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CONSTRUCTION OF A DIGITAL TWIN MODEL FOR A SYSTEM THAT MONITORS THE TECHNICAL CONDITION OF A NUCLEAR POWER PLANT POWER UNIT

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This study investigates the process of continuous monitoring and control of the technological process parameters at a nuclear power plant power unit using a digital twin model implemented on the basis of a system-cluster approach.

The task addressed relates to the lack of a comprehensive, integrated system for continuous monitoring of the technical condition of the power unit, capable of collecting, processing, and analyzing information from sensors and diagnostic subsystems in real time.

It is proposed to model the state of the technological equipment at a power unit using a digital twin and a system-cluster approach. Within the framework of the study, a system-cluster architecture of a digital twin was designed, which reflects the interaction among the physical, analytical, and control levels of the power unit at a nuclear power plant.

The work involved processing the technological process parameters coming from a sensor network with a frequency of 1–2 Hz, with a processing delay of no more than 1–3 s. The proposed information-fractal criterion provided an increase in the sensitivity of pre-accident detection by 15–25% compared to conventional methods, as well as made it possible to identify complex operating modes in the range of $D_f^{mon} = 0.45 - 0.8$.

The results have made it possible to solve the set tasks by integrating multi-scale fractal analysis, cluster organization of technical systems, and self-similarity modeling. The practical implementation of the digital twin has proven its capability to detect changes in the structure of the technological process with diagnostic accuracy at the level of 85–92%.

The implementation of the digital twin model in the information-control systems of the power unit makes it possible to increase the reliability, safety, and efficiency of control

Keywords: continuous monitoring system, system-cluster approach, fractal analysis, digital twin model

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1. Introduction

The state of war in which nuclear energy finds itself requires a radical change in approaches to ensuring the operational reliability and safety of power units (PUs) at nuclear power plants (NPPs) [1, 2]. Many facilities exceed their service life, and on the other hand, the equipment is subject to both planned and accidental wear and tear and the influence of random dynamic factors [3]. Conventional maintenance and control, based on periodic inspections and records of technical parameters exceeding permissible values, no longer meet the needs [4, 5]. Therefore, a new system is needed, more flexible, self-learning, predictive. In this case, the system should include dynamic relationships in time, inter-node, and probabilistic scenarios of deterioration of technological equipment [6, 7].

A likely solution to the above problems is to implement digital twin (DT) technology. Additionally, a virtual space in which the state of the technological process is depicted in real time (RT), changes are detected and probable failures are predicted, and recommendations for technical or operational solutions are provided [8, 9]. In this area, a fractal-cluster approach could be used in modeling and monitoring the technical states of NPPs [10]. This method allows one to structurally represent this complex technical system in the form of one of the interconnected clusters, which is integrated into a single control system. Clusters include physical parts (sensors, nodes, units) according to a functional scheme.

Thus, current research on constructing a model of a digital twin of a NPP power unit based on a fractal-cluster approach provides increased reliability, safety, and forecasting of the state of technological equipment.

2. Literature review and problem statement

The concept of a DT for simulating technological processes in nuclear reactors based on a multifractal model of neutron chain reactions is presented in study [11]. It is positive that the potential of fractal statistics for modeling hierarchical processes is demonstrated. However, the problem of clustering of the sensor network is not considered in the work. In [12], an analysis of the percolation phenomenon and fractal properties in critical reactor operating modes is given. It is worth noting that the fundamental foundations of critical processes are deepened but practical solutions for software and hardware systems (SHS) of automated process control systems (ACS TP) for NPP power units are not proposed.

Paper [13] describes a simulation model of a DT for online monitoring of NPP PUs. A significant advantage is that the model demonstrates high speed and accuracy. The disadvantage is that the issue of checking its cluster structure is not considered. In study [8], a hybrid learning interface of the DT for simulating a neutron reactor is given. Although the combination of the learning interface and the simulation model of neural technologies opens up new opportunities for training operational personnel, the authors did not consider the mechanisms of control and fractal-cluster organization.

In work [14], a fractal-cluster approach to detecting defects in fuel elements of fuel assemblies of a nuclear reactor is reported. The methodology increases the accuracy of defect diagnostics, but it is not integrated into the simulation model of DT and is not adapted for automated monitoring, control, and diagnostics. In paper [15], the application of the fractal approach to assessing corrosion deposits on the surface of the shell of fuel elements of a nuclear power plant reactor is described. The authors note that high accuracy of non-destructive testing has been achieved but, at the same time, there is an obvious lack of integration with digital technologies.

Study [16] showed that in the pre-accident state regimes of NPPs, the behavior of information signals becomes complicated precisely due to the emergence of a fractal component. Therefore, it is necessary to take into account all parts of the complex signal about the parameters of the technological process at NPPs. In paper [17], a simulation fractal-cluster model of the information space of the technological process is proposed. Such a system-cluster approach is consistent with the multiparameter structure of NPPs. It is especially useful for fractal analysis. At the same time, the work lacks clear criteria and indicators of pre-accident and emergency states of NPPs.

In [18], an analysis of digital technologies is described. It is shown that simulation models of DT are based on modeling graph neural networks. This approach allows one to build complex relationships between objects for real prediction of reactor dynamics. However, despite the high accuracy, the clustering of the sensor network is not taken into account. Study [19] focuses on the basics of fractal measurement of changes in the dynamics of process parameters. It is positive that a theoretical approach has been devised for future applied solutions. Along with this, it is noted that there are no specific solutions for technical monitoring, control, and diagnostics of NPP PU parameters. In [20], a method for optimizing the placement of sensors for collecting primary data for the simulation model of the NPP Combining models increases the reliability of monitoring, control, and diagnostics, but this approach lacks analysis of the complex structure of information signals.

Work [21] confirms the hypothesis that the dynamics of changes in the information space (technological parameters) are closely related to the probability of accidents. However, digital tools for practical implementation in DT are not disclosed. Study [10] describes a DT simulation model for virtual training of NPP operational personnel. The DT model system increases the efficiency of training operational personnel in a secure information environment but does not include modules for checking the reliability of signals.

In study [22], an algorithm for monitoring, control, and diagnostics of the technological process parameters of an NPP PU power unit was proposed. However, there is a need to adapt the DT simulation model to the sensor system to organize a cluster structure for the technological process. Publication [23] suggests an approach to diagnostics of technological processes based on several combinations of an integrated DT model. Combining models increases the reliability of monitoring, control, and diagnostics, but this approach lacks an analysis of the complex structure of information signals.

Our review of the literature [8, 10–23] showed the presence of a number of partially unresolved issues: the lack of clustering of the sensor network and insufficient consideration of the fractal nature of the data. In addition, the disadvantage of limited integration of DT models with information and control systems of software and hardware complexes of automated technological process control systems and insufficient adaptation to the specifics of the NPP EB is revealed.

The above allows us to state that it is advisable to conduct a study aimed at constructing a DT model for the monitoring system of NPP PU technical condition.

3. The aim and objectives of the study

The purpose of our study is to build a DT model based on clustering of the sensor network of the continuous monitoring system and fractality of the information signal of digital data for predicting pre-accident (emergency) states at PUs. This will allow for the following:

– to optimize the process of technical maintenance and repair;

– to increase the efficiency of technical control;

– to ensure reliable diagnostics of the condition of the equipment;

– to contribute to the reduction of technogenic risks;

– to extend the service life of the equipment and increase the economic efficiency of PU operation;

– to increase the accuracy of the analysis of the sensor network data and to implement the practical integration of the model into the information and control system of NPP APCS for an NPP power unit.

To achieve the goal, the following tasks were set:

– to design a system for monitoring the technical condition of an NPP power unit based on the digital twin model;

– to substantiate the use of information fractal dimensionality as an integral indicator of the complexity of signals and the efficiency of the continuous monitoring system;

– implement a prototype of DT based on the proposed model and test its operation under typical operational scenarios.

4. The study materials and methods

The object of our study is the process of continuous monitoring and control of parameters in the technological process at NPP PU using the DT model, which is implemented on the basis of a system-cluster approach.

The principal hypothesis assumes that the implementation of continuous monitoring of the technical condition of NPP PU by means of DT, which is built on the system-cluster approach, could make it possible:

– to ensure timely detection of pre-accident conditions;

– to increase the reliability of diagnostics and forecasting of technical parameters in RT;

– to reduce the risk of technological equipment accidents;

– to optimize the costs of equipment maintenance.

The study assumes that the signals from the sensors have fractal properties and can be represented in the form of time series. This, in turn, correlates with the technical condition of the technological equipment in NPP PU. It is also assumed that the network of PU sensors has a cluster structure, which is amenable to formalized analysis.

To implement the study, system-cluster and fractal analysis, mathematical modeling and elements of information theory were used. System-cluster analysis considers the NPP PU as a hierarchical system. In it, sensors and subsystems are combined into functional clusters according to the interrelationships of parameters. Fractal analysis studies multi-scale fluctuations of signals (temperature, pressure, vibrations). This is described by the indicators of fractal dimensionality and entropy, which are sensitive to hidden changes in the technical condition.

The experimental part of the study was implemented in a simulation environment in which the operation of NPP PU is modeled on the basis of open operational data. Clustering of the sensor network was performed using hierarchical grouping and information flow analysis. The data obtained in the process of the study allow us to assess the effectiveness of the model under conditions of continuous monitoring of the technical condition of NPP PU based on DT, which is built using the system-cluster approach.

Our study was performed using a personal computer based on an Intel Core i7 processor with 16 GB of RAM and a 512 GB SSD. The visualization and interface of the digital twin were implemented using HTML, CSS, and JavaScript technologies.

Open operational data from nuclear power plants and generated time series were used as the source data. The total amount of data exceeded 10^6 values and included parameters of temperature (300–320°C), pressure (up to 15.7 MPa), vibrations, and electrical characteristics of the equipment. Data preprocessing included noise filtering (moving average, 5 s window), normalization, and trend removal, which increased the reliability of analysis.

5. Analyzing the results of research on designing a power unit condition monitoring system based on a digital twin model

5. 1. Design of a system for monitoring the technical condition of a power unit at a nuclear power plant based on a digital twin model

The technological process of a 1000 MW NPP power unit is proposed to be represented as a hierarchical cluster structure that has fractal properties. Therefore, in our work, to build a DT model for the monitoring system of technical condition of NPP PU, a system-cluster approach was proposed. It was proposed to take into account the physical and analytical control levels as clusters.

As information on the state of the technological process in a nuclear reactor, a reactor cluster was selected, which assesses the state of the fuel element (FE) cladding using control sensors in the power unit technical condition monitoring system.

Thus, the 1000 MW power unit technical condition monitoring system integrates physical, analytical, and control clusters into a single digital twin model.

All clusters do not operate in isolation but under a mode of constant data exchange, which is implemented through a multi-level communication system. Information from sensors of the reactor or secondary circuit can directly affect the control algorithms in the safety system. The prediction of the heat carrier behavior model can cause adaptation in the operation of the turbine assembly. Deep integration of clusters with horizontal and vertical interconnections allows the power unit to act as a single self-regulating organism with a high level of adaptability and reliability, as shown in Fig. 1.

Fig. 1 illustrates how the system-cluster approach is implemented. The system is represented by a nuclear power plant, which corresponds to the fractal-cluster theory – cluster-cluster aggregation. The next element is the subsystem “Power Unit”, which is a cluster group. In turn, the subsystem “Power Unit” includes a reactor cluster, a primary circuit cluster, a secondary circuit cluster, and a safety system cluster.

For a deep assessment of the technical condition of each subcluster, which are part of the clusters of the “Energy module” subsystem, it is proposed to use information theory and signal theory. At the first level, an analysis of the entropy of the information signal was carried out (1)

$$H_{sig}(x) = -\sum_{i=1}^{n} p(x_i)\log_2 p(x_i), \quad (1)$$

where $H_{sig}(x)$ is the entropy of the information signal; x is a variable that describes the discretized signal (pressure or temperature); x_i is a discrete value of a separate signal; $p(x_i)$ is the probability of its occurrence; n is the number of discrete signal states.

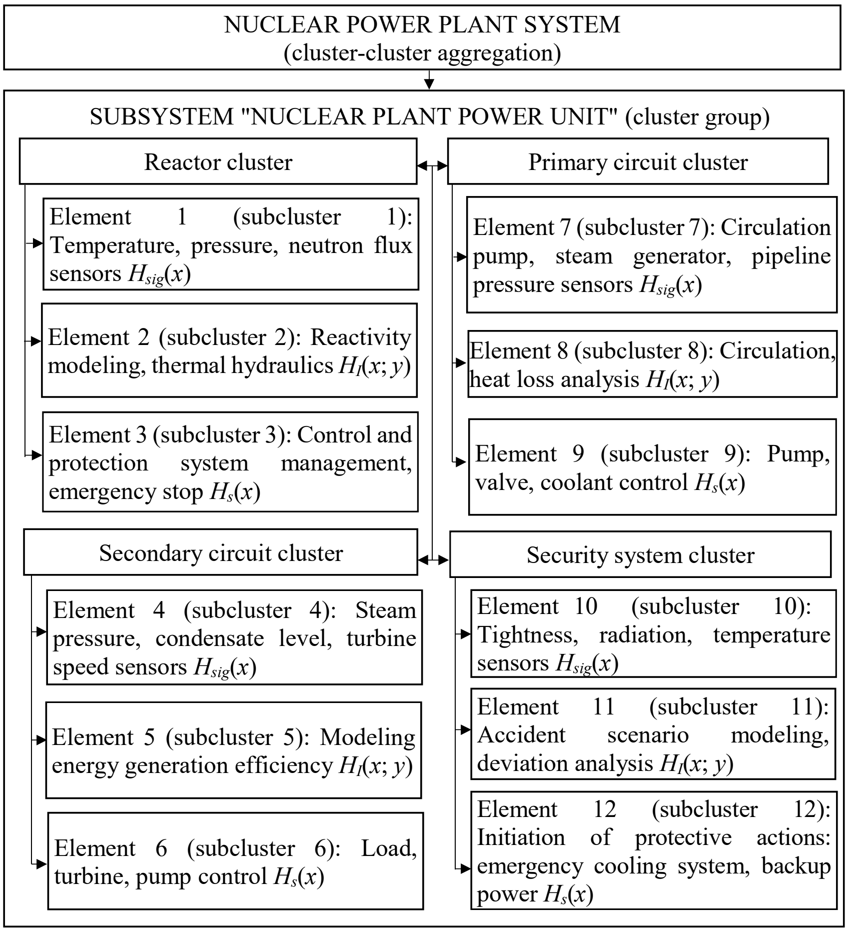

Fig. 1. Hierarchical structure of the nuclear power plant power unit management system based on the system-cluster approach

At the second level, the assessment of information interdependence between clusters by mutual information is described by the following formula (2)

$$H_I(x;y)=\sum_{i,j} p(x_i,y_j)\log_2\left(\frac{p(x_i,y_j)}{p(x_i)p(y_j)}\right), \quad (2)$$

where $H_I(x; y)$ – mutual information; x_i, y_j – values of signals x and y; $p(x_i)$, $p(y_j)$ – probabilities of occurrence of values x_i and y_j; $p(x_i, y_j)$ – joint probability of simultaneous observation of x_i and y_j. In this case, n, m – number of possible states of signals.

Next, at the third level, frequency analysis was performed using the method of discrete Fourier transform (3)

$$X(f_k)=\sum_{t=0}^{T-1} x(t)\cdot e^{-j2\pi f_k t/T}, \quad (3)$$

where $X(f_k)$ is the spectral component of the signal; $x(t)$ is the signal in the time domain at a certain time t; T is the total number of signal samples; f_i is the frequency component; j is the conditional unit. Based on the frequency analysis, the spectral entropy was calculated from the following formula (4)

$$H_s(x)=-\sum_{k=1}^{K} P_k \log_2 P_k; \quad P_k=\frac{\left|X(f_k)\right|^2}{\sum_{j=1}^{K}\left|X(f_j)\right|^2}, \quad (4)$$

where $H_s(x)$ – spectral entropy of the signal; K – number of frequency components; P_k – normalized power at frequency f_k.

From formula (4) it was obtained that each parameter for the value of spectral entropy does not allow us to assess the real level of the state of the technological process of NPP PU. For this purpose, a system of criteria and indicators was formed for calculating the integral indicator of the state of the technological process of the 1000 MW power unit according to expression (5)

$$\sum I_n=\alpha_1 R_{cl}+\alpha_2 F_{cl}+\alpha_3 S_{cl}+\alpha_4 B_{cl}, \quad (5)$$

where $\sum I_n$ – integral indicator of the state of technological equipment of the 1000 MW NPP PU;

R_{cl} – reactor cluster index;

F_{cl} – primary circuit cluster index;

S_{cl} – secondary circuit cluster index;

B_{cl} – safety system cluster index;

α_n – weighting factors.

Thus, the system-cluster approach in information and control systems of the SHS APCS TP provides a practical tool for preventing pre-accident and emergency situations. That allowed us to lay a basis for the development of continuous monitoring and diagnostics systems using DT.

5. 2. Information fractal dimensionality as an indicator of signal complexity and efficiency of monitoring the technical condition of the power unit

For qualitative and quantitative assessment of the state of the technological process of the 1000 MW NPP PU, it is proposed to use the value of the information fractal dimensionality of the signal according to expression (6)

$$D_f^{sig}=\lim_{\varepsilon\to 0}\frac{H(\varepsilon)}{\log_2(1/\varepsilon)}, \quad (6)$$

where D_f^{sig} is the value of the information fractal dimensionality of the signal; ε is the scale value (time window, binarization interval, etc.); $H(\varepsilon)$ is the entropy of the signal at the corresponding level of detail.

Signals of technical origin, such as temperature, pressure, vibration, contain both regular and stochastic components. They have the properties of self-similarity, i.e., fractality. From this point of view, the classical entropy of the signal $H_{sig}(x)$ is a partial case of information complexity. The value of the information fractal dimensionality of the signal models the systemic variability of information in the information environment of the technological process.

To take into account the degree of filling of the information environment, the volume of the information space of the technological process was determined, according to expression (7)

$$V_{fil}^{deg}=\left(\frac{S_{Vfact}}{S_{V\max}}\right)^{D_f^{sig}}, \quad (7)$$

where V_{fil}^{deg} is the degree of filling of the volume of the information space; S_{Vfact} is the actual length of the signal or the volume of data that was used for analysis; $S_{V\max}$ is the maximum possible or specified length of the signal within the selected observation system.

Including this metric in the general information fractal model, a generalized formula for assessing the quality of information monitoring of the technical condition of NPP PU was derived (8)

$$\left|D_f^{mon}\right| = \alpha \cdot \frac{H_{sig}(x)}{\log_2(1/\varepsilon)} + \beta \cdot \frac{H_s(x)}{\log_2(1/\Delta f)} + \\ +\gamma \cdot \frac{H_I(x;y)}{\log_2(1/\varepsilon)} + \sigma \cdot \log_2 V_{fil}^{deg}, \quad (8)$$

where D_f^{mon} is the information-fractal criterion of the state of NPP PU. The weighting coefficients of the information-entropy model of assessing the state of complex technical systems and their functional purpose are given in Table 1.

The indicator D_f^{mon}, is an information-fractal criterion of the state of NPP PU, a multidimensional functional of the information properties of the signal and the spatial-temporal structure of its observation.

The permissible and characteristic values of the information-fractal criterion of the state D_f^{mon} for various subsystems in NPP PU, according to formulas (1) to (8), are given in Table 2.

Thus, the introduction of the range of changes in the information-fractal criterion of the state of NPP PU allowed for diagnostics taking into account the structural depth of the information signal. The proposed approach formed a scientifically sound basis for building predictive, self-learning monitoring systems within the concept of digital twins of NPP PUs.

5. 3. Practical implementation of a digital twin for a system-cluster model of monitoring the technical condition of a power unit

Under current conditions of evolution of digital technologies, the DT of a nuclear power plant unit is its computer model copy, which repeats the operation of a real power unit and constantly receives data from control systems. Thanks to DT, it is possible to monitor the operation of units, conduct technical diagnostics, plan repairs, and support automatic (according to a certain algorithm) decision-making. At the lower level of this system, a network of monitoring system control sensors operates. They are installed in areas of important threshold values, which constantly record the main technological parameters and transform data into a DT model (Fig. 2).

These data are sent to the central server every 1–3 seconds, depending on the importance of the parameter. The pressure in the primary circuit (standard: 15.7 MPa) is monitored with a frequency of 2 Hz, while the temperature in the pipelines (standard: 300–320°C) is monitored with a frequency of 1 Hz. The data is filtered from surges and noise, in particular vibration signals – using the sliding transformation method with a 5-sec window; temperature signals – with calibration drift check; current signals – with interval zeroing. At the middle level, an analytical system operates, which uses fractal-cluster analysis methods to assess the complexity of the signal dynamics. The general view of the "Diagnostics" dialog box of the power unit digital twin is shown in Fig. 3.

From Fig. 3 it is clear that the assessment of the state of the technological process depends on the dynamics of changes in the value of the information fractal dimensionality of each information fractal criterion of the DT model of NPP PU.

Table 1

Weight coefficients of the information-entropy model for assessing the state of complex technical systems and their functional purpose

Coefficient	Characteristic	Physical content	Conditions for weight gain
α – weighting factor of the signal entropy in the time domain [0.4; 0.6]	Regulates the impact of $H_{sig}(x)$	Characterizes the degree of randomness (instability) of the signal within a time interval ε	Increases when the dynamic variability of the parameter is critical for the safety or stability of the system (reactor plant, HCP circuit)
β – weighting factor of the spectral entropy of the signal [0.2; 0.4]	Regulates the impact of $H_s(x)$	Displays the dispersion of signal energy across the spectrum and the appearance of atypical harmonics	Increases when critical changes appear in the frequency domain (vibration diagnostics of rotors, mounts, pump units)
γ – weighting factor of mutual information between signals [0.1; 0.3]	Adjusts the effect of mutual information between signals x and y	Characterizes the information interdependence of signals of different subclusters or systems	Increases when cluster interaction is a source of risk (effect of steam generator temperature on turbine vibrations, pressure dependence on electrical disturbances)
σ – average coefficient of the degree of filling of the information space. It is determined depending on the complexity of the system	Regulates the impact of V_{fil}^{deg}	Describes the completeness of the signal's use of the potential information space, taking into account fractal complexity	Increases in subsystems with large data volumes or high signal structural complexity; important in estimating the dimensionality of the information space

Table 2

Value of the information-fractal criterion of the state of NPP PU

Subsystem / sensor channel	Signal change pattern	Range of D_f^{mon}	Interpretation of technical condition
Reactor plant (temperature, neutron flux)	Stable with smooth fluctuations	0.2–0.35	Operational mode
Main circulation pump (MCP)	Average level of vibrations and hydro fluctuations	0.3–0.5	Normal mode
Steam generator (temperature, pressure)	Presence of spectral perturbations, correlations	0.45–0.65	Potentially complex mode
Emergency cooling system	Intermittent, uncontrolled behavior	0.6–0.8	Pre-emergency mode
Condenser/secondary circuit	Signal with noticeable spectral dispersion	0.4–0.6	Mode that needs attention
Auxiliary systems (ventilation, water)	Moderate information activity	0.25–0.45	Stable-safe mode

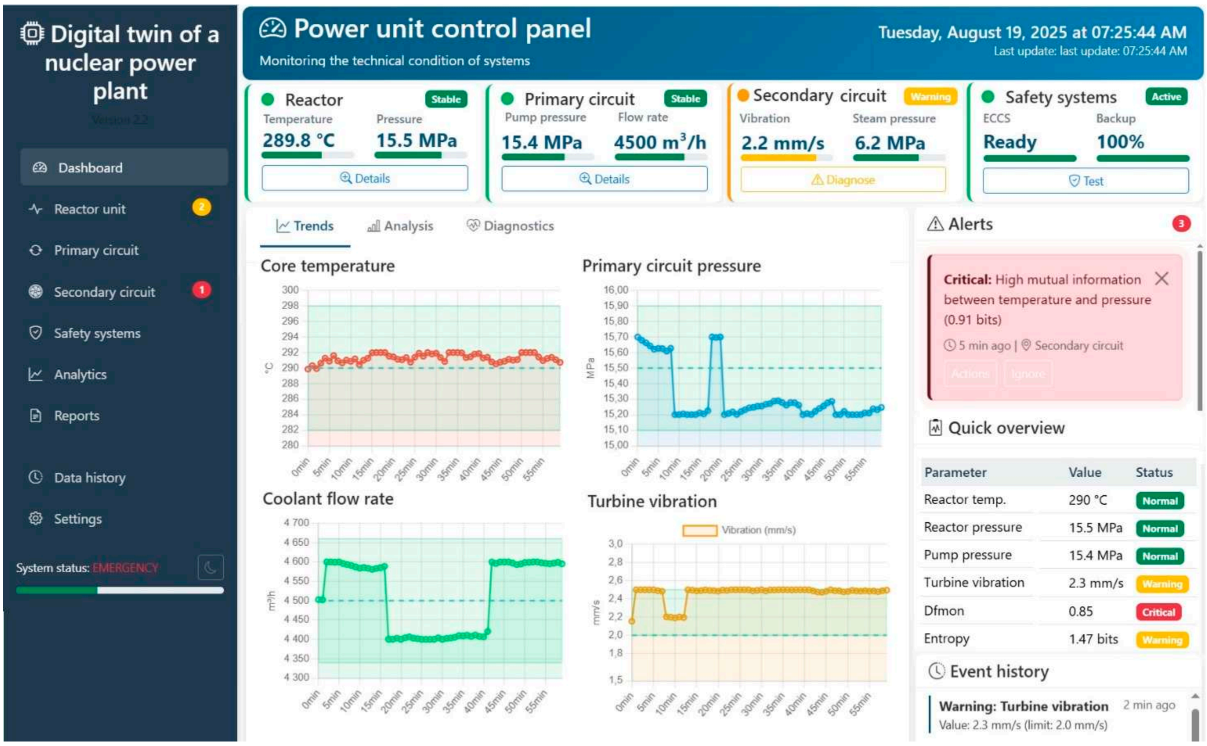

Fig. 2. General view of the information panel for the digital twin model of a nuclear power plant unit

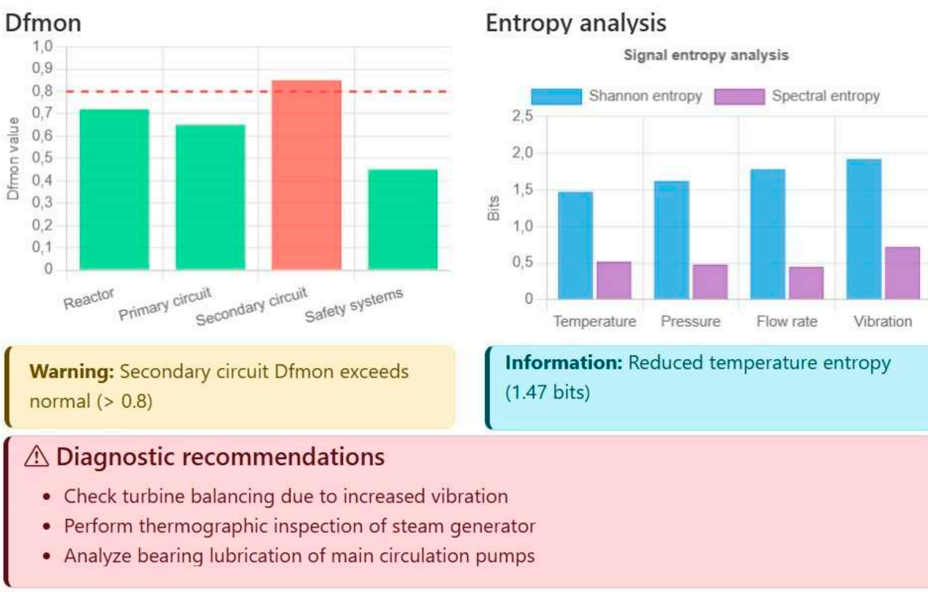

Fig. 3. General view of the "Diagnostics" dialog box of the power unit digital twin

6. Discussion of results based on building a digital twin model for monitoring the technical condition of a power unit

In our work, unlike the approaches from [24, 25], a system-cluster approach was implemented, which made it possible to build a hierarchical structure (Fig. 1) of the control system for the 1000 MW NPP PU. Comparison with the approach in [18], which is based on graph neural networks, shows that the proposed model is characterized by lower computational complexity, which is important for implementation in real time. In papers [14, 15], fractal analysis is used to solve local diagnostic problems but its integration into digital models is absent.

An analysis of the entropy of the information signal was carried out at the first (1), second (2), and third levels (3), which led to the conclusion from formula (4) that each parameter for the value of spectral entropy does not make it possible to assess the real level of the state of the technological process in NPP PU. For this purpose, a system of criteria and indicators was formed for calculating the integral indicator of the state of the technological process of the 1000 MW power unit in accordance with expression (5).

The use of the value of the information fractal dimensionality (6) allowed us to qualitatively and quantitatively assess the level of the state of the technological process of the 1000 MW NPP PU. The value of the information fractal dimensionality of the signal, due to the introduction of a digital twin, allowed us to model the systemic variability of information in the information environment of the technological process.

To take into account the degree of filling of the information environment, the volume of the information space of the technological process was determined from expression (7). That made it possible to take this volume into account as a metric in the general information fractal model and derive a generalized formula for assessing the quality of information monitoring of the technical condition of NPP PU (8). To assess the state of complex technical systems and their functional purpose, weight coefficients of the information-entropy model were proposed (Table 1).

The practical implementation of the digital twin model showed that the assessment of the state of the technological process depends on the dynamics of changes in the value of the information fractal dimensionality of the skin information-fractal criterion of the DT model of NPP PU, as shown in Fig. 3.

Future research should be aimed at synchronizing the digital twin model for all six NPP power units.

The limitations inherent in this study include the dependence of the adequacy of the proposed digital model on the reliability of input data for the automated monitoring system.

The disadvantage of our study is the complex formalization of the procedure for processing primary signals from control sensors to the algorithm for calculating the integral cluster index.

In the future, in further research, it is advisable to consider the implementation of automated monitoring systems for decision-making, in real time, based on the proposed criteria.

7. Conclusions

1. A system for monitoring the technical condition of a power unit has been built, based on a digital twin model using a system-cluster approach, which allowed us to calculate an integral indicator of the state of the technological process of a 1000 MW power unit at a nuclear power plant. Unlike conventional systems, the proposed system takes into account horizontal and vertical relationships between clusters, as well as simultaneously uses signal entropy, mutual information, and spectral entropy.

2. Analytical expressions for the value of fractal dimensionality were obtained, which allowed us to assess the level of more than 5 thousand parameters in the technological process of a 1000 MW power unit. Unlike classical entropy methods, the proposed expressions take into account self-similarity and multi-scale nature of technological process signals.

3. A practical implementation of a digital twin model of a power unit was carried out, in which data is transmitted from sensors to the central server every 1–3 s, and parameter control is executed with a frequency of up to 2 Hz. As a result, we have established that the critical state of the technological process is determined by the increase in the information fractal dimensionality and the D_f^{mon} criterion. In particular, when transitioning from the normal mode to the pre-accident the D_f^{mon} value increases from 0.3–0.5 to 0.6–0.8, which enables detection of dangerous trends that lead to exceeding the limit parameters of the technological process.

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study and the results reported in this paper.

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Data availability

All data are available, either in numerical or graphical form, in the main text of the manuscript.

Use of artificial intelligence

The authors declare the use of the AI tool: LLM model ollama/qwen2.5:32b version 2025; Claude Anthropic Claude Opus 4.6 version 2026; ChatGPT (OpenAI GPT-5, version 2025), number 5.0.1.

The AI tool was used in the sections “Introduction”, “Literary data analysis and problem statement”, “Discussion”, “Conclusions”.

The AI tool was used for editing and grammar checking.

The results provided by the AI tool were checked by manual testing on real texts of the authors’ scientific publications;

The results provided by the AI tool reduced the impact of human grammatical errors when formulating conclusions for the study.

Authors’ contributions

Viktoriia Prokhorova: Conceptualization; **Mykola Budanov**: Methodology; **Kostiantyn Brovko**: Validation; **Pavlo Budanov:** Investigation; **Vyacheslav Melnykov**: Formal analysis; **Ihor Kyrysov**: Resource; **Oleh Velykohorskyi**: Visualization; **Andrii Nosyk**: Software; **Oleh Karpenko**: Funding acquisition.

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