THE ISSUE OF ASSESSING THE TECHNICAL CONDITION OF INDUSTRIAL EQUIPMENT UNDER CONDITIONS OF UNCERTAINTY

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Annotatsiya: Ushbu maqolada sanoat uskunalarining texnik holatini baholash jarayonida yuzaga keladigan noaniqliklarni kamaytirish va diagnostika aniqligini oshirishga qaratilgan gibrid intellektual modellarni qo‘llash masalalari yoritilgan. An’anaviy diagnostika usullari ko‘pincha ma’lumotlar yetishmasligi, ish sharoitlarining o‘zgaruvchanligi, datchiklarning noaniqligi hamda inson omilining ta’siri sababli yuqori ishonchlilikdagi qarorlar qabul qilishni ta’minlay olmaydi. Shu munosabat bilan maqolada noaniq mantiq (fuzzy logic), neyron tarmoqlar, ekspert tizimlari va mashinaviy o‘rganish modellarini integratsiyalashga asoslangan gibrid yondashuv taklif etiladi.

Kalit so‘zlar: gibrid intellektual modellar, texnik diagnostika, noaniqlik, noravshan mantiq, neyron tarmoqlar, ma’lumotlarni tahlil qilish, nosozliklarni aniqlash, diagnostika aniqligi.

Аннотация: Данная статья освещает вопросы использования гибридных интеллектуальных моделей, направленных на снижение неопределенностей и повышение точности диагностики, возникающих в процессе оценки технического состояния промышленного оборудования. Традиционные методы диагностики зачастую не могут обеспечить принятие высоконадежных решений из-за нехватки данных, изменяющихся рабочих условий, неточности датчиков и влияния человеческого фактора. В связи с этим в статье предлагается гибридный подход, заключающийся в интеграции нечеткой логики (fuzzy logic), нейронных сетей, экспертных систем и моделей машинного обучения.

Ключевые слова: гибридные интеллектуальные модели, техническая диагностика, неопределенность, нечеткая логика, нейронные сети, анализ данных, обнаружение неисправностей, точность диагностики.

Abstract: This thesis highlights the issues of using hybrid intelligent models aimed at reducing uncertainties arising in the process of assessing the technical condition of industrial equipment and increasing diagnostic accuracy. Traditional diagnostic methods often cannot provide high-reliability decision-making due to lack of data, variable working conditions, sensor inaccuracy, and human factors. In this regard, the article proposes a hybrid approach, consisting of the integration of fuzzy logic, neural networks, expert systems, and machine learning models.

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Keywords: hybrid intelligent models, technical diagnostics, uncertainty, fuzzy logic, neural networks, data analysis, fault detection, diagnostic accuracy.

Introduction.

At modern industrial enterprises, the reliable and uninterrupted operation of equipment is of critical importance for ensuring production safety, economic efficiency, and reducing the likelihood of man-made (technogenic) accidents. The main challenge in the process of technical diagnostics of industrial equipment lies in the fact that data obtained from sensors and measurement systems may be inaccurate, noisy, incomplete, or contradictory. Under such conditions, classical statistical or deterministic models are unable to achieve sufficient accuracy.

Trends associated with Industry 4.0, IoT (Internet of Things) platforms, intelligent sensors, and Big Data necessitate further automation and optimization of technical diagnostic systems. In this context, hybrid diagnostic models that combine multiple intelligent methods and are capable of operating under uncertainty are considered a highly relevant solution [1,4].

Hybrid intelligent models that integrate modules such as fuzzy logic for inference, machine learning, Bayesian statistics, Dempster–Shafer evidence theory, and neural networks enable reliable diagnosis even when based on imprecise data. This makes it possible to reduce the risk of technogenic accidents, extend equipment operating cycles, and optimize preventive maintenance programs.

PROBLEM STATEMENT. Uncertainties in assessing the technical condition of industrial equipment arise mainly due to the following factors: sensor noise and measurement errors, incomplete data, contradictory signals, and the stochastic nature of the equipment's technical state [3].

During equipment condition monitoring, data received from sensors are characterized by significant uncertainty, which must be critically taken into account in diagnostics and prognostics. This uncertainty originates from several fundamental sources. First, it is caused by noise and measurement errors inherent in the sensors themselves, which manifest as dynamic variability (random fluctuations) in vibration sensor readings, thermal inertia (response delay) in temperature sensors, and shifts in statistical values (calibration drift) in pressure sensors. Second, incomplete data frequently occur due to the failure of individual sensors or packet loss during data transmission, resulting in gaps and discontinuities in time series. Third, uncertainty arises from contradictory signals, when different sensors exhibit different responses to the same physical state, or when multiple independent sources provide differing state estimates at the same point in time. Finally, the stochastic nature of the equipment's technical condition itself introduces uncertainty, since degradation processes and internal

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phenomena—such as random variations in vibration levels or the emergence of microscopic defects in bearings or the rotor—are inherently random and unpredictable. The combination of these factors necessitates the use of robust data processing and analysis methods capable of effectively handling noise, incompleteness, and conflicting information [2].

Under such complex conditions, hybrid models provide uncertainty reduction and enable diagnosis that is "close to human reasoning."

SOLUTION APPROACH. In this study, the following hybrid architecture was proposed for assessing the technical condition of industrial equipment: a fuzzy logic module, a machine learning module, a data integration block, and an uncertainty reduction module.

Fuzzy Logic Module. Primary diagnostics are performed using a fuzzy inference system (FIS), which emulates linguistic assessment similar to the expert judgment of a human specialist.

The input data consist of equipment condition indicators measured by sensors, including vibration amplitude, temperature, pressure, and noise spectrum.

For fuzzification (the transformation of crisp numerical values into fuzzy sets), the linguistic terms "low," "medium," and "high" are applied.

At this stage, primary diagnostic assessments are computed and expressed in the form of fuzzy values.(Fig 1.) [5].

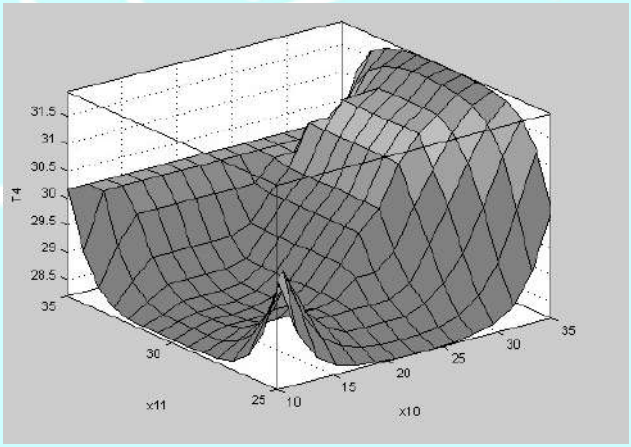


Fig 1. Presentation of Diagnostic Analysis Data of Liquid Pumps Supplying the Absorber Based on Fuzzy Logic.

1. Machine Learning (ML) Module. The ML module is designed to predict the probable type of fault and the likelihood of its progression.

Based on sensor data (signals), the following statistical and spectral features were extracted:

Root Mean Square (RMS), peak-to-peak value, kurtosis, and skewness.

Spectral features derived from the Fast Fourier Transform (FFT), Short-Time Fourier Transform (STFT) signals, and Mel spectrograms were also used.

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To train the prognostic model, state-of-the-art deep learning and machine learning techniques were applied:

- Stochastic Gradient Descent (SGD);
- Adaptive Gradient methods (Adagrad);
- Recurrent neural networks with Long Short-Term Memory (LSTM);
- One-dimensional Convolutional Neural Networks (1D CNN).

2. Data Integration and Uncertainty Reduction.

To enhance the reliability of the final diagnosis and to account for the uncertainty inherent in the outputs of individual modules (fuzzy logic and ML), evidence-based data integration is employed.

The fusion of results is performed using Dempster–Shafer (D–S) evidence theory or Bayesian integration (Bayesian networks).

Bayesian networks are used to reassess the probability of faults for each feature by incorporating prior knowledge and observed data.

Dempster–Shafer (DS) theory provides a mathematical framework for combining conflicting and incomplete evidence from multiple sources, resulting in a unified and more substantiated diagnosis.

At this stage, an integrated confidence level (also referred to as the isolation accuracy index) is formed, representing the final and most reliable diagnosis of the equipment condition.

The proposed research methodology was tested on real industrial facilities, namely an air compressor and a centrifugal pump. The study was based on more than 32,000 measurements collected from 10 sensors over a period of two months.

Experimental evaluation stages:

- Data filtering and normalization;
- Design of the rule base;
- Training of machine learning models (80/20 split for training and testing);
- Hybrid fusion (Bayesian / D–S);
- Model accuracy evaluation.

Table 1.

Results obtained using different methods.

Method	Accuracy (%)	Early detection capability	Reliability
Classical ML	76–82%	Low	Medium
Fuzzy-logic only	84–88%	Medium	Medium
Bayesian model	83–87%	Medium	High

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Proposed hybrid model	92–96%	High	High

It was observed that under real operating conditions, the hybrid model is **1.1–1.2 times more effective** than conventional machine learning models in the early detection of microscopic defects and vibration anomalies.

DISCUSSION. The study demonstrated that:

1. The fuzzy logic module formalizes the expertise of human specialists and exhibits high robustness to imprecise data;
2. The machine learning model identifies hidden patterns within large-scale datasets;
3. Bayesian or Dempster–Shafer integration enables a unified and reliable diagnosis even when based on contradictory data;
4. The hybrid model is highly suitable for real-time diagnostics on Industry 4.0 platforms.

CONCLUSION. The proposed hybrid intelligent model significantly reduces the impact of data uncertainty, enhances the capability to prevent technogenic accidents, and contributes to extending the service life of industrial equipment. Furthermore, it can be fully integrated into preventive (predictive) maintenance systems and applied to pumps, compressors, turbines, electric motors, and other rotating machinery.

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