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NEUROMODELING OF OPERATIONAL PROCESSES

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ABSTRACT

Context. The problem of synthesis a neural network model of operational processes with the determination of the optimal topology, which is characterized by a high level of logical transparency and acceptable accuracy, is considered. The object of the study is the process of neural network modeling of operational processes using an indicator system to simplify the selection of the topology of neuromodels.

Objective of the work is to synthesis a neural network model of operational processes with a high level of logical transparency and acceptable accuracy based on the use of an indicator system.

Method. It is proposed to use a system of indicators to determine the topological features of ANN, which is the basis for modeling operational processes. The assessment of the level of complexity of the task obtained on the basis of information about the input data and the values of the criteria for assessing the specificity of the task allows to categorize the task to one of the types of complexity in order to determine the approach to the synthesis of a neuromodel. Complexity category OS allows, based on analytical data about the selection of input data, to obtain the exact number of neurons in the hidden layer for the synthesis of a neuromodel with a high level of logical transparency, which significantly expands their practical use and reduces the cost of subsequent operational processes.

Results. The obtained neuromodels of operational processes based on historical data. The use of the indicator system made it possible to significantly increase the level of logical transparency of the models, while maintaining high accuracy. Synthesized neuromodels reduce the resource intensity of operational processes by increasing the level of previous modeling.

Conclusions. The conducted experiments confirmed the operability of the proposed mathematical software and allow to recommend it for use in practice when modeling operational processes. The prospects for further research may consist in the use of more complex methods of feature selection to fix the group relationships of information features for the construction of more complex models.

KEYWORDS: modeling, operational processes, indicator system, neuromodel, sampling, training, error.

ABBREVIATIONS

ANN is an artificial neural net;
CTS is complex technical system;
IoT is Internet of Things;
MT is maintenance of technical system;
OC is organized complexity;
OS is organized simplicity;
NF is natural frequency.

NOMENCLATURE

J is informative weight of independent attribute;

n is a number of input features that characterize sample instances;

N_i is a multiple neurons at the network input;

N_{i_l} is a neuron at the network input;

N_o is a multiple neurons at the network output;

N_{o_p} is a neuron at the network output;

N_h is a multiple neurons of the hidden network layer;

N_{h_r} is a hidden network layer neuron;

$Num_{elemtype}$ is a number of element types in the neural network4

NN is a neural network;

NN_{struct} is a structure of neural network;

l is a number of neurons at the network input;

$Lev_{accmeas}$ is a measurement accuracy level;

Lev_{fctr} is a level of significant and less significant and/or non-significant factors4

Lev_{manag} is a level of possible control and management;

Lev_{task} is a conditional difficulty level of the task;

$Lev_{smplfctn}$ is a level of possible simplification of the structure;

m is a number of dependent (categorical) features of sample instances;

p is a number of neurons at the network output;

q is a number of connections between neurons in the network;

r is number of neurons in the hidden network layer;

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$Sample$ is a data set;

w is a multiple of connections between neurons;

w_q is a connection between neurons in the network;

x_n is a independent attribute of the sample instance;

X is a set of independent attribute (variables);

y_m is a value of the dependent variable (attribute) of the sample instance;

Y is a set of values of dependent variables.

INTRODUCTION

The quality of modern CTS is largely determined by their reliability. One of the most significant factors of reliability changes is the operating conditions and the adopted operation strategy, which should be understood as a set of organizational and technical measures for maintenance and restoration of serviceability or operability of failed objects. The decrease in the intensity and volume of such measures negatively affects the reliability indicators of the CTS To the greatest extent, this trend is characteristic of systems that operate autonomously, without the possibility of carrying out preventive control and restoration (diagnostics and repair) measures or with the possibility of carrying them out in a reduced volume. Such features are inherent in road transport objects, marine objects and special-purpose systems [1–5].

During the operation of the CTS of this class, periodically, after a while t_{stat}, they leave stationary points (bases, airfields, airports, etc.) to perform tasks for their intended purpose during the time t_{work}. In this case, the object can be in conditions that ensure its immediate use with intensity λ_{usng} or it is in reserve (shelving). During this time, objects can be monitored only superficially, in a small volume (control inspection, state check, etc.) with intensity $\lambda_{contusng}$ and duration $t_{contusng}$. During inspections and, possibly, based on the results of continuous monitoring, failures that occur with intensity are detected λ_0. Failures lead to an inoperable state before returning to a stationary point (base) where serviceability or working capacity is restored during the time t_{rep}. The intensity of the reserve demand is determined by product failures and the intensity of successful completion of tasks for the intended purpose, i.e. $\lambda_{usng} + \lambda_0$ [1, 3].

During CTS locate in a stationary point (base, airport) at the facility, in addition to restoring serviceability, MT is carried out with frequency t_{PTM} and duration t_{TM}. MT is also carried out after making n_{TM} flights (exits) (when the number $n_{TM} > 2$). Meanwhile MT, especially in the case of a long stay on the base, the object may also fail with the parameter ω_0. The resulting failures are eliminated during the next maintenance or during checks before departure for the flight. The duration of these checks t_{PTM} ($t_{PTM} > t_{TM}$) has a significant impact on the failure rate when performing tasks offline outside of stationary points, i.e. $\lambda_0 = f(t_{PTM})$ and $\lambda_0 \geq \omega_0$ moreover, equality is achieved when $t_{PTM} = t_{TM}$. In the simplest case $\lambda_0 = \omega_0 \cdot \frac{t_{TM}}{t_{PTM}}$ [1–4].

During modeling, it is convenient to represent the considered process of CTS operation as a random process in a discrete phase space. The phase space of the process includes two states (the first MT and the second MT), as well as indicators of natural oscillations. Taking into account the availability of historical experimental data, an ANN will be used as the basis for the model [1–5].

ANN are statistical computational models applied to a variety of practical tasks, including diagnostics (technical and medical based on multimedia data about an object), assessment, forecasting, etc. [6, 7]. During process of supervised learning ANN trains on the example of already known data, that is, so it is exist a predefined correct answer for all the initial data. The main idea of training a neural network is to set up a configuration in which the model's responses will be as close as possible to the correct ones. However, at the moment there are many ANN topologies that can be used as a neuromodel. So some can provide a context for each subsequent prediction (recurrent ANN). This helps the ANN to maintain the state in which the decision was made. Therefore, it is so important at the initial stage to correctly assess the complexity of the problem for further selection of the ANN topology and the choice of the training approach for the synthesis of the most optimal model [6, 7]..

The task of studying the process is to obtain a model that will reflect the behavior inherent in the source data. Such a task can be attributed to the number of template recognition tasks. Regarding the event log as training data, we will be trained to evaluate the results for each event in the ANN log. The ultimate goal will be to synthesize a model based on the ANN representing a neuromodel of the operational process encoded in the event log

The object of study is the process of synthesis neuromodels of operational processes with a high level of interpretability and acceptable accuracy of operation.

Using the assessment of the complexity level, it is possible at the initial stage to determine the approach to the synthesis of the model based on the ANN.

The subject of the study is a neural network model of operational processes, characterized by a high level of interpretability and acceptable accuracy.

Using the information about the modeling task and the evaluation of the input data, it is necessary to synthesize a neuromodel.

The purpose of the work is to build and study neuromodels of operational processes with the previous definition of structural features based on the assessment of the level of complexity of the task.

1 PROBLEM STATEMENT

The operational process can be represented as a modeling problem. Where, at the initial stage, a set of various characteristics (features) of the operation of the object (system) that is being studied is available [8, 9]. A set of

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characteristics is represented by a set of conditionally independent features $X = \{x_1, x_2, ...x_n\}$ of an object consisting of the n number of such. As a rule, such characteristics are the values of the results of the operation of the object measured using special sensors, sensor systems or devices [6–9].

In accordance with these independent features, a set of values of the dependent characteristics of the object is compared: $Y = \{y_1, y_2, ...y_m\}$ consisting of m elements. It is assumed that to some extent each independent feature x_k affects the value of the corresponding one y_l. The degree of this influence can be represented as the information weight of an independent attribute [6–9].

Then the neuromodel of the operational process can be represented as an ANN NN consisting of structural elements and a set of parameters $NN = (struct, param)$. The structure of such a neuromodel is determined by sets of computational nodes: neurons and connections between them: $struct = \{N, c\}, N = \{N_i, N_h, N_o\}, c = \{c\}$. In turn, the aggregates of the set of neurons are divided into subsets by layers: the neurons of the input layer $N_i = \{N_{i_1}, N_{i_2}, ..., N_{i_l}\}, l = 1,2,...,|N_i|$, the output layer $N_o = \{N_{o_1}, N_{o_2}, ..., N_{o_p}\}, p = 1,2,...,|N_o|$ and the hidden one $N_h = \{N_{h_1}, N_{h_2}, ..., N_{h_r}\}, r = 1,2,...,|N_h|$. The subset of links consists of the links themselves and their weighting coefficients: $c = \{c_1, c_2, ...c_k\}, k = 1,2,...,|c|$, $w = \{w_k\}$.

Accordingly, the task can be represented as a synthesis of the ANN with optimal structure and accuracy $NN = (struct, param)$, based on a sample of initial data about the object under study during operation $Sample = \langle X, Y \rangle$.

2 REVIEW OF THE LITERATURE

The idea of ANN is to model (repeat) the behavior of various processes based on historical (experimental) information. The ANN itself is a set of special mathematical functions with many parameters that are configured in the process of learning from previous data. Then the trained ANN processes the initial real data and gives its forecast of the future behavior of the studied system. The essence of ANN is the desire to imitate the processes taking place. In its structure, the neural network is similar to the human brain and is also capable of learning [6–8].

The main difference between models based on ANNs and growth curves or regression methods is that if these methods adjust a real process or phenomenon to a standard mathematical function, then ANNs select the parameters of a system of equations, bringing it to real life [7].

Schematically, an artificial neural network consists of a layer of input signals, an output layer and several internal layers (Fig. 1).

The processes of building and training a network in a software package that supports the creation of neural networks are as follows: the values of input variables are fed to the input, the type of connection and weight coefficients are selected randomly, then the values of the output variable are calculated. The obtained values are compared with the real ones, after that, the weights and the type of network are adjusted, aimed at reducing the error. The general scheme is shown in Fig. 2 [6–9].

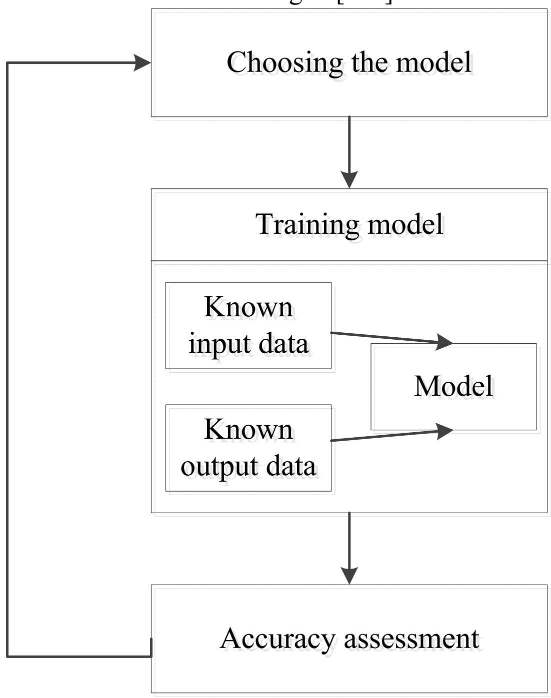

Figure 2 – General scheme of training process

An important issue is also the organization of the transmission of the same historical (experimental) data. Thus, with the correct organization of data transmission and storage processes, it is possible to organize a complex system within the IoT technology, which will be aimed at online diagnostics and MT the operability of the technical system [10–11]. Such an organization involves the installation of deployed sensor networks on technical elements and nodes. Sensor networks provide automated recording of operational indicators with a specified time lag, which can reach miles and microseconds. All recorded data is transferred to the cloud, where a data bank is formed. Wireless network data transmission technologies are used for transmission. An external computing server or several such servers have access to the accumulated data bank. These installations can perform real-time analysis of constantly updated data. Among the possible types of analysis, the following can be distinguished [10–11]:

– data verification: checking the truth and correctness of the received data (for example, filling in empty data or tracking unexpected run-ups in indicators);

– statistical data analysis: identifying and visualizing the simplest patterns and relationships between data. Data normalization and standardization can also be included here;

– data reduction: reducing the dimension of data is sometimes necessary to optimize resource consumption in

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data analysis. Thus, the selection of informative features, preliminary data mining and other operations help to speed up the process of further processing (for example, the synthesis of models based on data), and sometimes also improve accuracy (by removing noisy data).

Also, an important task of the server in such systems of the synthesis, updating (additional training) or modernization of new or pre-built models [10–11].

Such models, based on constantly updated data, can more accurately diagnose, monitor, or make a forecast. All the results generated by the models are redirected to the workstation (this can be done via the cloud or directly), since in some systems the results obtained either have to pass moderation, or may require the involvement of the operator.

Thus, for the most part, such an organization of IoT systems is aimed at maintaining the operability of technical systems: diagnostics, non-destructive control or forecasting of operability. The general principle is shown in Fig. 3.

However, the organization of an IoT system or simpler solutions is associated with an assessment of the complexity of the simulated problem for choosing a model synthesis strategy based on the ANN and choosing the appropriate topology.

3 MATERIALS AND METHODS

As it was given in the previous section, the modeling task can be unified for a specific task after a certain comprehensive assessment of its complexity. Given that the structure of ANN ($NN = (struct, param)$) allows to most subtly encode the relationships between the input data ($X = \{x_1, x_2, ...x_n\}$), it is necessary to accurately select the synthesis option for such a non-network model. Based on the values of the indicators to assess the complexity of the task it can be choose a way $Lev_{Task} = \{Inf_{sample}, Lev_{smplfctm}, Lev_{fctr}, Lev_{accmeas}, Lev_{manag}\}$ to synthesize the most acceptable structure [12].

In the case when a problem with input data $Sample = \langle X, Y \rangle$ that is questionable can be modeled (there is a question about the accuracy of the data, their excess or a high degree of interconnectedness), it is necessary to resort to input data preprocessing. Thus, the selection of informative features will allow to exclude uninformative features $Sample^{|} = \langle X^{|}, Y \rangle$, which will subsequently increase the level of logical transparency of the neuromodel. By spending more time on data preprocessing, it is possible to significantly reduce the time resources at the stage of model synthesis based on the ANN [12].

Stepwise regression methods can be used to feature selection. Stepwise regression is a method that iteratively checks the statistical significance of each independent variable in a linear regression model [8, 9]. This is done through iteration, that is, the process of obtaining results or solutions by repeating rounds or cycles of analysis. Automatic testing with the help of statistical software packages allows you to save time and reduce the number of errors. A bidirectional exception is a combination of forward and reverse exclusion methods that check which variables should be included or excluded [8, 9].

Firstly, it must be sorted $x^- = \arg\max J(X_n - x)$, where $x \in X_n$. After that it must be update6 $X_{n-1} = X_n - x^-$. Finally, internal iteration calculation must be update.

Such manipulation on the first step guarantees that it will be removed a feature, x^- from our feature subset X_n. Moreover, x^- is the feature that maximizes our criterion function upon removal, that is, the feature that is associated with the best classifier performance if it is removed from X_n.

Secondly, pull must be update based on the rule $x^+ = \arg\max J(X_n + x)$, where $x \in Y - X_n$ with special condition:

$$J(X_n + x) > J(X_n), \quad (1)$$

so in this case have: $X_{n+1} = X_n + x^+$. And again internal iteration calculation must be update.

Second manipulation search for features that improve the classifier performance if they are added back to the feature subset. If such features exist, we add the feature x^+ for which the performance improvement is maximized. If internal iteration calculation came to the 2 or an improvement cannot be made (i.e., such feature x^+ cannot be found), go back to exclusion manipulation; else, repeat the adding.

However, after the selection of features, the problem can be considered already in the category of OS, when a simple direct propagation ANN is sufficient for modeling, and the number of neurons in the hidden layer is calculated based on the statistical characteristics of the data sample [12]:

$$\begin{aligned} &Lev_{Task}\{..., Lev_{accmeas} = 1\} \to OC \\ &Lev_{Task} \xrightarrow{Feature\,Selection} \{..., Lev_{accmeas} = 0\} \to OS. \end{aligned} \quad (2)$$

4 EXPERIMENTS

The blades of the single stage compressor engine TV3-117, made of alloy BT8 and having operational damage to the feather of the engine blades, were selected as the object of research. The studies were carried out on two engines operated under the same conditions, but having different operating hours and, accordingly, different degrees of damage to the blades. Engine D1 have 1971 h and D2: 990 h. Operational damage to the pen creates not only a stress concentration, but also leads to a change in the geometry of the blades. For research, 20 blades with

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no gross mechanical damage were selected from two engines [13–16].

The study of the geometry of the blades consisted in measuring the chord, C_1 and C_2 in sections from A2–A2 to A8–A8. The measurement results indicate that the greatest change in the geometry of the blade parameters occurs in the peripheral zone (sections A7–A7 and A8–A8) [13–16].

The table shows that x_1, x_4, x_7, x_{10}, x_{13}, x_{16}, x_{19}: B, the value of the chord, in Table 1 in different sections; x_2, x_5, x_8, x_{11}, x_{14}, x_{17}, x_{20}: C_1, the thickness of the input edge; x_3, x_6, x_9, x_{12}, x_{15}, x_{18}, x_{21}: C_2, the thickness of the output edge; x_{22}: HB, the hardness of the initial blade, HRC.

x_{23}: $\sigma_{0,2}$, yield strength of the starting material, MPa; x_{24}: $\sigma_{в}$ tensile strength, MPa; y_1: T_1 total operating time; y_2: T2 operating time up to first repair, h; y_3 is the frequency of natural vibrations of the blades, Hz.

5 RESULTS

The table 1 shows the part of the sample that was used for the experiments.

Table 2 presents regression models for different engines and their aggregates. The models are based on a reduced number of input features.

Table 3 presents ANN-based models in matrix form.

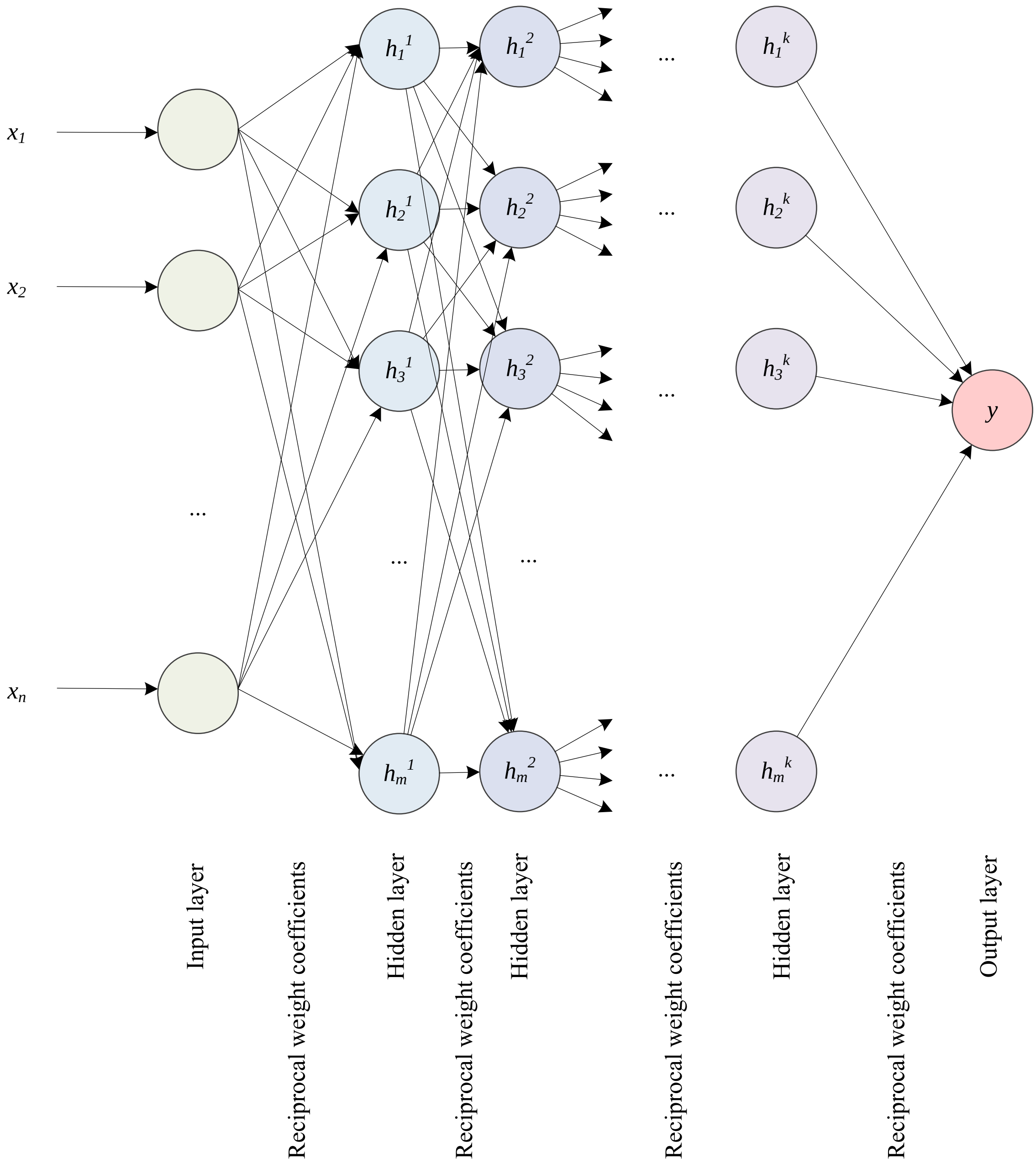

Figure 1 – General scheme of simple topology of ANN

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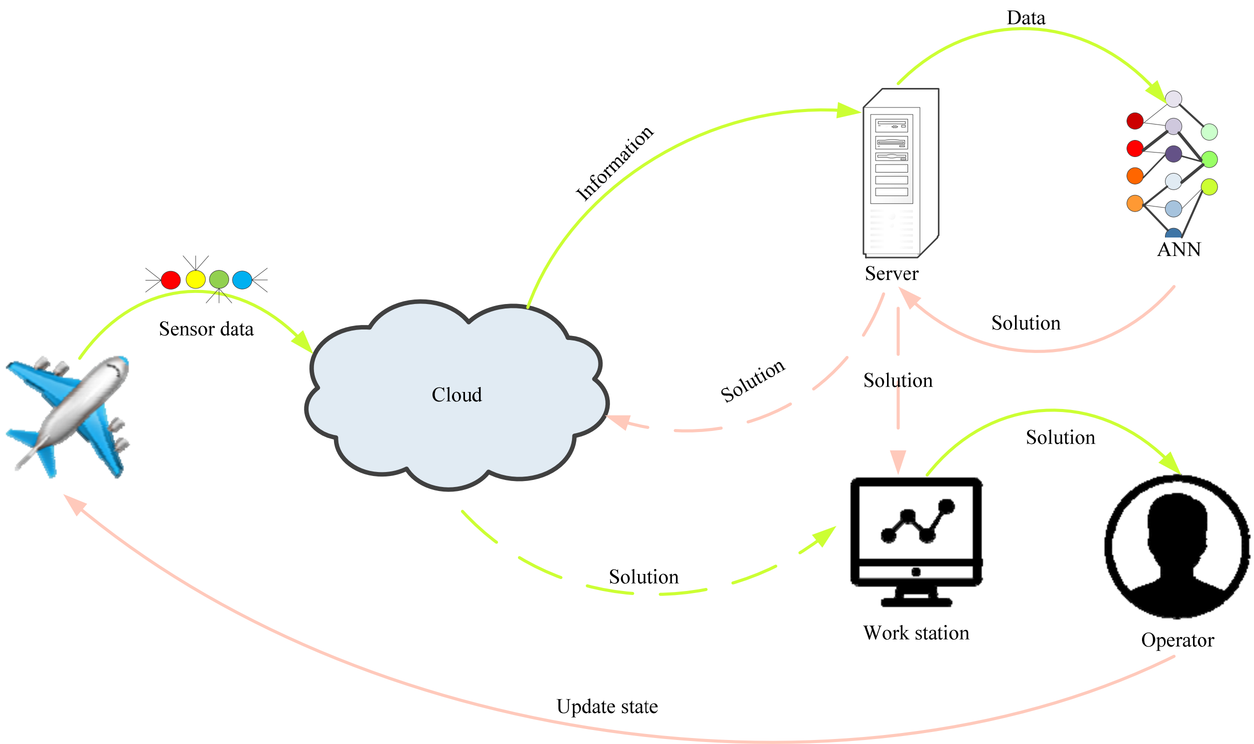

Figure 3 – General scheme of interaction in IoT systems for operational process

Table 1 – General information about data set

Blade A2–A2			Blade A3–A3			Blade A4–A4			…	T_1	T_2	NF
$B_{2–2}$	$C1_{2–2}$	$C2_{2–2}$	$B_{2–2}$	$C1_{2–2}$	$C2_{2–2}$	$B_{4–4}$	$C1_{4–4}$	$C2_{4–4}$	…			
x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	…	y_1	y_2	y_3
26.50	1.33	0.64	27.00	0.00	0.00	590.00	0.97	0.48	…	0.00	0.00	590.00
27.10	1.35	0.66	27.60	0.00	0.00	620.00	0.99	0.50	…	0.00	0.00	620.00
25.90	1.31	0.62	26.40	0.00	0.00	650.00	0.95	0.46	…	0.00	0.00	650.00
26.53	1.39	0.54	26.91	1971	621	647.3	0.89	0.42	…	1971	621	647.3
26.60	1.37	0.68	26.77	1971	621	646.7	0.90	0.44	…	1971	621	646.7
26.44	1.53	0.60	26.83	1971	621	642.4	0.98	0.40	…	1971	621	642.4
26.52	1.25	0.62	26.92	1971	621	643.1	0.81	0.45	…	1971	621	643.1
26.72	1.35	0.57	27.16	1971	621	648.5	0.91	0.38	…	1971	621	648.5
26.70	1.57	0.70	27.07	1971	621	668.6	0.99	0.45	…	1971	621	668.6
26.25	1.46	0.62	26.65	1971	621	645.2	0.96	0.44	…	1971	621	645.2
26.20	1.42	0.58	26.60	1971	621	649.4	0.97	0.50	…	1971	621	649.4
26.51	1.42	0.65	26.85	1971	621	648.8	0.93	0.44	…	1971	621	648.8
…	…	…	…	…	…	…	…	…	…	…	…	…
26.63	1.20	0.59	27.01	1.15	0.44	27.86	0.95	0.35	…	990	451	627.4

Table 2 – Regression models for engines after feature selection

	Depended attribute	Independent feature	Weight	Depended attribute	Independent feature	Weight	Depended attribute	Independent feature	Weight
First engine	y_1	Free member	5493.3	y_2	Free member	1730.8	y_3	Free member	1015.7
		x_3	787.81		x_3	248.21		x_6	71.182
		x_{13}	–174.09		x_{13}	–54.85		x_{16}	–0.85927
		x_{15}	–15979		x_{15}	–5034.5		x_{17}	46.001
		x_{16}	907.93		x_{16}	286.06		x_{18}	–160.38
		x_{17}	–3533.5		x_{17}	–1113.3		x_{19}	–11.27
		x_{18}	19309		x_{18}	6083.6		x_{20}	–161.8
		x_{19}	–735		x_{19}	–231.58		x_{21}	70.668
		x_{20}	–4496.7		x_{20}	–1416.8			
		x_{21}	–5967		x_{21}	–1880			

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Table 2 continued

Second engine	y_1	Free member	–6329,7	y_2	Free member	–2883,5	y_3	Free member	989,16
		x_5	104.18		x_5	47.46		x_4	–3.2178
		x_{16}	577.55		x_{16}	263.1		x_{16}	–17.851
		x_{17}	–887.97		x_{17}	–404.52		x_{17}	–57.823
		x_{18}	–6417		x_{18}	–2923.3		x_{18}	–132.7
		x_{19}	–194.56		x_{19}	–88.633		x_{19}	10.239
		x_{20}	426.08		x_{20}	194.1		x_{20}	24.261
		x_{21}	–8265.3		x_{21}	–3765.3		x_{21}	–22.105
General sample for two engines	y_1	Free member	15976	y_2	Free member	6146	y_3	Free member	1236.9
		x_{13}	111.95		x_{13}	39.731		x_{13}	–31.607
		x_{14}	1444.9		x_{14}	–31.269		x_{14}	58.769
		x_{15}	–2869.8		x_{15}	–1359.9		x_{15}	–66.747
		x_{16}	213.64		x_{16}	38.801		x_{16}	17.876
		x_{17}	–3010.7		x_{17}	–472.48		x_{17}	–64.156
		x_{18}	3429		x_{18}	788.81		x_{18}	47.107
		x_{19}	–780.91		x_{19}	–254.39		x_{19}	–6.5416
		x_{20}	–2449.6		x_{20}	–411.03		x_{20}	–79.377
		x_{21}	–1397		x_{21}	–532.82		x_{21}	51.834

Table 3 – Neural networks models for engines in matrix format

		Number of layer	Number of neuron at layer	Number of input of neuron								
				0	1	2	3	4	5	6	7	8
First engine	y_1	1	1	0.4658	–1.5179	1.2285	–0.3745	–1.3876	1.4247	0.8189	–0.7037	–0.0544
			2	1.1000	–0.2338	0.1421	0.5441	–0.5349	–1.2274	–0.3497	–2.2515	–2.1745
			3	–0.8452	0.9026	–1.2838	0.1328	0.7307	2.2389	0.7699	0.3432	–1.4166
			4	0.3374	5.4603	–2.0717	4.4364	–9.3008	1.9159	–6.5536	–8.9370	–3.4884
		2	1	–2.6817	–0.0401	–1.2972	11.3049					
	y_2	1	1	1.5418	0.9468	1.8911	–0.8538	–1.6638	0.2718	–1.057	–3.2833	0.0146
			2	0.9662	0.1809	–1.1613	–0.6279	–1.7703	0.2904	–1.172	–1.3198	0.9192
			3	0.968	0.2189	1.5918	1.7624	–2.655	1.5395	–2.8073	–2.7069	–0.2501
			4	0.2781	0.2975	1.2749	0.8646	0.6666	0.9116	–0.7911	0.5896	–0.4745
		2	1	3.0727	–0.618	4.0588	–1.8339					
	y_3	1	1	0.9422	1.8965	–0.8817	–1.287	1.7724	1.622	0.9202		
			2	–2.947	–4.7925	2.8078	2.4996	–4.2739	–2.8727	–2.5115		
			3	–1.199	0.6908	–1.5036	–1.2848	–0.8571	–0.6933	1.133		
			4	–0.4857	–0.5768	–0.2348	–0.1187	–0.4004	1.2633	–0.3987		
		2	1	0.288	–2.7685	1.8958	–1.0539					
Second engine	y_1	1	1	0.4939	–0.4511	1.4086	0.1413	7.6385	–0.9269	–3.1648		
			2	–2.6959	–7.3992	–2.4984	6.6421	–0.9476	4.9028	–2.6633		
			3	0.2274	–0.7406	1.3095	0.7900	–0.4079	–0.6326	4.0847		
			4	0.9888	–5.0414	–0.1517	5.6668	1.8127	–2.8537	2.3601		
		2	1	–2.528	–3.8282	–4.4303	–5.4362					
	y_2	1	1	–0.0252	–1.239	–0.593	–0.4079	–0.2391	–0.2076	0.5937		
			2	–0.7033	–3.6831	0.6049	3.3973	1.3224	0.1675	5.3631		
			3	–1.0152	–0.1636	1.4365	1.9574	2.3268	–0.3212	2.9033		
			4	0.2268	1.4866	–0.3067	0.1771	0.9589	–0.5183	0.7572		
		2	1	1.7026	–3.2254	–2.798	1.4379					
	y_3	1	1	1.0348	0.9792	–3.1372	0.9754	–2.5656	2.457	–1.0045		
			2	5.2574	–6.495	–0.4098	3.5421	1.8056	–3.8595	–1.2348		
			3	–5.4322	–2.435	2.1287	–1.3974	–0.585	0.6515	5.4371		
			4	–1.0328	5.7223	1.4171	1.3843	–1.9217	0.2199	–2.1831		
		2	1	–3.6321	0.0455	3.8178	2.2159					
General sample for two engines	y_1	1	1	1.5137	–1.5685	–2.5358	–0.7641	8.9924	–6.6683	0.5498	9.3855	–2.607
			2	–12.005	1.4226	0.1941	–1.0293	36.1094	–11.951	0.5653	16.5209	8.7779
			3	17.6653	0.7479	–17.545	–12.728	–6.4936	–7.7768	–8.5848	11.3728	–3.6221
			4	–8.5863	5.8129	4.6873	–5.543	2.7865	11.7949	–17.555	–12.495	1.3517
		2	1	–4.3625	–6.5875	–1.5977	1.2776					
	y_2	1	1	–1.1947	1.8355	–1.0277	–0.9955	–2.4798	3.4032	–1.4717	–4.0901	4.664
			2	1.3742	–1.8717	–0.0821	–0.1832	4.4903	–2.391	1.5867	6.7386	–2.3275
			3	2.1382	–0.0421	–2.9346	1.556	0.0176	–3.4581	–0.6713	0.0464	–4.587
			4	1.7524	–1.8059	–1.381	1.121	1.8792	–2.9072	–0.2687	1.6761	–4.4536
		2	1	–0.6609	1.7264	1.9347	2.0265					
	y_3	1	1	4.1667	0.7699	–0.0491	0.5137	3.3659	–1.0307	0.9681	–2.0161	1.0408
			2	0.5733	1.4045	–0.3144	3.7791	0.2089	–4.0823	2.4539	0.9196	2.6012
			3	–0.1248	0.2645	0.5078	–1.5247	–0.127	1.0278	–1.0693	–0.6277	–0.783
			4	2.8772	3.0926	0.5896	–4.3669	0.689	1.8098	–3.1684	–2.1971	0.1409
		2	1	–1.3179	3.2033	–0.7647	1.5967					

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6 DISCUSSION

At first, the task for modeling was assigned to the OC category. However, after preprocessing the input data, information-important features were selected. Accordingly, after data reduction, the task was transferred to the OS group. In the end, the input sample was not excessive, and the risks of human influence were excluded. The only significant complicating factor is poorly conditioned correlation matrices.

Further calculations showed that the use of 6–8 neurons in the hidden layer is sufficient to build a neural model with acceptable accuracy.

Analyzing the initial results, we should note a fairly large run-up in the model training time: from 4 seconds (the largest indicator among the ANN-based models) to 34.37 for linear regression models.

The results obtained on the data after the reduction showed that the accuracy increased when constructing a neural model with a certain structure based on a system of indicators, and the time was significantly reduced.

In addition, it should be noted the high level of logical transparency of the obtained models based on the ANN.

CONCLUSIONS

The urgent scientific and applied problem of determining the optimal and logically transparent structure of a neuromodel for modeling the operational processes is solved.

The scientific novelty lies in the fact that using the feature selection methods for pre-processing of input data allows to re-define the level of task complexity and use more resource-efficient methods for synthesis model based on ANN. Such models have the optimal, logically transparent topology and hight level of accurancy.

The practical significance lies in the fact that such approches that were used allow speed up the process of synthesis 8.6 times. Moreover, such models based on ANN demonstrate better accuracy average by 6%.

Prospects for further research are using additional information as input data set for trackeng implicit factors on operational processes. In this case using more complex topologies of ANN with modern methods for training can demonstrate good results.

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НЕЙРОМОДЕЛЮВАННЯ ЕКСПЛУАТАЦІЙНИХ ПРОЦЕСІВ

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АНОТАЦІЯ

Актуальність. Розглянуто завдання побудови нейромережевої моделі експлуатаційних процесів з визначенням оптимальної топології, яка відрізняється високим рівнем логічної прозорості та прийнятною точністю. Об'єктом дослідження є процес нейромережевого моделювання експлуатаційних процесів із застосуванням індикаторної системи для спрощення вибору топології нейромоделей.

Мета роботи полягає в побудові нейромережевої моделі експлуатаційних процесів з високим рівнем логічної прозорості і прийнятною точністю на основі використання індикаторної системи.

Метод. Запропоновано використовувати систему індикаторів для визначення топологічних особливостей штучних нейронних мереж, які є базисом для моделювання експлуатаційних процесів. Оцінка рівня складності задачі отримана на основі інформації про вхідні дані та значень критеріїв оцінки специфічності задачі дозволяє категоризувати задачу до одного з видів складності, щоб визначити підхід до синтезу нейромоделі. Категорія складності організована простота дозволяє на основі аналітичних даних про вибірку вхідних даних отримати точну кількість нейронів в прихованому шарі для синтезу нейромоделі з високим рівнем логічної прозорості, що значно розширює їх практичне використання і знижує вартість наступних експлуатаційних процесів.

Результати. Отримані нейромоделі експлуатаційних процесів на основі історичних даних. Використання системи індикаторів дозволило в значній мірі збільшити рівень логічної прозорості моделей, зберігаючи високу точність. Синтезовані нейромоделі знижують ресурсоємність промислових процесів за рахунок збільшення рівня попереднього моделювання.

Висновки. Проведені експерименти підтвердили працездатність запропонованого математичного забезпечення і дозволяють рекомендувати його для використання на практиці при моделюванні експлуатаційних процесів. Перспективи подальших досліджень можуть полягати у використанні більш складних методів відбору ознак для фіксації групових взаємозв'язків інформаційних ознак для побудови більш складних моделей.

КЛЮЧОВІ СЛОВА: моделювання, експлуатаційні процеси, система індикаторів, нейромодель, вибірка, навчання, помилка.

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НЕЙРОМОДЕЛИРОВАНИЕ ЭКСПЛУАТАЦИОННЫХ ПРОЦЕССОВ

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АННОТАЦИЯ

Актуальность. Рассмотрена задача построения нейросетевой модели эксплуатационных процессов с определением оптимальной топологии, которая отличается высоким уровнем логической прозрачности и приемлемой точностью. Объектом исследования является процесс нейросетевого моделирования эксплуатационных процессов с применением индикаторной системы для упрощения выбора топологии нейромоделей.

Цель работы заключается в построении нейросетевой модели эксплуатационных процессов с высоким уровнем логической прозрачности и приемлемой точностью на основе использования индикаторной системы.

Метод. Предложено использовать систему индикаторов для определения топологических особенностей искусственных нейронных сетей, которые являются базисом для моделирования эксплуатационных процессов. Оценка уровня сложности задачи полученная на основе информации про входные данные и значений критериев оценки специфичности задачи позволяет категоризировать задачу к одному из видов сложности, чтобы определить подход к синтезу нейромодели. Категория

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сложности организованная простота позволяет на основе аналитических данных про выборку входных данных получить точное количество нейронов в скрытом слое для синтеза нейромодели с высоким уровнем логической прозрачности, что значительно расширяет их практическое использование и снижает стоимость последующих эксплуатационных процессов.

Результаты. Полученные нейромодели эксплуатационных процессов на основе исторических данных. Использование системы индикаторов позволило в значительной степени увеличить уровень логической прозрачности моделей, сохраняя высокую точность. Синтезированные нейромодели снижают ресурсоемкость промышленных процессов за счёт увеличения уровня предыдущего моделирования.

Выводы. Проведенные эксперименты подтвердили работоспособность предложенного математического обеспечения и позволяют рекомендовать его для использования на практике при моделировании эксплуатационных процессов. Перспективы дальнейших исследований могут заключаться в использовании более сложных методов отбора признаков для фиксации групповых взаимосвязей информационных признаков для построения более сложных моделей.

КЛЮЧЕВЫЕ СЛОВА: моделирование, эксплуатационные процессы, система индикаторов, нейромодель, выборка, обучение, ошибка.

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