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APPLICATION OF CLUSTER ANALYSIS AND AUTOREGRESSIVE NEURAL NETWORKS FOR THE NOISE DIAGNOSTICS OF THE IBR-2M REACTOR

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The pattern recognition methodologies and artificial neural networks were used widely for the IBR-2M pulsed reactor noise diagnostics. The cluster analysis allows a detailed study of the structure and fast reactivity effects of IBR-2M, and nonlinear autoregressive neural network (NAR) with local feedback connection allows one to predict slow reactivity effects. In this paper, we present results of a study on pulse energy noise dynamics and prediction of liquid sodium flow rate through the core of the IBR-2M reactor using cluster analysis and an artificial neural network.

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INTRODUCTION

The pulse energy noise of the IBR-2M reactor is caused by the operation of various technological systems, including the reactor core cooling system and the moving reflectors. Owing to the high sensitivity of the reactor to reactivity perturbations, the total pulse energy noise may reach $\pm 22\%$ in the stabilization mode. These noises directly affect the safety as well as the reliability of reactor operation. The goal of this work is to investigate the dynamics of the pulse energy noise at the IBR-2M during a reactor cycle and to predict liquid sodium flow rate through the core.

BRIEF DESCRIPTION OF THE IBR-2 REACTOR AND EXPERIMENTAL DATA

The IBR-2M reactor is located at the Joint Institute for Nuclear Research (Dubna, Russia) and operates with the design power of 2 MW. The IBR-2M core capacity is 69 fuel elements, which are sleeve-like PuO_2 pellets. The coolant is liquid sodium, pumped through the

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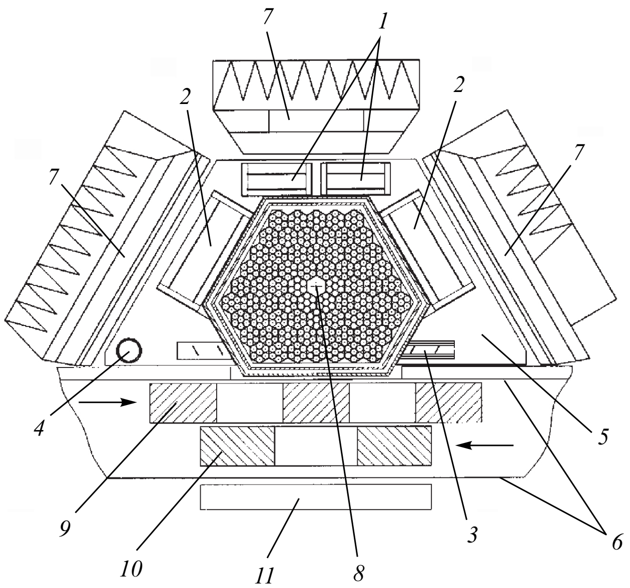

Fig. 1. Cross-sectional view of the IBR-2M core: *1* — emergency protection blocks; *2* — compensation block; *3* — intermediate control block; *4* — automatic regulator; *5* — stationary reflector; *6* — moving reflector jacket; *7* — grooved water moderators; *8* — external neutron source; *9* — MMR; *10* — AMR; *11* — flat water moderator

emergency protection blocks by two induction pumps. There are two aligned blades rotating with different speeds past one of the core faces. They are the main moving reflector (MMR) and the auxiliary moving reflector (AMR) of the reactivity modulator. The reactivity level is adjusted by the control and protection system (CPS) elements, which are movable tungsten blocks in an array of fixed steel reflectors. The arrangement of the CPS elements with respect to the IBR-2M core is shown in Fig. 1. The reactor core is surrounded by water moderators for thermal neutron users.

Pulse energy amplitudes were investigated via measurements with three independent detectors arranged around the core. Hence, the current pulse integral was measured for verifying the main measurements. Each successive power pulse was measured in one of the typical reactor cycles with the sodium flow rate through the core equal to 100 m^3/h. The measurements were carried out for 10.5 days, beginning with the moment when the reactor reached the power of 2 MW and ending when the power was dropped at the end of the cycle. The recorded time series were about $\sim 10^7$ successive pulse energy values, which were processed using statistical and cluster analysis procedures. The main element of the statistical analysis was the spread of values, and the object of the cluster analysis was the power spectrum of pulse energy fluctuations.

The original time series to be predicted (liquid sodium flow rate) are recorded within the four days of reactor cycle. The measurement period (sampling frequency) amounted to 0.1 s.

The basic analysis procedures and results of investigation of the pulse energy noise and sodium flow rate are presented below.

CLUSTER ANALYSIS OF THE PULSE ENERGY NOISE

The dynamics of the pulse energy noise at the IBR-2M has been investigated using cluster analysis. The hierarchical cluster algorithm is used here [1] as it is more flexible than other methods, thus allowing a detailed study of the structure and differences in values of pulse energy noise.

Figure 2 shows the variation in the power spectrum of the IBR-2M pulse energy fluctuations during the reactor operation cycle at nominal power of 2 MW. As is evident from Fig. 2, several high-intensity peaks are in the power spectrum. These peaks are due to the axial (normal to core surface) vibrations of the moving reflectors [2, 3].

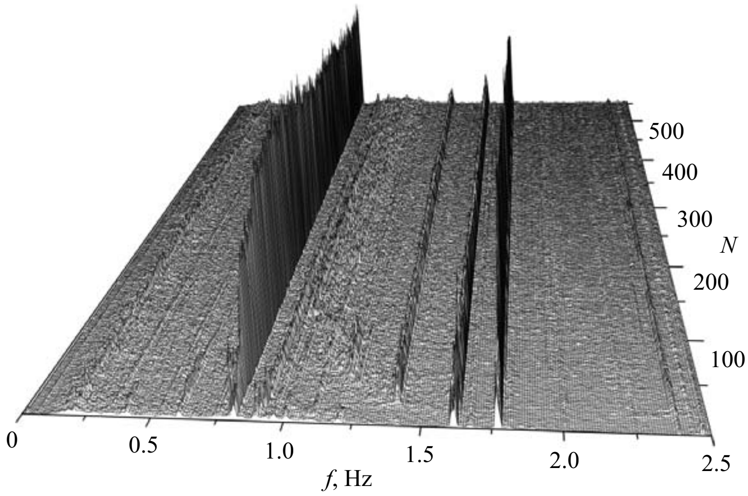

Fig. 2. Variation in the power spectrum of the IBR-2M pulse energy fluctuations during one of the typical reactor operation cycles at the power of 2 MW. The measurement duration is 10.5 days; 552 spectra are presented

In the present case, the objective of the cluster analysis was to classify a great amount of IBR-2M noise state data. Each successive power spectrum of the pulse energy fluctuations (hereinafter referred to as the spectrum), reflecting the reactor noise state in the time interval of $\sim$ 28 min (8192 successive pulse energy values), was represented by a point in the multidimensional Euclidean space. The Euclidean distance between the ith and kth points is given by $d_{ik} = \left[\sum\limits_{j=1}^{p}(x_{ij} - x_{ik})^2\right]^{1/2}$. The space dimension was 256 coordinates, i.e., the number of points in the spectrum. The cluster structures are shown in Fig. 3, "compressed" from the 256-dimensional to the two-dimensional space.

The power spectrum of the pulse energy fluctuations is divided into four clusters. The first three clusters include spectra of the transition region that lasts 1.7 days after the reactor reaches the nominal power of 2 MW. The fourth, and main, cluster corresponds to the stationary reactor noise established after 1.7 days when the reactor begins operating at its nominal power. For this fourth cluster, the noise intensity varies in time, tending to decrease

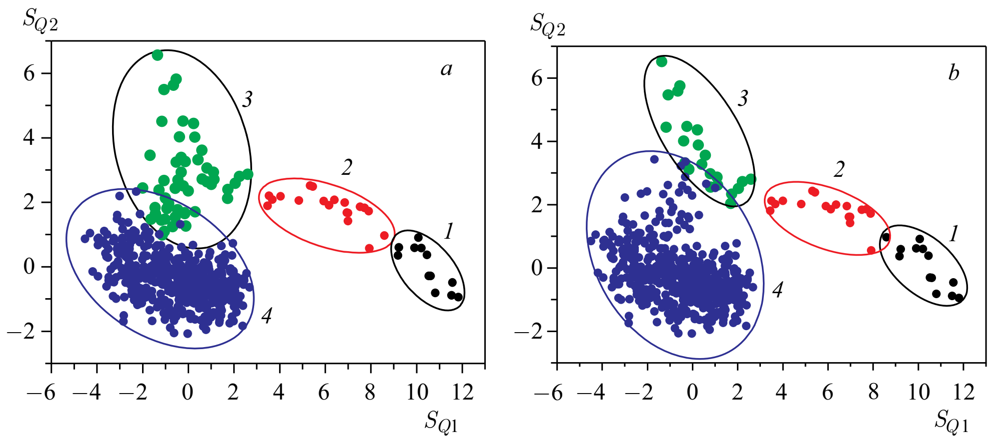

Fig. 3. Cluster structures compressed from the 256-d to the two-d space for the total pulse energy fluctuations (*a*) and the fluctuations due to the axial vibrations of the moving reflectors (*b*)

by $\sim$ 12% to the end of the cycle; this decrease in noise only slightly affects the spectral composition of the noise. Thus, the power noise is generally stabilized in 1.7 days.

PREDICTION OF LIQUID SODIUM FLOW RATE THROUGH THE CORE OF THE IBR-2M REACTOR

The variation in the temperature and flow rate of liquid sodium through the core affects the reactivity fluctuation and power. Reactivity fluctuation $\rho_G(t)$ by a change in sodium flow rate from G_0 to $G(t)$ at time (t) can be written as follows: $\rho_G(t) = dK/dG[G(t) - G_0]$, where $\dfrac{dK}{dG} = \left.\dfrac{\Delta K}{\Delta G}\right|_{W,T=\text{const}}$ is reactivity coefficient of sodium flow rate, $G(t)$, G_0 is the current and average value of sodium flow rate through the core. By the small change in the power and sodium flow rate ($\sim$ 10%), the value of reactivity coefficient can be reduced to the value $-0.7 \cdot 10^{-2}$ $\beta_{\text{eff}}/\text{m}^3/\text{h}$ [4, 5].

Nonlinear autoregressive neural network (NAR) with local feedback connection was used for prediction of liquid sodium flow rate through the core IBR-2M [6]. NAR type of neural network with feedback connection was widely applied for noisy time series prediction. The prediction results are more accurate in comparison with the common feed-forward networks [7].

Using mathematical notation, the output of a neuron can be expressed as follows:

$$y = f\left(b + \sum_i w_i x_i\right),$$

where b is the bias for neuron, f is the activation function, w_i are the weights, x_i is the input, and y represents the output [5, 7, 9]. NAR uses some of past values of actual time series to predict next values as determined by the following equation: $\hat{G}(t) = f(G(t-1) + G(t-2) + \ldots + G(t-d))$, where $G(t)$ is the input (liquid sodium flow rate through the core of the

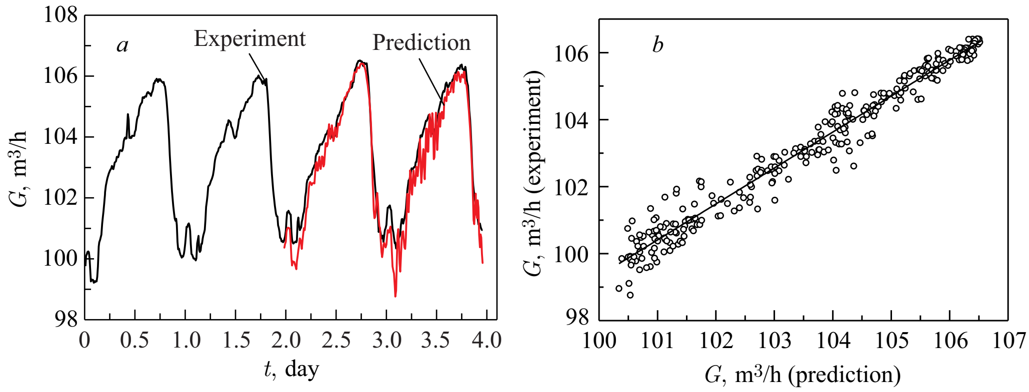

Fig. 4. Comparison between measured daily liquid sodium flow rate through the core of the IBR-2M and predicted one by the proposed model NAR (*a*). Experimental results versus predicted data (*b*)

reactor); $\hat{G}(t)$ is the output (predicted values); f is an activation function; d is the feedback delay, where the future values depend only on regressed d previous values of output signal.

The goal was to predict next two days data points from two previous days. In the NAR training phase, Levenberg–Marquardt method for the back-propagation algorithm was chosen [10, 11]. The comparison results of liquid sodium flow rate prediction and the linear relationship between experimental and predicted data are shown in Fig. 4. The correlation between them is very strong ($R = 0.98$).

CONCLUSIONS

The result of a cluster analysis, shown as the power noise, is successively divided into three to four stable structures (clusters). The first two clusters are observed between 0 to 14 h after the maximum power has been reached. Then, 1.2 days later, the transition region ends, and the reactor noise state is stabilized 1.7 days after the maximum power is reached. It is corroborated that the transition region of the reactor noise is caused by a change in the vibration state of the moving reflectors.

The nonlinear autoregressive neural network predicts slow changes in liquid sodium flow rate up to two days with an error of $\sim 5\%$.

Application of hierarchical cluster analysis and nonlinear autoregressive neural network for noise diagnostics of IBR-2M allows one to get more detailed information than standard methods.

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