COMPOSITE PROGNOSTICATION MODEL OF EMERGENCIES AT THE HAZARDOUS INDUSTRIAL ENTERPRISES

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Abstract: A complex of prognostication models focused on its implementation in the control systems of hazardous industrial enterprises. Methods of prognostication of the emergencies on the basis of thermodynamic, linguistic and neural network concepts are considered. The results of the comparative analysis of these emergencies prognostication models are given for the extreme technological processes. Recommendations are given on the composite implementation of these models in the industrial systems of accident-free management. The composite model of prognostication and integrated criterion of accident-free management is offered as a functionality which represents the superposition of indicators of each model.

Key words: prognostication models, industrial enterprises, hazardous processes, composite implementation

1. INTRODUCTION

Analyzing the most recent opportunities of the development of accident-free management systems, there’s obviously the need for the formation of the generalized criterion to integrate mathematical instruments of prognostication in a fail-safe format.

Numerous decision-making models are used for random or accidental processes based on various prognostication methods. Figure 1 shows the composition of three decision-making models. Let's consider each model separately.

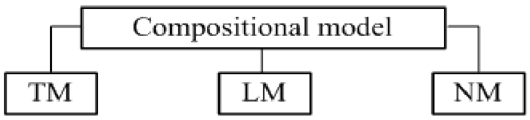

Figure 1. Composite decision-making model diagram, comprising: TM – thermodynamic model; LM – linguistic model; NM – neural network model

2. THERMODYNAMIC MODEL

In the thermodynamic model the flow of a technological process is represented as a behavior of a Brownian particle in some space of states, hence, the function of state is introduced for both the analysis and for drawing up the forecast of further development of the process, this function of state generalizes in itself the changes of all parameters. Prognostication of an emergency is realized with the Hurst statistical method based of the analysis of the process persistence indicator [1]:

$$E(t) = E(t-1) + \frac{n^{-H}}{\Gamma(H+0.5)} \cdot \left\{ \sum_{i=1}^{n} i^{H-0.5} x_{1+n(M+t)-i} + \right.$$
$$\left. + \sum_{i=1}^{n(M-1)} ((n+i)^{H-0.5} - i^{H-0.5}) \cdot x_{1+n(M-1+t)-i} \right\},$$

where E(t) – a deviation of the vector of state of the y(t) system from its average value in the timepoint t, where t accepts the integer values; Γ – gamma function; x – the massif of normally distributed random numbers with zero mean value and single dispersion; n – a number of steps of numerical integration in the time interval $\Delta t = [t-1; t]$; M – a number of Δt intervals analyzed in the model; N – an indicator of persistence of a swing, or the Hurst exponent characterizing the existence of statistical non-stationary nature of the process y(t), H=[0; 1].

Key parameter of this model is the indicator N which is the characteristic of a relative swing:

$$\sigma(\tau) = \sqrt{\frac{1}{\tau} \sum_{t=1}^{\tau} [\Delta E(t)]^2};$$

where ΔE (t) – an elementary increment of y(t) at the t step [2].

In case of 0,5<H<1 the persistent (supported, or trend-stable) behavior of the process is observed. If for some time in the past positive (negative) increments of process were observed, their respective increase (reduction) shall be expected in the future.

The case 0<H<0,5 indicates the anti-persistence of the process. Such type of system is often called «a return to an average», or the system with self-alignment properties. If the system demonstrates the growth during the previous period, then most likely, in the next period the recession will begin. To the contrary, if there was a decrease, then the rise is probable without delay. Such row is more changeable, than the random series because it consists of frequent reverse events of the «recession rise» type.

At H=0,5 the process deviation from an average are completely random and do not depend on the previous values.

Thus, monitoring the approximation of the N indicator to H=1 value one can estimate the tendency of the process to its overrun the admissible limits, and thus to expect the possibility of an emergency.

3. LINGUISTIC MODEL

Recognition of an image of an emergency within the linguistic model is achieved by means of fuzzy logic toolkit. The basis of the emergencies recognition system utilizing the fuzzy logic is the knowledge base built on the base of the experts poll. The knowledge base represents a set of indistinct rules $R^{(k)}, k = 1, \dots N$, of the type shown below:

$$R^{(k)}: \text{IF} \left(x_1 \text{ это } A_1^k \text{ AND } x_2 \text{ это } A_2^k \dots \text{AND } x_n \text{ это } A_n^k\right)$$
$$\text{THEN} \left(y_1 \text{ это } B_1^k \text{ AND } y_2 \text{ это } B_2^k \dots \text{AND } y_m \text{ это } B_m^k\right),$$

where N – the number of indistinct rules, A_i^k - indistinct sets: $A_i^k \subseteq X_i \subset R, i = 1, \dots, n$, B_j^k - indistinct sets: $B_j^k \subseteq Y_j \subset R, j = 1, \dots, m$, $x_1, x_2, \dots, x_n$ - input variables of the linguistic model, $y_1, y_2, \dots, y_m$ - output variables of the linguistic model [3].

The measure of proximity to an emergency defined with this model is, in essence, the function of belonging of the process state to the critical state and it can change within the L=[0; 1].

4. NEURAL NETWORK MODEL

When the neural network is used as the mathematical model of emergency recognition, the training selection is formed on the basis of knowledge of experts either, with variation of process parameters within the limits of extreme values.

The y(x) function used for prognostication may be represented as

$$y_{j_k}(x) = f\left(\sum_{i_k} b_{i_k j_k k} \cdot \dots \cdot f\left(\sum_{i_2, j_2} b_{i_2 j_2 2} \cdot f\left(\sum_{i_1, j_1} b_{i_1 j_1 1} x_{i_1 j_1 1} + b^0_{j_1 1}\right) + b^0_{j_2 2}\right) + \dots + b^0_{j_k k}\right)$$

where x, y – vectors of input and output variables of the network; b, b^0 – vectors of the configured settings (weight coefficients); f (b, b^0, x) – function of neurons activation; i – input to neuron number; j – neuron number in a layer; r – layer number in the network; x_{ijr} – an element i of x vector, applied to the j neuron in r layer. Then the process of training of k-layer network can be presented as a problem of search of the unknown parameters b, b^0providing these values to the output values $y_{j_k}(x)$ which would minimize a training error E:

$$E = \sum_s \sum_j (y_{sj} - y_{sj,эт})^2 \to \min$$

where s – number of the training selection for which the actual display $x \xrightarrow{O(x)} y$ is established; $y_{эт}$ – is the reference value of the displayed O(x) [4].

At the output of the trained network we obtain the function of the degree of proximity to the emergency situation N = [0,1].

Comparative analysis of emergencies prognostication models is given in Table 1. Having the same value of the proximity to an emergency in the outputs of all these models makes it possible to build the composite model comprising the advantages of each individual model.

Table 1. Comparative analysis of prognostication models

Model	Advantages	Shortcomings
Linguistic	The model can be upgraded in the process of data accumulation. It has good interpolating properties.	Weaker extrapolating properties in comparison with neural network.
Neural	The extrapolating properties are better, than in the linguistic model.	In the situation when the new data must be inputted and the need to save «history», the efficiency of the network's learning ability is low.
Thermodynamic	His model is effective for a long-term prognostication in comparison with both the neural network and the linguistic model, which means the sufficient warning about an emergency beforehand.	The model requires a large number of experimental data, mostly «fresh» which cannot be provided quickly in some cases. The analysis composed of rare and random values of the rows can result in the wrong forecast.

5. COMPOSITE PROGNOSTICATION MODEL

The variety of the existing methods of prognostication raises a question of the choice of a mathematical apparatus to be used for the particular technological process. At the same time various methods are capable to give both the current, and long-term forecast [5]. Using several alternative prognostication methods the best reliability is reached.

Thus, the system of accident-free management of technological processes using the tools of the contemporary information technologies, the hybrid models can be built combining, e.g., the linguistic model, neural network and thermodynamic concepts [6]. Composition of three models of prognostication of emergencies is shown in Figure 2.

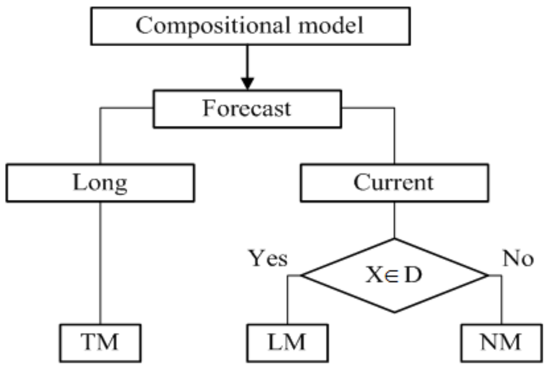

Figure 2. Composite model of prognostication of emergencies: X –current values of parameters, D – training space

According to the model shown in Figure. 2 the process of prognostication of emergencies includes the long-term and current forecasts. The current forecast is based on the linguistic and neural network models, and the long-term forecasts is provided by the thermodynamic model. At the same time in the situations that are not supported with the available training selections, the neural network model is preferable [7].

6. INTEGRATED CRITERION OF AN ACCIDENT-FREE MANAGEMENT

The choice of the criterion identifying the critical state of a process is in most cases cannot be made with guarantee with the sufficient degree of probability. The criterion uniting in itself three models of prognostication is composite integrated criterion too. Each system of prognostication is characterized by the indicator: for thermodynamic model it is the indicator of persistence N which changes from 0 to 1; for linguistic model it is a measure of proximity to emergency L (which can accept values from 0 to 1); and for neural network model the indicator is the function of the degree of proximity to an emergency N (changing from 0 to 1).

At the same time it is just natural to assume that the reaction of the of an accident-free management system to an emergence of the critical state is the extremely fast reaction on the critical parameter revealed by the diagnostic aids and prognostication for the purpose of its reduction to nominal limits, on the condition of sufficiency of time available for the reaction t_{zapasa} and the time of this reduction t_{priv} defining the speed of the corresponding control path (regulation). From this it follows that some functionality representing the superposition of each model indicators [8] can be offered as the required criterion of state S=F (H, L, N, t_{zapasa}, t_{priv}), which considers simultaneously not only the current values of the functional indicators of process defining t_{zapasa} but also the available speed of t_{priv} of the control system. In this sense such functionality is integrated.

Let's disclose the content of this criterion. Let's accept that the state S of the controlled technological process (object) can be referred to one of the following situations:

$$S = \begin{cases} S_1, & A = 0; \\ S_2, & A = 1,\ t_{zapasa} \geq t_{priv}; \\ S_3, & A = 1,\ t_{zapasa} < t_{priv}, \end{cases}$$

where **S_1** – is a normal situation. Parameters of the process are within the limits of nominal rates, and the system of emergency prognostication does not indicate an approaching emergency: the forecast for the accident is A=0; **S_2** – is the state of preemergency. The dynamics of the parameter (parameters) of a process gives the positive forecast for an emergency (the accident) A=1, but tzapasa time which the previous forecast reserves before the accident surpasses t_{priv} time that is necessary for the system for accident's prevention, $t_{zapasa} \geq t_{priv}$, that is the stock of real time is sufficient for the converting of technological process from the S_2 condition to S_1 condition; **S_3** – the accident. Here the term «accident», or, more precisely, the «emergency», indicates not only that the accident has happened, i.e., that the process reached its ultimate state, but also that at the positive forecast A=1 the process has become or is uncontrollable, or that the control system has not enough time for the prevention of accident: $t_{zapasa}<t_{priv}$. In this situation all operation of a technological object must be stopped [9].

7. CONCLUSION

Ample opportunities on a flexible formation of the criterion of accident-free management of technological processes at the hazardous industrial enterprises should be expected upon the transition to the multicomponent model of the decision-making model comprising, in particular, the composition of possible models described above.

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