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Modeling of Temporal Stability to Critical States for Predicting Operational Safety of Turbogenerators

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Abstract: The study is devoted to the creation of a method for predicting the temporal stability under conditions of dynamic and static effects during process of operation of a turbogenerator. The method is based on the restoration modeling the operating mode of the turbogenerator under critical conditions; the model assumes an adaptive response at the initial stage of the critical state recognition. The deep neural network teaching technique whilst the classification of spectrogram anomalies is provided.

Key words: Forecasting, adaptive reaction, safety of industrial objects, critical condition, reaction modeling, temporal stability

INTRODUCTION

Currently, to determine the critical state of turbogenerators, emphasis is placed on identifying defects and assessing their impact on turbine operation in order to eliminate destructive factors. External factors that lead to an aggravation of the state of the turbogenerator are usually known before the occurrence of frequency flashes of vibrations which allows us to speak of a raging malfunction.

The safety of industrial turbogenerators as well as shaft inserts, bearings and static components is important for ensuring the operability of thermal power plants (hereinafter-TPPs) which in turn determines the stability of the development of national and regional production processes. This makes it necessary to include systems for ensuring the stable operation of the units in the control loop. That will allow carrying out preventive monitoring of the operation of technical devices before the onset of a critical situation and causing damage. With this approach to the safety of TPPs, it is possible to increase the temporal stability of the operation of the nodes, i.e., to minimize faults within a predetermined period of time.

The prognostic model of operation of complex technical systems is based on the function of determining the reliability of a technical system. Considering the multicomponent nature of the technical system and the dynamic nature of internal and external factors, reliability can be defined as the ability of an object to predict, maintain stability, absorb impacts, respond, adapt and recover under undesirable effects or internal states (Himavathi *et al*., 2007).

For the case of scientific and technical problems associated with complex technical and information systems in the practical field of consideration the reliability will be defined as the degree of safety of complex technical systems. Then, the temporal stability of the elements of the turbogenerator will be defined as the possibility of restoring the normative values of the parameters of the functioning of aggregates and technical elements with the aim of leading to a “return to the working state” (stability) in the event of adverse consequences caused by natural or human factors (Budadin *et al*., 2014).

The proposed method for assessing the safety of an object is based on determining the reliability of the facility by collecting and analyzing information on four aggregated groups of measures to improve reliability: preparedness, mitigation measures, response capabilities and recovery mechanisms. Figure 1 presents a structural diagram of the seven reliability components with processes that ensure the temporal stability of the turbogenerator. This approach sets the monitoring base for developing the questionnaire to identify the necessary information for assessing the reliability of the TPP system at the facility level.

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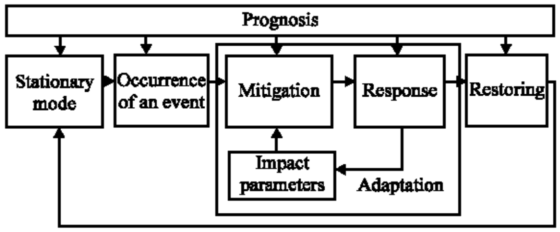

Fig. 1: Functional diagram for ensuring the temporal stability of theturbogenerator

With the increase in the number and complexity of the elements of the turbogenerator, the number of possible problems that need to be taken into account in assessing temporal stability and forecasting risks will also increase. Since, a comprehensive evaluation of temporal stability is carried out both for the individual aggregate, the component and the stability of the entire turbogenerator design, it is necessary to take into account the hidden interrelationships between the nodes and external factors.

Such uncertainties include the inclusion of stochastic relationships (for example, the composition of specific chains of events), lack of data, limited time and financial security which makes it more difficult to obtain a complete picture of the integrated safety assessment of the turbogenerator.

In part, these problems can be solved by applying a "system approach" to assessing reliability over time (Ivchenko *et al*., 2014; Ostroukh *et al*., 2015; Bekhtin *et al*., 2014; Krug *et al*., 2015). In this case, it is proposed to assess the reliability of individual subsystems at different levels with the construction of a forecast in the short term. When considering higher-level systems, it is possible to determine the most important for the reliability assessment of a low-level system. In turn, in relation to systems of a lower level, the most important components are determined from among those that are available.

DESCRIPTION OF THE MODEL OF TEMPORAL STABILITY

In the case of application of fault detection methods based on mathematical models, it is suggested to take into account the object configurations. With regard to internal connections used in the detection of faults and the possibility of fault detection, the situation can be substantially improved due to the presence of additional measurements.

Therefore, for the formation of the feature space in the construction of the temporal stability model it is necessary to determine the parameters of the main types of malfunctions of turbine generators of TPPs. Consider, for example, factors affecting temporal stability in the example of a group of faults related to the turbine rotor imbalance class.

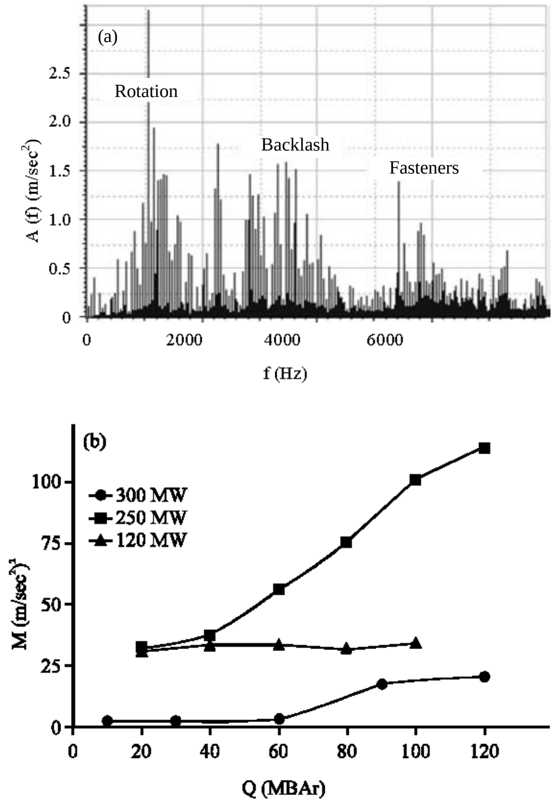

Fig. 2: Parameters of malfunctions of units of a design of a turbogenerator on a temporal scale of a trend for vibration measurements; A(f), m/sec^2; P = 250 MW; Q = 120 MBAr

The unbalance of rotating rotor masses is one of the most common defects in equipment which leads to a sharp increase in vibration (Nazolin and Polyakov, 2006).

Rotation of any solid body can take place without effort on the part of other bodies, only if the axis of rotation coincides with one of its three main axes of inertia passing through the center of gravity. If the axis of rotation of the rotor does not coincide with its main axis of inertia, the forces that cause increased vibration will act on the supports (Fig. 2).

Figure 2 shows frequency bursts which indicate an increasing factor in reducing the reliability of the turbogenerator design. In this case, it is possible to influence the cause of the fault, for example, by changing the bearing clearances. Such a situation can be taken into account in the system for managing node parameters.

Thus, when constructing the forecast, it is important to determine the cause-effect relationships and the factors that lead to malfunctions. In determining such connections, it is possible that there is no complete information on the state of aggregates in which case it is necessary to apply the method of abductive inference that can be realized, for example, using a deep neural network (Yu *et al*., 2014). We give an explanation.

For the case m+1 when simple hypotheses H_j j = 0, 1, ..., m are put forward to determine the true state of a turbogenerator. To construct a rule for choosing a solution, we use the criterion of minimum mean risk.

The use of any predetermined rule for choosing a solution, due to the random nature of the considered failure factor of the node is associated with the possibility of erroneous decisions. The observed sample of explanations $\bar{x} = (x_1, x_2, ..., x_n)$ may turn out to be in the region of the set X_k by k = 0, 1, ..., m at which the decision γ_k will be made that the true state is S_k, although in reality the indicated sample is related to another state S_j, $j \neq k$. The presence in the sequence of solutions is not only right but also wrong is the price for decisions made with incomplete information.

The consequences of erroneous decisions are taken into account by the loss function (matrix) which prescribes to each erroneous solution, i.e., each combination S_j and γ_k, $j \neq k$ a fee:

$$\ddot{\mathrm{I}}_{jk} = \ddot{\mathrm{I}}\left(S_j, \gamma_k\right) > 0 \quad (1)$$

Along with this, values can be introduced:

$$\ddot{\mathrm{I}}_{jj} = \ddot{\mathrm{I}}\left(S_j, \gamma_j\right) < \ddot{\mathrm{I}}_{jk},\ j \neq k \quad (2)$$

It is related to making the right decision (Akimov, 2013). For a given state, the average loss value when using a definite decision rule for a solution of inductive output, i.e., way of partitioning the sample space into regions and establishing their correspondence to a set of solutions in a sufficiently long sequence of experiments is approximately equal to the average value in the sample space (mathematical expectation) of losses:

$$r_j = \sum_{k=0}^{m} \ddot{\mathrm{I}}_{jk} P\left\{\gamma_k / S_j\right\} = \sum_{k=0}^{m} \ddot{\mathrm{I}}_{jk} P\left\{\bar{x} \in X_k / S_j\right\} \quad (3)$$

where, $P\{\gamma_k/S_j\}$ the conditional probability of the sample falling into the domain X_k, if the state actually takes place S_j. The conditional average loss r_j for the state S_j asit is known in literature as conditional risk. By averaging the conditional risk for all states, we obtain:

$$R = \sum_{j=0}^{m} p_j r_j = \sum_{j=0}^{m}\sum_{k=0}^{m} p_j \ddot{\mathrm{I}}_{jk} P\left\{\bar{x} \in X_k / S_j\right\} \quad (4)$$

where, p_j is the a priori probability of the state S_j. This value can be taken as a criterion of the quality of the abductive inference. This rule consists in splitting the sample space into m disjoint domains X_k and assigning to each of the regions one of the solutions γ_k that the hypothesis H_k is true.

Arguing in this way, we can prove that the minimum value of the average risk R realizes a partition of the sample space, under which the domain X_k, k = 0, 1, ..., m is determined by the system of m inequalities:

$$\sum_{i=0}^{m} \left(\ddot{\mathrm{I}}_{ij} - \ddot{\mathrm{I}}_{ik}\right) \frac{p_i W\left(\bar{x}/S_i\right)}{p_0 W\left(\bar{x}/S_0\right)} \geq 0,\ j = 0, 1, ..., m,\ j \neq k \quad (5)$$

The domain is determined from condition:

$$X_0 = X - \sum_{k=1}^{m} X_k \quad (6)$$

By introducing new variables:

$$y_i = \frac{p_i}{p_0} l_i\left(\bar{x}\right) = \frac{p_i W\left(\bar{x}/S_i\right)}{p_0 W\left(\bar{x}/S_0\right)},\ i = 1, 2, ..., m \quad (7)$$

i.e., mapping the points of the sample space to the m-dimensional likelihood ratio domain, we can write the inequalities in the form:

$$\sum_{i=1}^{m} \left(\ddot{\mathrm{I}}_{ij} - \ddot{\mathrm{I}}_{ik}\right) y_i \geq \ddot{\mathrm{I}}_{0k} - \ddot{\mathrm{I}}_{0j},\ j = 0, 1, ..., m,\ j \neq k \quad (8)$$

The domain defined by the system of inequalities (Eq. 8) is determined by the intersection of planes in an m-dimensional space.

Depending on which of the m non-overlapping regions of the space defined by the system of m inequalities, the solution of the system place into, one of the (m+1) solutions is taken, each of which corresponds to one of the regions of space and the true state of the object is determined.

This decision algorithm is valid for the case when the hypotheses are far. The algorithm for solving the case when the hypothesis is close is now at the development stage. Figure 3 shows the algorithm of the model. The definition of sustainability is achieved through a unique

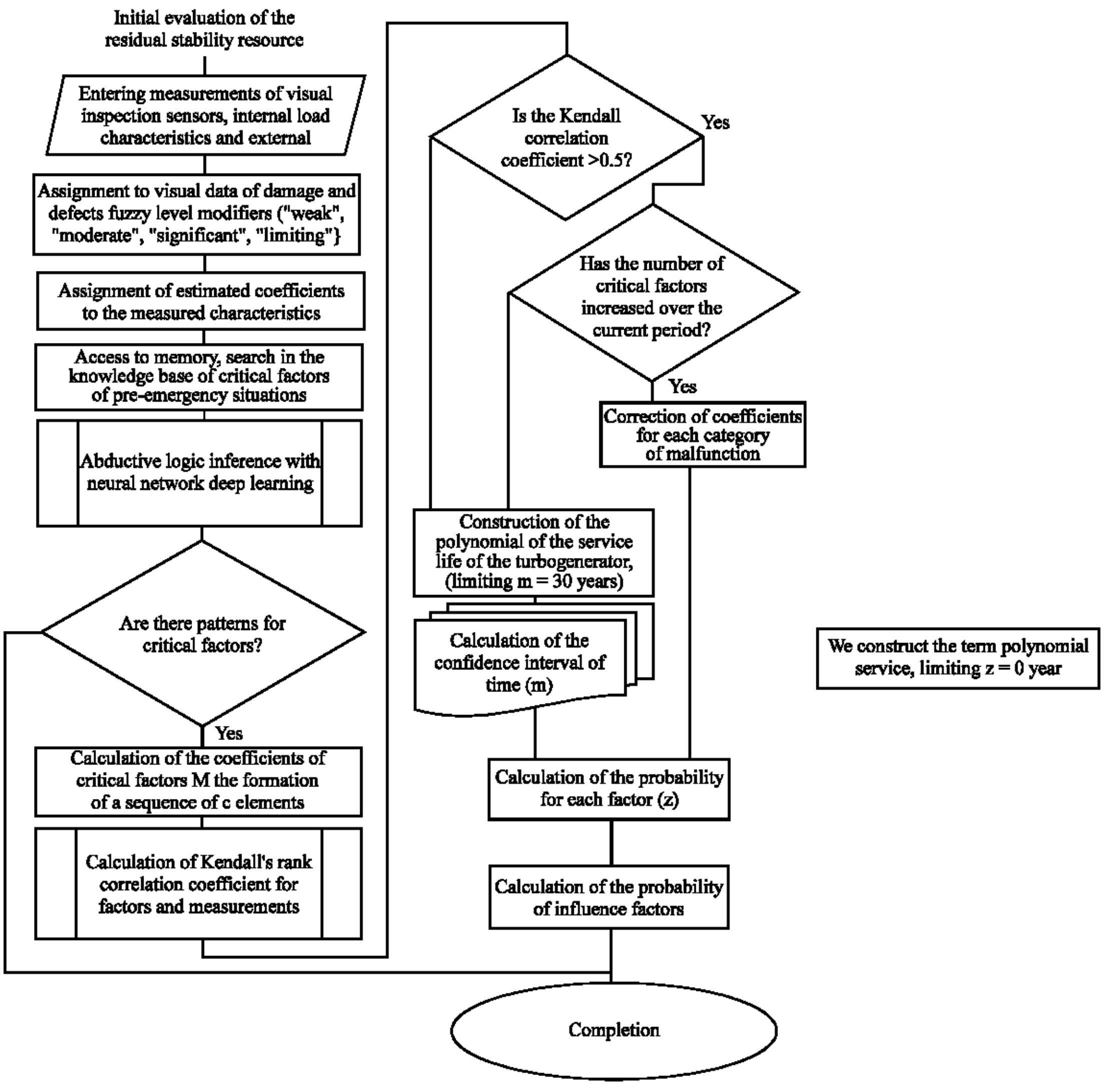

Fig. 3: Algorithm for applying the method of calculating temporal stability on the feedback response

evaluation of each stage. The forecast in the normal state is a stage to identify threats and control the system's vibes in the time perspective.

The appearance of the event is the triggering of signal components about the appearance of a side (detrimental) effect on the functional components of the turbogenerator and its evaluation.

Anti-action actions aimed at minimizing the impact of harmful factors of influence. Response to side effects the launch of processes aimed at recovery after side effects, subject to elimination of side effects. Recovery the launch of processes aimed at rehabilitation of the exposed parts of the turbogenerator to the level of the normal state.

Normal state signals from parts of the system are within the specified limits. All parts of the system function normally. Figure 3 shows the model of temporal stability for ensuring the safety of turbogenerators.

THE FORECAST OF THE TURBOGENERATOR STATE

The prognosis of the state of a turbogenerator can be attributed to probability model while the characteristics of the state of a structure can be expressed in elements of the theory of fuzzy sets (Ostroukh *et al*., 2014).

It is proposed to consider the parameters of the turbine and the loads acting on it as random functions of time (Akimov *et al*., 2016). The deterministic condition of the marginal inequality, he replaced by the marginal inequality with the assigned reliable probability P_γ during the specified lifetime [0, T]:

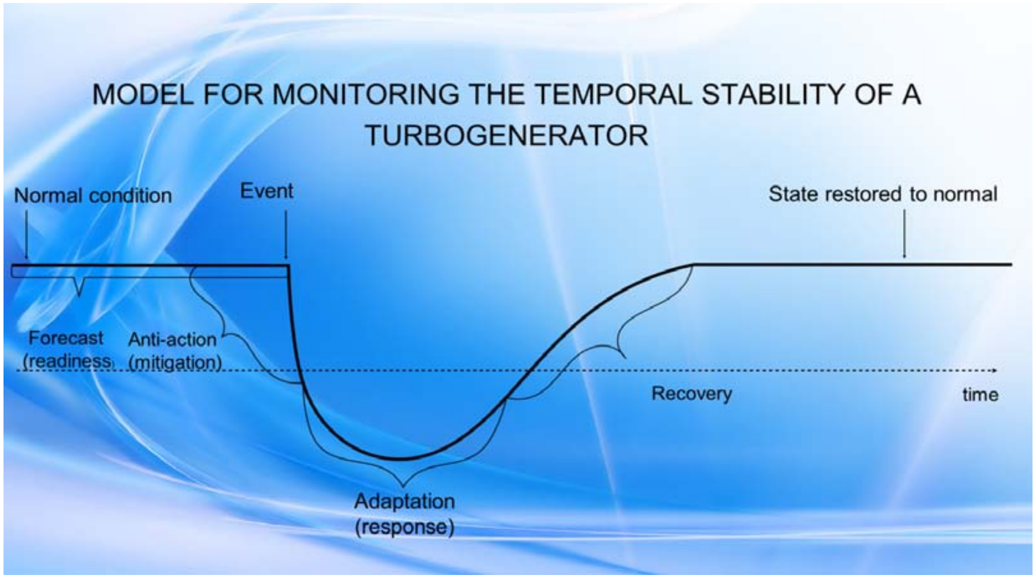

Fig. 4: Model for monitoring the temporal stability of a turbogenerator

$$P_i(t) = \text{Bep}\{\Phi_i(t)>R_i(t)\} \geq P_\gamma \quad (9)$$

Where:

$\Phi_i(t)$ = The parameters of the bearing capacity
$R_i(t)$ = load parameters; $t\in[0, T]$

The probability of failure-free operation taking into account (Eq. 9) takes the form:

$$P_i(t) = \text{Bep}\{Y_i(t) = \Phi_i(t)-R_i(t)>0/t\} \quad (10)$$

The shortcomings in solving such problems include "the absence of a unified system for measuring failure factors".

The value characterizing the change in risk over time is called the risk function. It is expressed by the probability of failure in a relatively short period of time:

$$H(T) = \frac{f(T)}{1-F(T)} \quad (11)$$

Where:

F(T) = The distribution function
f(T) = The probability density function
T = The time of the anticipated failure
1-F(T) = The probability of failure-free operation at the time T
H(T) = The fraction of objects that have retained their operability by the time T and failed during the interval (T, T+dT)

The probability of failure of the system F(T) in the time interval (0, T) is determined by the equation:

$$F(T) = 1\text{-exp}\left[-\sum_i \int_{T_0}^{T} H_i(T\text{-}T_0)dT\right] \quad (12)$$

Where:

H(T) = The risk function for the i-th type of failure
T_i = The time point after which the i-th type failure can occur

The learning algorithm represents the work of a neural network such as DeepLearning which consists in adding and removing (changing) knowledge base rules with new input parameters of the neural network which form a new indicative space in the convolutional layer. At each level abstract signs of a specific causal malfunction of the turbogenerator are presented based on the features of the previous level with a more detailed representation. Thus, the deeper we advance, the higher the level of abstraction. In neural networks multiple layers are a set of levels with feature vectors that generate output data. Based on the results of the self-learning of the characteristic space and the recognition results new knowledge base rules are formed (Akimov, 2011). The model of knowledge base rules is represented as follows:

- R1: IF x1 IS μ(u)11…AND…xnIS μ(u)1n, THEN y IS B1...
- R2: IF x1 IS μ(u)21…AND…xnIS μ(u)2n, THEN y IS B2...

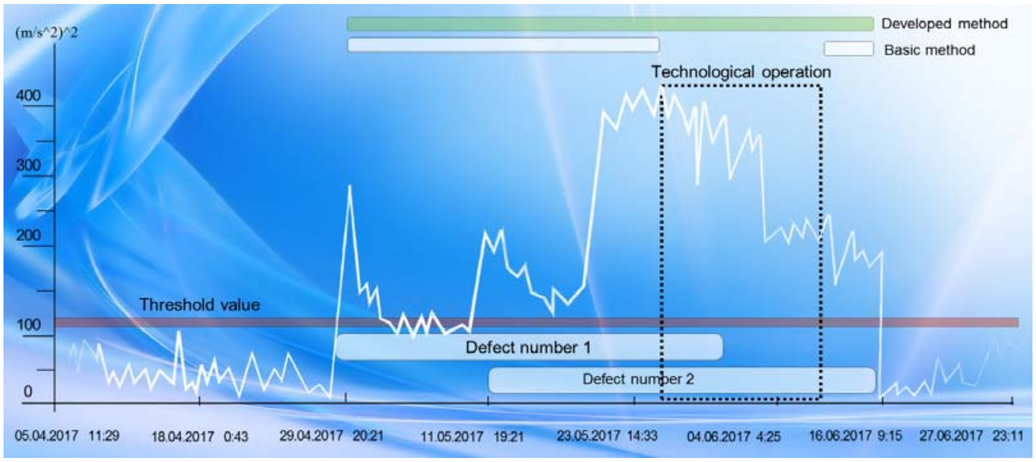

Fig. 5: Coverage of the developed forecast model of the process of modeling the impact factors

The rule for the situation is as follows:

- R1: IF the level of low-frequency vibrations is significant AND the level of backlashes of the inserts IS significant, THEN increased rotor mismatch IS a strong fault factor
- R2: IF the level of mechanical oscillations IS weak and the level of low-frequency vibration IS weak AND the level of temperature difference IS significant, THEN the temperature difference IS a strong factor for the onset of friction

ADVANTAGES OF USING THE RISK ADAPTATION MODEL IN FORECASTING

In the case of applying logical approaches as a diagnostic tool some knowledge should be used for reasoning which provides explanations for the deduced conclusions. But traditional logic has its limitations, especially under incomplete or uncertain information. In this case the solution of the problem becomes the identification and establishment of cause-effect relationships. In such situations the use of such logical conclusions as inductive, deductive and inference by analogy is impossible because for their work they require the availability of all information about the system being diagnosed.

Therefore, when solving the problem of identifying and establishing cause-effect relationships, an abductive (Akimov *et al*., 2012) derivation should be used to explain the observed (or established) facts in the modeling of the impact factors (Fig. 5).

To verify the results of the operation of the neural net and expert opinions we use the rank correlation of Kendall. The computation of rank correlation takes place according to the following equation:

$$\tau = 1 - \frac{4}{n(n-1)}R,\ R = \sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\left[\left[x_i < x_j\right] \neq \left[y_i < y_j\right]\right] \tag{13}$$

The number of inversions formed by the values of y_i, arranged in the ascending order of the corresponding x_i. In the table "standard normal probabilities" we find the nearest value as well as the area on the right under the distribution curve P:

$$Z_{teor} = 1;\ P = 0.74$$

We calculate the significance level by the equation: p<2P in our case p<0.74. The reasons in this case correlate with expert estimates.

Assuming that the exponents of the influence of the factors x vary monotonically with time and the variance of the indices D(x) does not change, the method described in ISO 10816-1 "vibration is used to predict critical vibrational states. Monitoring of the state of machines based on the results of vibration measurements on non-rotating parts".

CONCLUSION

A methodological approach is proposed for predicting the safety of turbo generators and temporal reliability of elements and functional assemblies of polymer composite materials on the basis of promising methods for estimating vibration measurements and the chronological analysis of the results of the detection of critical state factors, their operation, diagnostics and control, under critical influence with feedback elements. Calculations were carried out using software products based on the methods of artificial intelligence based on deep learning.

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