sum_{j=1}^{6}\left(\boldsymbol{K_j} \cdot \boldsymbol{B_{2j}}\right) = \mathbf{0.281} \quad (8)$$

$$\boldsymbol{S_3} = \sum_{j=1}^{6}\left(\boldsymbol{K_j} \cdot \boldsymbol{B_{3j}}\right) = \mathbf{0.50} \quad (9)$$

4.2 Building a Potentially Unsafe Object Emergency Probability Prediction Subsystem

A generalized regression network (GRNN) was selected as a neural network. The predicted value will be related to the probability density of the joint distribution of the values of input and output signals [11]. For the GRNN it is possible to consider a

Gauss kernel function (Table 5). The first intermediate radially symmetric layer of neurons of the GRNN receives signals from the input layer and transmits signals to the second intermediate layer [12]. For the output of the i-th neuron of the first hidden RBF layer, the value of the output signal of the l-th neuron of the second intermediate layer can be calculated:

$$\boldsymbol{u_i = \sum_{i=1}^{n} v_i} \quad (10)$$

where: n is the max number of neurons in the RBF in the layer. For the weight coefficient of the ωi i-th neuron of the first hidden RBF layer of the generalized regression network (GRNN), the sum of weights is equal:

$$v_0 = \sum_{i=1}^{n} \omega_i, \quad (11)$$

Table 3 Benefit coefficient matrix

Criteria, x_i		Criteria, x_j					
		x_1	x_2	x_3	x_4	x_5	x_6
Prediction accuracy	x_1	1.00	0.50	0.50	0.50	0.50	0.50
Simplicity	x_2	1.50	1.00	0.50	1.50	0.50	1.50
Ergonomics	x_3	1.50	1.50	1.00	1.50	0.50	1.50
Reliability	x_4	1.50	0.50	0.50	1.00	0.50	0.50
Installation simplicity	x_5	1.50	1.50	1.50	1.50	1.00	1.50
Implementation cost	x_6	1.50	1.50	0.50	1.50	0.50	1.00

Table 4 Calculation of neural prediction quality criteria value coefficient

Criteria, x_i	First calculation		First iteration			Second iteration			Third iteration			Final
	b_i	K_i	$b^{`}_i$	$K^{`}_i$	ΔK%	$b^{``}_i$	$K^{``}_i$	ΔK%	$b^{```}_i$	$K^{```}_i$	ΔK%	K^*_i
Prediction accuracy X_1	3.5	0.095	20.3	0.096	1.042	115.88	0.097	1.031	657.56	0.548	82.309	0.097
Simplicity X_2	6.5	0.176	36.3	0.171	2.841	204.63	0.171	0	1160.56	0.968	82.33	0.171
Ergonomics X_3	7.5	0.203	43.3	0.204	0.49	244.38	0.204	0	1385.06	1.155	82.337	0.204
Reliability X_4	4.5	0.122	24.3	0.115	5.738	138.13	0.115	0	784.56	0.654	82.422	0.115
Iteration simplicity X_5	8.5	0.23	51.3	0.242	4.959	291.63	0.243	0.412	1653.06	1.378	82.371	0.243
Implementation cost X6	6.5	0.176	36.3	0.171	2.841	204.63	0.171	0	1160.56	0.968	82.33	0.171
Overall	37	1.002	211.5	1	5.738	1199.3	1.00	1.031	6801.38	5.671	82.422	1.00

Table 5 Value calculation of artificial neural network prediction target function per their type

Criteria	VARIANT	Experts, ratings from "1-100":					Average rating	Pair comparison				bi=Σaij		K'i	K'i * Bij		
		1	2	3	4	85			V_1	V_2	V_3						
Prediction accuracy x_1	1	85	75	75	75	70	79.00	V_1	0	1.5	1.5	3	0.375	0.097	0.036		
	2	75	60	80	80	85	73.00	V_2	0.5	0	0.5	1	0.125	0.097		0.012	
	3	65	65	80	85		76.00	V_3	0.5	1.5	0	4	0.500	0.097			0.049
											Sum:	8	1.000				
Simplicity x_2	1	10	12	15	20	40	16.40	V_1	0	0.5	0.5	1	0.167	0.171	0.029		
	2	12	15	20	30	50	23.40	V_2	1.5	0	0.5	2	0.333	0.171		0.057	
	3	18	20	27	20	50	27.00	V_3	1.5	1.5	0	3	0.500	0.171			0.086
											Sum:	6	1.000				
Ergonomics x_3	1	40	45	55	50	70	50.00	V_1	0	0.5	0.5	1	0.167	0.204	0.034		
	2	50	55	60	60	75	59.00	V_2	1.5	0	0.5	2	0.333	0.204		0.068	
	3	60	57	70	75	75	67.40	V_3	1.5	1.5	0	3	0.500	0.204			0.102
											Sum:	6	1.000				
Reliability x_4	1	80	85	85	80	75	80.00	V_1	0	0.5	0.5	1	0.167	0.115	0.019		
	2	70	90	90	90	95	83.00	V_2	1.5	0	0.5	2	0.333	0.115		0.038	
	3	80	95	95	85	95	90.00	V_3	1.5	1.5	0	3	0.500	0.115			0.058
											Sum:	6	1.000				
Installation simplicity x_5	1	90	90	85	60	65	79.00	V_1	0	1.5	1.5	3	0.300	0.243	0.073		
	2	80	85	70	65	80	73.00	V_2	0.5	0	1.5	2	0.200	0.243		0.049	
	3	70	65	65	55	80	67. 00	V_3	0.5	0.5	0	5	0.500	0.243			0.122
											Sum:	10	1.000				
Implementation cost x_6	1	50	60	70	50	70	60.00	V_1	0	0.5	0.5	1	0.167	0.171	0.029		
	2	60	80	80	65	80	73.00	V_2	1.5	0	0.5	2	0.333	0.171		0.057	
	3	80	85	75	70	85	79.00	V_3	1.5	1.5	0	3	0.500	0.171			0.086
											Sum:	6	1.000		0.219	0.281	0.50

And finally, the output layer, which gives the final value of the signal, which is used as a forecast:

$$\mathbf{y_1} = \frac{\mathbf{u_i}}{\mathbf{v_0}} \tag{12}$$

The output signal of a neural network has a probabilistic meaning, and therefore it is easy to interpret. In Figure 3, the red line is the time series value, and the blue line is the prediction value using the GRNN neural network.

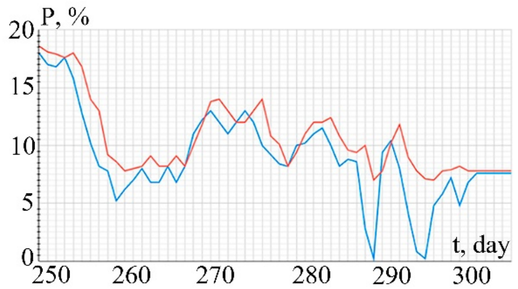

Fig. 3 Graphs of the results of potentially unsafe object emergency probability prediction

It was found that the prediction quality depends on the method of forming the volume of three sets: training, testing, and control. The best prediction quality is obtained when the ratio of the volumes of the above sets in the ratio 64:18:18. The optimal values of the algorithm parameters are: the learning rate coefficient η=0.65, the learning moment coefficient μ=0.85, the number of iterations before memorization N=23, the value of the change in the learning rate coefficient α=0.1. The number of neurons in the hidden layers of the network is determined for each time series individually.

5. DISCUSSION

Dubey et al. [13] emphasize that the methodological recommendations developed at this time to eliminate the consequences of an emergency at high-risk facilities do not cover the full range of circumstances that can lead to such situations. It is quite justified to gradually develop the practice of a set of measures to eliminate the consequences of emergencies [14]. At the same time, Lawless et al. [15] draw attention to the fact that the issue of regulating the assessment of the real state of high-risk facilities under the regulations of the current legislation is essential. All issues of monitoring the state of potentially unsafe objects should be regulated by the norms of the current legislation.

Vasant et al. [16] note that during the planning of a set of measures to monitor the state of a potentially unsafe object, the probability of temporary changes in data on the state of these facilities under the influence of several external factors should be taken into account. It is impossible to exclude such factors from the list of risk factors for emergencies at potentially unsafe objects, as this will not contribute to the formation of an objective assessment of the situation [17]. Wood et al. [18] raised several problematic aspects of the use of AI. Predicting the probability of an emergency at potentially unsafe objects is a mandatory aspect of AI systems, based on which systems for monitoring the condition of these facilities are formed [19-21].

Topical issues of the quality of information support of artificial intelligence systems that perform the functions of monitoring the state of potentially unsafe objects are indirectly raised in the scientific study of Ochella et al. [22]. The lack of information support can significantly affect the performance of artificial intelligence systems, which will affect the final quality of monitoring the probability of emergencies in those areas that are monitored by artificial intelligence systems [23-26]. The comparison of the results obtained in this study with the results and conclusions of several researchers on the accepted and compatible topics demonstrates their compliance with each other.

6. CONCLUSION

The scientific study of the current state of monitoring systems for potentially unsafe objects allows us to state that there are certain drawbacks to existing monitoring systems. To effectively eliminate them, the use of artificial intelligence based on artificial neural networks for early detection of the probability of an emergency at a potentially unsafe object was proposed. Moreover, the scientific research of the modern potentially unsafe object emergency monitoring state systems allowed to development of a method of predicting an emergency based on a generalized regressive artificial neural network. This, in turn, allows us to fully implement the potentially unsafe object state monitoring system with early prediction of the emergency probability subsystem. A systemic complex development based on an artificial neural network with a hash-table for improved processing speed supports the issue solution, while the development of database architecture, which includes a fully developed neural network display table and acquired prognosis data storage tables.

The selection of neural network architecture fully satisfies the set goal. At the same time, the proposed artificial neural network adaptation algorithm allows to implementation of data time attributes into its architecture, which implements a principle of continuous learning. Proper implementation of a similar approach requires the employment of major calculation power. However, to solve the issues of monitoring and predicting the emergency probability on potentially unsafe objects and given the low data stream input, the requirements are not difficult to implement. As such, the implementation of the proposed approach is applicable. Potentially unsafe object emergency probability prediction for properly working monitoring systems issue solution is manageable only by employing generalized regression artificial neural network with a learning base of relatively large data volumes.

This research does not include data on how the proposed approach would perform in situations with high data stream input. Therefore, further research will investigate the scalability of the proposed approach for different levels of data input.

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