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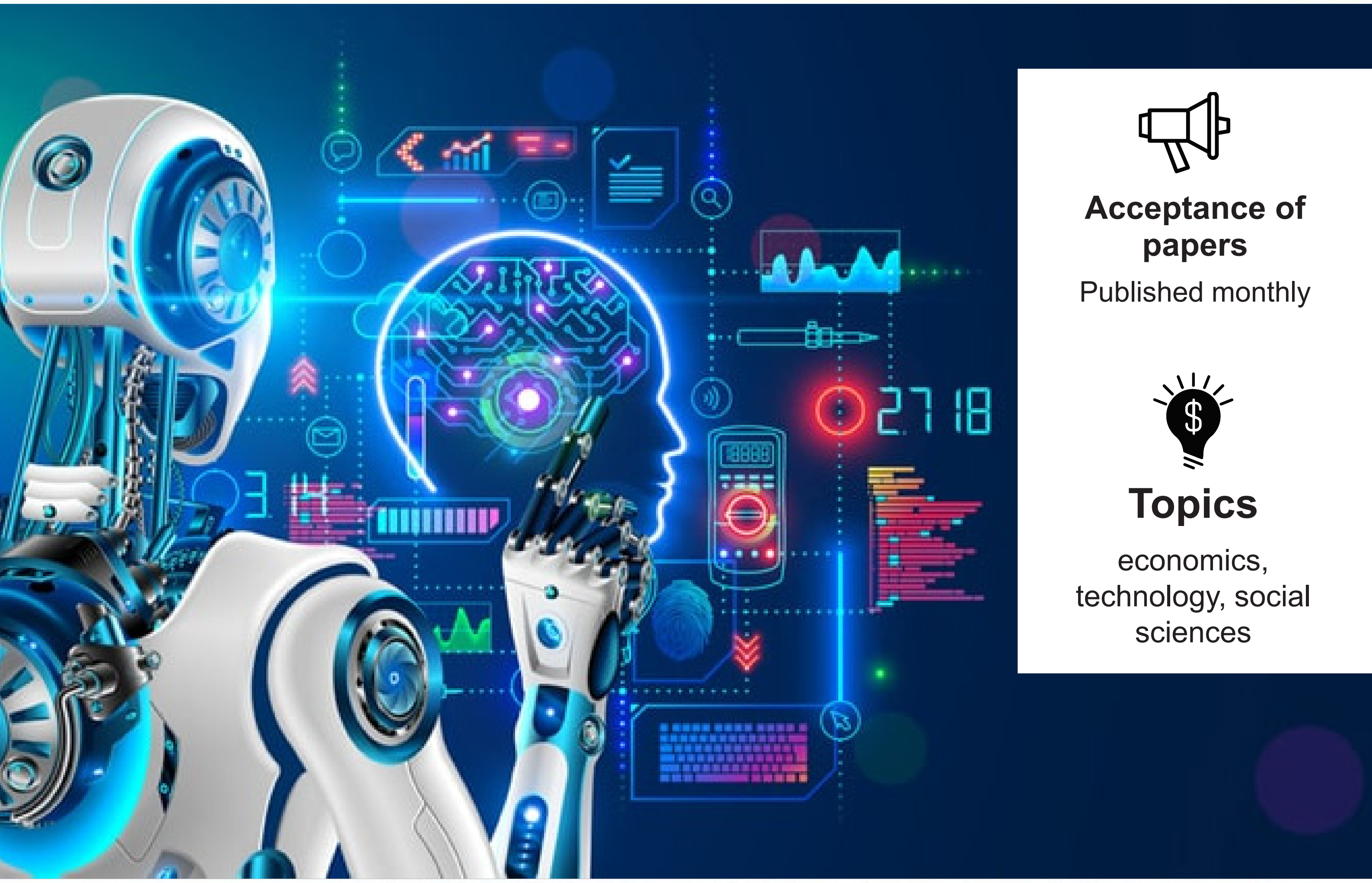

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CONTENTS

INTELLECTUALIZATION OF TECHNICAL MEANS FOR CONTROLLING TECHNOLOGICAL REFINING PROCESSES

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Abstract: The article presents a scientifically grounded concept for the intellectualization of technical means for monitoring refining technological processes, aimed at increasing the accuracy, reliability, and validity of measurement information under conditions of uncertainty and external disturbances. Modern trends in the development of intelligent sensors, methods of self-control, self-diagnosis, and self-calibration, as well as algorithms for intelligent processing of measurement signals based on fuzzy logic, neural networks, and cognitive models, are considered. Special attention is paid to the integration of intelligent measuring instruments into automated technological process control systems and Industry 4.0 digital production platforms. The results of the analysis of the effectiveness of the proposed methods and their practical implementation in industrial conditions are presented.

Key words: intelligent sensors, measuring instruments, self-control, self-calibration, cognitive analysis, refinement, Industry 4.0.

Annotatsiya: Maqolada noaniqlik va tashqi buzilishlar sharoitida oʻlchov maʼlumotlarining aniqligi, ishonchliligi va haqqoniyligini oshirishga qaratilgan rafinatsiyalash texnologik jarayonlarini boshqarishning texnik vositalarini intellektuallashtirishning ilmiy asoslangan konsepsiyasi keltirilgan. Intellektual datchiklar rivojlanishining zamonaviy tendensiyalari, oʻz-oʻzini nazorat qilish, oʻz-oʻzini diagnostika qilish va oʻz-oʻzini kalibrlash usullari, shuningdek, oʻlchash signallarini noravshan mantiq, neyron tarmoqlar va kognitiv modellar asosida intellektual qayta ishlash algoritmlari koʻrib chiqilgan. Texnologik jarayonlarni avtomatlashtirilgan boshqarish tizimlari va Industry 4.0 raqamli ishlab chiqarish platformalariga intellektual oʻlchash vositalarini integratsiyalashga alohida eʼtibor qaratilgan. Taklif etilgan usullarning samaradorligini tahlil qilish va ularni sanoat sharoitida amaliyotga joriy etish natijalari keltirilgan.

Kalit soʻzlar: intellektual datchiklar, oʻlchov vositalari, oʻz-oʻzini nazorat qilish, oʻz-oʻzini kalibrlash, kognitiv tahlil, rafinatsiya, Industry 4.0.

Аннотация: В статье представлена научно обоснованная концепция интеллектуализации технических средств контроля технологических процессов рафинации, ориентированная на повышение точности, надежности и достоверности измерительной информации в условиях неопределенности и внешних возмущений. Рассмотрены современные тенденции развития интеллектуальных датчиков, методы самоконтроля, самодиагностики и самокалибровки, а также алгоритмы интеллектуальной обработки измерительных сигналов на основе нечеткой логики, нейронных сетей и когнитивных моделей. Особое внимание уделено интеграции интеллектуальных средств измерения в автоматизированные системы управления технологическими процессами и цифровые производственные платформы Индустрии 4.0. Приведены результаты анализа эффективности предложенных методов и их практической реализации в промышленных условиях.

Ключевые слова: интеллектуальные датчики, средства измерения, самоконтроль, самокалибровка, когнитивный анализ, рафинация, Индустрия 4.0.

INTRODUCTION

The modern development of industry is characterized by the complication of technological processes, increased requirements for product quality, energy efficiency, environmental safety, and the reliability of equipment operation. Under these conditions, the technical means of controlling technological parameters acquire key importance, as it is precisely measurement information that forms the basis for automated technological process control systems (ATPCS), decision support systems, and digital counterparts of production facilities [1-3].

Traditional measuring instruments, as a rule, are aimed at registering one parameter and transmitting an unprocessed signal to the upper control level. Such an approach was justified in the early stages of automation, however, in modern conditions, it leads to an increase in the load on controllers, a decrease in the speed of decision-making, and an increase in the risk of using unreliable measurement information. This problem is particularly acute when technological objects operate under conditions of uncertainty, instability of parameters, and degradation of sensitive elements [4,5].

The concepts of “Industry 4.0”, “Internet of Things” and “cyber-physical systems” envision the transition to distributed intelligent data processing, where a significant portion of analytical and diagnostic functions is transferred to the field level. In this regard, the intellectualization of technical control tools is becoming one of the key directions in the development of modern measuring technology. Intelligent sensors and measurement systems must have the functions of self-control, self-diagnosis, self-calibration, and assessment of the reliability of measurement information in real time [6-8].

Intelligent control tools are gaining particular importance in the chemical, petrochemical, food, and energy industries, where measurement accuracy directly affects the output of finished products, energy consumption, and emissions levels. Using intelligent signal processing methods allows not only for increased measurement accuracy but also for predicting the state of measurement channels, early detection of failures, and reduced operating costs.

The purpose of this article is to develop and comprehensively substantiate the concept of intellectualizing technical means of controlling technological processes based on cognitive and predictive models, as well as to present an expanded scientific analysis of methods and algorithms for intelligent processing of measurement information.

REVIEW OF LITERATURE ON THE SUBJECT

The intellectualization of technical means for controlling technological refining processes has evolved at the intersection of intelligent data processing, sensor self-diagnostics, and cyber-physical integration. Early research emphasized the need to move beyond conventional single-parameter measurement devices toward systems capable of embedded reasoning and adaptive decision-making. A foundational contribution in this direction was made by Jianbo Yu, Lifeng Xi, and Xiaojun Zhou in 2008, who demonstrated that integrating knowledge-based artificial neural networks with genetic algorithms enables intelligent monitoring and fault diagnosis in manufacturing processes. Their work showed that hybrid AI architectures significantly improve diagnostic accuracy under uncertain and nonlinear operating conditions, which is highly relevant for refining processes characterized by parameter instability and noise.

The transition toward cyber-physical systems further strengthened the conceptual basis of intellectualized control tools. Korshunov, Aleksandrov, and Tamvilius in 2020 proposed a cyber-physical system architecture for monitoring the technical condition of heat networks, highlighting distributed intelligence, real-time data fusion, and tight coupling between physical processes and digital analytics. These principles are directly applicable to refining processes, where continuous interaction between sensors, control algorithms, and physical equipment determines operational efficiency and safety. Complementing this perspective, Weiss, Schleiss, Schneider, and Trapp in 2018 addressed the integration of self-adaptive systems into safety-critical environments, emphasizing reliability, fault tolerance, and controlled adaptability. Their findings underline that intellectualization must be accompanied by rigorous assurance mechanisms, especially in technologically complex refining systems.

Sensor networks and communication infrastructures form the backbone of intelligent control environments. Dong-Seong Kim and Hoa Tran-Dang in 2018 provided a comprehensive overview of industrial wireless sensor networks, emphasizing their role in distributed monitoring and control. They demonstrated that intelligent sensor nodes with local processing capabilities reduce data transmission loads and improve response times, which is essential for refining processes requiring prompt corrective actions. However, the effectiveness of such intelligent sensing infrastructures depends critically on metrological reliability, calibration, and self-control.

Metrological aspects of intellectualization have been systematically addressed in the works of Heinz Zwanziger and Eduard Sorkau in 2020, who analyzed theoretical and practical approaches to calibration of analytical methods. Their work established that advanced calibration techniques are a prerequisite for trustworthy intelligent measurements. Building on this foundation, a series of studies by Yusupbekov, Ruziev, and Shodiev between 2021 and 2023 significantly advanced the concept of intelligent and virtual analyzers. In 2021, Yusupbekov, Ruziev, and Shodiev introduced multi-model virtual analyzers for technological process parameters, demonstrating that combining multiple mathematical models enhances robustness and adaptability. Ruziev and Shodiev in the same year further showed that virtual analyzers contribute to the intellectualization of industrial process control systems by enabling indirect measurement and predictive estimation where direct sensing is impractical.

Subsequent research deepened the cognitive and self-diagnostic dimensions of intelligent measurement tools. Ruziev in 2022 proposed a cognitive approach to self-monitoring of intelligent sensors, introducing mechanisms for self-assessment, anomaly detection, and adaptive correction. In parallel, his work on intelligent sensors with metrological self-control emphasized autonomous verification of measurement accuracy, reducing dependence on external calibration procedures. These ideas were extended in collaborative studies with Karpovich in 2023, where the intellectualization of monitoring processes for complex technological productions was framed as a system-level transformation involving sensors, control logic, and decision support.

Recent contributions by Yusupbekov and Ruziev in 2023 formalized methods for metrological self-checking and error diagnosis in intelligent measurement devices. These studies highlighted that self-checking and diagnostic algorithms are not auxiliary features but core components of intellectualized technical means. Together, the reviewed literature demonstrates a clear evolution from intelligent monitoring and hybrid AI models toward fully integrated, cognitively enhanced, and metrologically self-reliable control tools. This body of research provides a solid theoretical and methodological foundation for the intellectualization of technical means used in controlling technological refining processes, where accuracy, adaptability, and reliability are decisive factors for sustainable and efficient operation.

RESEARCH METHODOLOGY

The focus of this work is on technical devices designed to measure and control the parameters of production processes in the chemical, petrochemical, food, and energy sectors. These devices are operated under complex conditions characterized by uncertainty, random interference, variable operating modes, and deterioration of the characteristics of sensitive components. These include sensors that measure flow rate, temperature, pressure, level, and concentration, which are integrated into automated technological cycle control systems [9-11].

This work examines the methods and algorithms for intelligent processing of signals received from measuring channels. Special attention is paid to mathematical models describing measurement errors, as well as neural and neuro-fuzzy algorithms designed to compensate for them. In addition, software and hardware tools that ensure self-control and self-calibration of measuring systems are being investigated.

The research is based on fundamental concepts of measurement theory, probability theory and mathematical statistics, automatic control theory, digital signal processing, and artificial intelligence. In this case, a systematic approach is applied, allowing the measuring instrument to be considered as a complex dynamic system with inputs, outputs, and internal characteristics. The implementation of artificial intelligence methods such as fuzzy logic, neural networks, and cognitive algorithms has made it possible to increase the intellectual level of measurement systems. The research is conducted according to the following structure: first, the sources of errors arising during measurement are analyzed. Then, a mathematical model of the measuring tract is created. Further, an intelligent algorithm for signal processing is being developed. After this, self-control and self-calibration procedures are implemented. Finally, an experimental assessment of the effectiveness of the proposed methods is carried out [12-14].

The measurement channel is presented as a nonlinear model that takes into account the main systematic and random errors:

$$y(t) = K \cdot x(t) + b + \sum_{i=1}^{n} f_i(z_i t) + \varepsilon(t), \quad (1)$$

where: $x(t)$ – true value of the measured parameter, K – conversion coefficient, b – zero shift, $f_i(z_i t)$ – functions of influencing factors, $\varepsilon(t)$ – random error.

For the approximation of nonlinear characteristics of the measurement channel, a multilayered direct propagation neural network is used. The input vector of the neural network includes the measured parameter value, temperature, operating time, and additional diagnostic characteristics.

$$\hat{y} = f(\sum_{i=1}^{n} w_j \cdot x_j + \theta) \qquad (2)$$

where: w_j – weighting factors, θ – threshold shift, f – activation function. Network training is carried out by the method of error reverse propagation with minimization of the loss functional.

Self-control is implemented by comparing the current measured value with the predicted value of the neural model. Upon exceeding the permissible deviation, a self-calibration procedure based on adaptive adjustment of model weight coefficients is initiated.

Self-calibration is based on the adaptive adjustment of model parameters during operation, which allows compensating for characteristic drift without removing the device from operation.

ANALYSIS AND RESULTS

This approach is implemented through the use of time and information redundancy in data. During the device creation process, a knowledge base is formed, which is supplemented by regulated calibration data and expert knowledge obtained from models and experimental data specific to this technological cycle. Processing of the received information is carried out in several stages, taking into account the peculiarities and patterns of development of measuring signals. Data is used to create a knowledge base that allows generating the reference signal value or determining its accompanying characteristics (noise, change dynamics, etc.). Analysis of these characteristics allows us to assess the accuracy of measurements and draw conclusions about the operability of the intelligent measuring device. As a result, a knowledge base is formed, stored in the memory of the device itself [15-18].

The measuring parameter obtained by primary transducer 1 is converted into electrical voltage by secondary transducer 2. Then, using analog-to-digital converter 3, the signal takes on a digital form and enters microprocessor 4. Inside the microprocessor, in the cognitive analyzer 5, the received data is processed, after which the final value is recorded in the energy-independent memory 6, which ensures the preservation of information even when the power is off. Cognitive analyzer 5, developed using software, processes the incoming signal by applying knowledge from its database. The obtained results allow him to determine the current state of the measuring device. Interface 7, designed for the exchange of information and measurement data, provides interaction with other devices and updates the knowledge base (Figure 1).

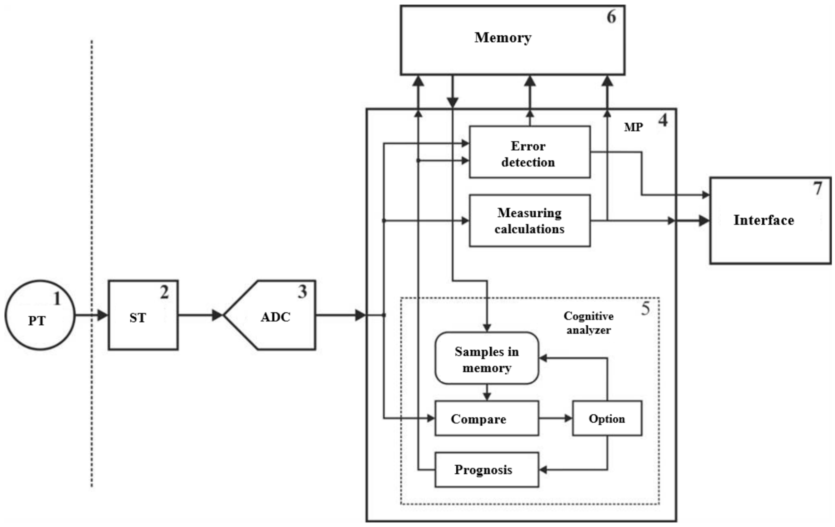

Figure 1. Method of metrological self-control of intelligent measuring devices

To assess the accuracy of measurements, the cognitive analyzer, taking into account the possibility of distortion of standard signals, creates a reference signal. With its help, it is possible to calculate the error of the measured signal and judge the operability of the measuring device. The reference signal is usually formed based on existing data about the current process, including noise, change dynamics, and other characteristics of the measured signal. Then, the current measured signal is compared with the created sample. By comparing the obtained results, it is possible to draw a conclusion about how much the measured signal corresponds to the expected one.

Numerical models were used to study the influence of temperature fluctuations, additive noise, and gradual drift of sensitive sensor characteristics on measurement accuracy. Using the RMSE (t) graph, the evolution of the root mean square error accumulated by the intelligent sensor during operation is visualized. At the adaptation stage, when the model is just starting to work, RMSE takes on high values. This is due to the lack of available data and uncalibrated weighting factors of the neural architecture. With an increase in the volume of incoming measurements and adjustment of model parameters, the RMSE curve changes exponentially, gradually smoothing and stabilizing (Figure 2).

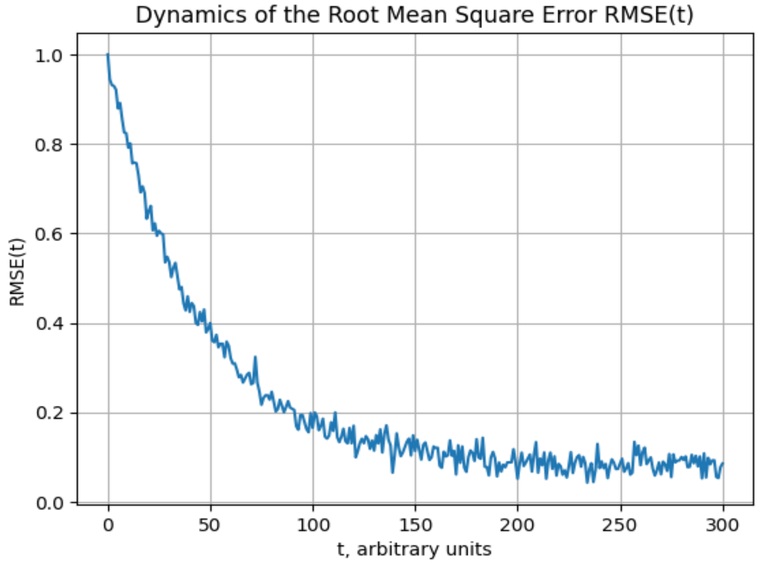

Figure 2. RMSE (t) dynamics and interpretation of results

The shape of the graph Δy (t) indicates the rapid suppression of disturbances and the minimal delay in compensation. This is especially important for dynamic technological processes, where delays in the measurement channel can lead to a deterioration in control quality (Figure 3).

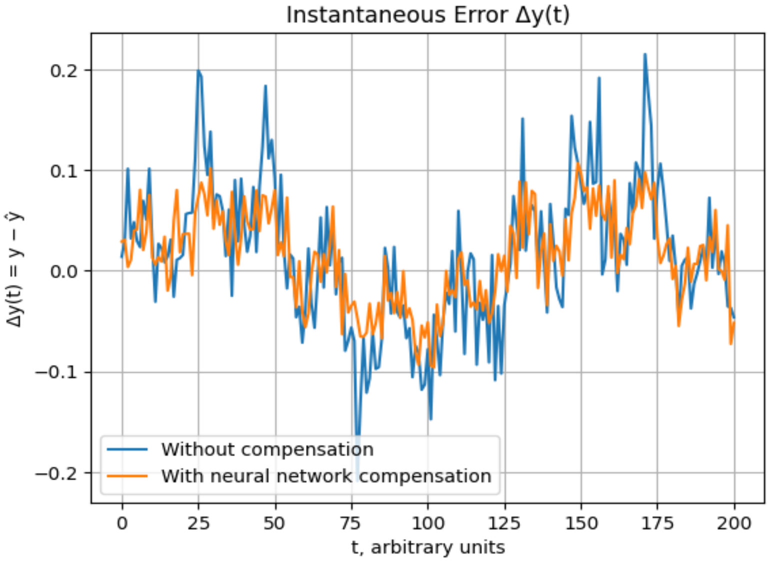

Figure 3. Analysis of the difference $\Delta y\ (t) = y\ (t) - \hat{y}\ (t)$

The learning graph showing the change in the Loss loss function depending on the number of eras indicates a stable convergence of the algorithm. The initial epochs are characterized by a rapid decrease in Loss, which emphasizes the active process of fine-tuning of weight parameters. Subsequently, the curve slows down and stabilizes at a certain level, indicating the optimal balance between the model's accuracy and its resistance to overtraining (Figure 4).

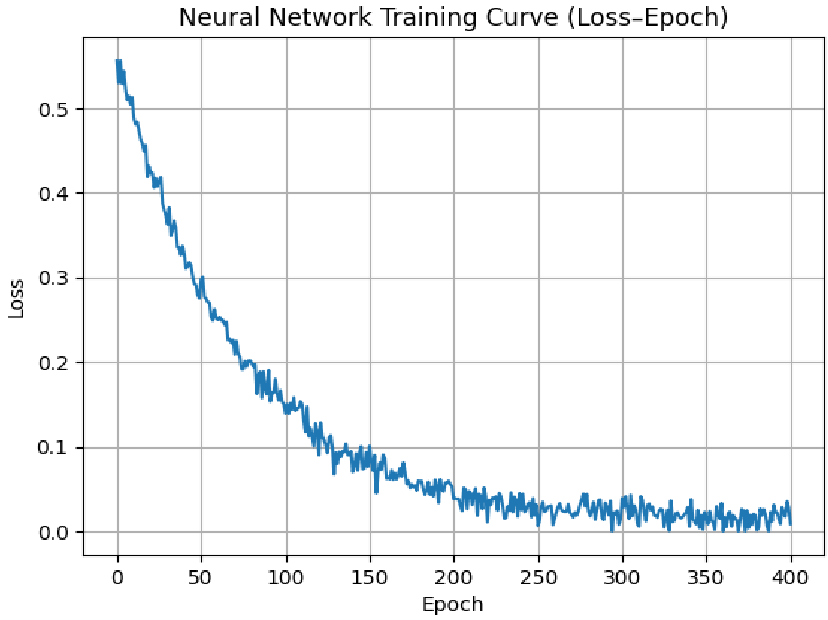

Figure 4. Neural model learning curve (Loss-Epoch)

The absence of oscillations and secondary minima on the Loss-Epoch graph confirms the correct choice of neural network structure and learning coefficient. Such a curve shape is characteristic of stable and well-generalized models.

The time diagrams y (t) and ŷ (t), obtained during industrial operation as part of the ATPCS, show a high degree of signal shape overlap when the technological regime changes. Short-term discrepancies between measured and predicted values are quickly compensated by model adaptation (Figure 5).

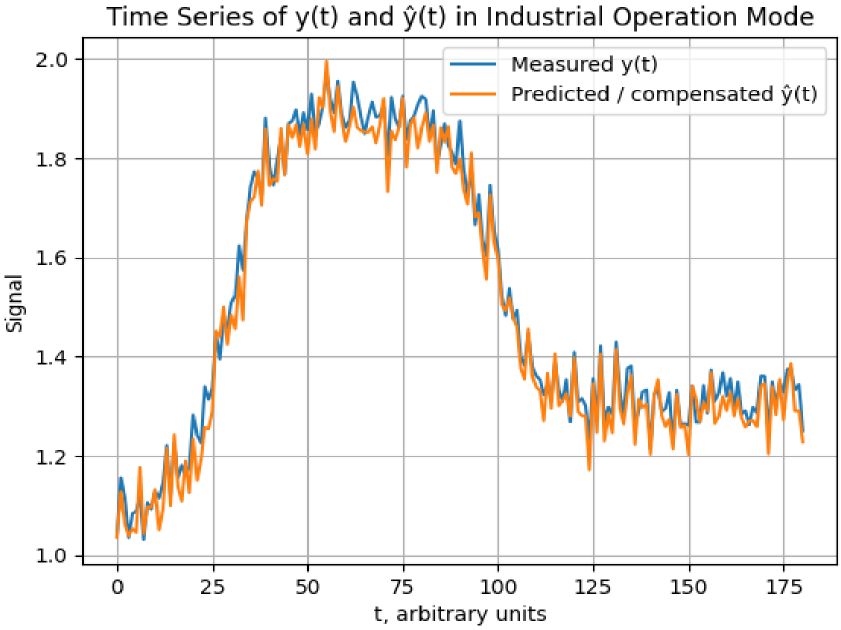

Figure 5. Time diagrams of an industrial experiment

Experimental tests were conducted as part of the ATPCS at the industrial facility. The time diagrams y (t) and ŷ (t) show the coincidence of signal shapes when the technological regime changes; discrepancies are short-lived and quickly compensated by model adaptation. The temperature effect compensation graph illustrates the decrease in temperature drift: after the intelligent algorithm is activated, the characteristic slope decreases, and the scatter of measured values is significantly reduced. This confirms the effectiveness of temperature compensation in real production conditions (Figure 6).

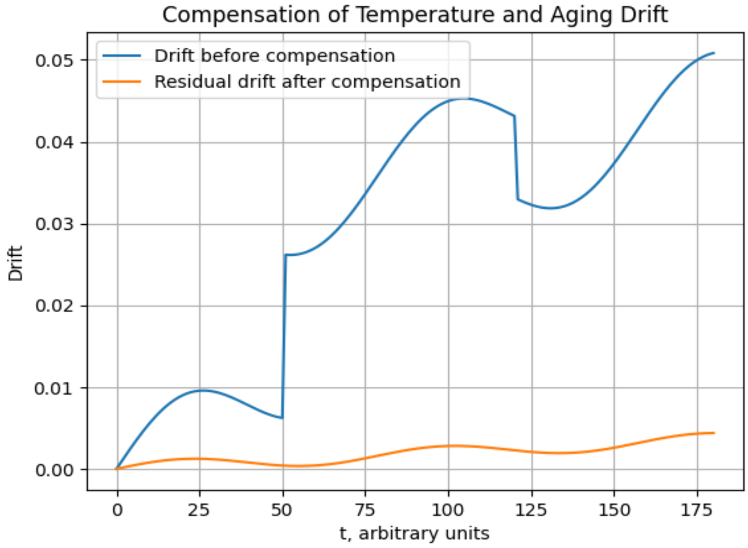

Figure 6. Temperature and resource drift compensation

To assess the operability of the measuring instrument, a graph |y (t) − ŷ (t) | with a superimposed threshold line Δadd is used. In the proper state of the measuring channel, the error curve is located below the threshold value. With the gradual degradation of the sensitive element, an increase in the amplitude |y − ŷ| and periodic crossing of the threshold are observed (Figure 7).

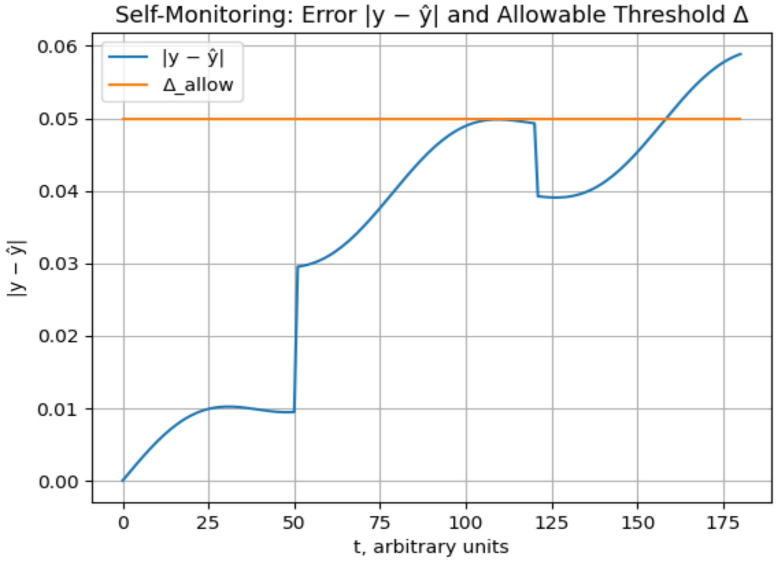

Figure 7. Self-control schedules and Δadd threshold

This effect allows for the detection of the initial signs of malfunction long before the actual failure. Thus, the self-control schedule serves as an early diagnostic tool and the basis for predicting the technical condition of the measuring instrument.

The transition process graphs of the controller, constructed for a system with a traditional and intelligent sensor, show a reduction in over-regulation and setting time. Intelligent compensation of measurement errors leads to a more accurate assessment of the controlled object’s state, which positively affects the quality of regulation.

As a result, the load on the ATPCS central controllers is reduced, and the overall stability of the control system is increased. The use of neuro-fuzzy algorithms in intelligent signal processing, as confirmed both by models and experiments, leads to a reduction in the root mean square error of measurements in the range from 15% to 25%. Such an increase in accuracy is especially noticeable under conditions where measurements are subject to temperature and vibration interference (Figure 8) [19,20].

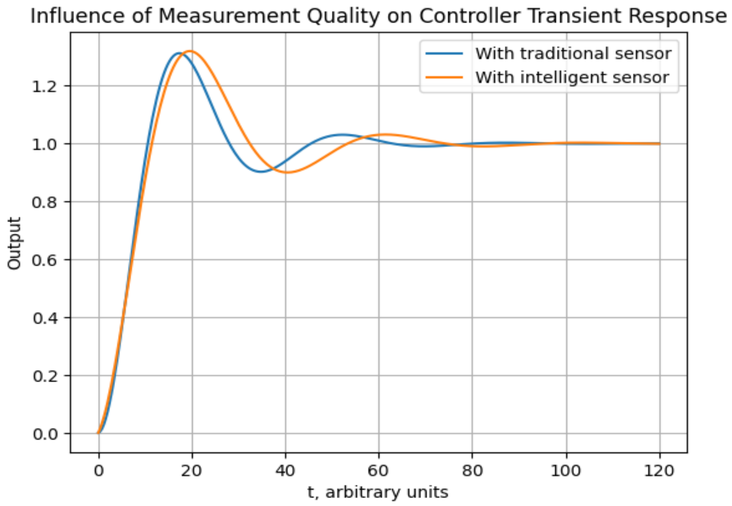

Figure 8. Influence of the regulator on transient processes

Industrial operation of intelligent control systems has led to a decrease in the number of false starts and an increase in the reliability of the control system. The implementation of self-control has made it possible to quickly identify problems with measurement channels at the initial stage of their development.

The obtained results confirm that the intellectualization of control instruments is an effective direction for the development of measurement technology for complex technological processes. Unlike traditional approaches focused on static calibration and centralized processing, the proposed architecture provides distributed adaptation and diagnostics at the field level.

Comparison with classical methods of linear compensation shows that neural models better approximate nonlinearities and are resistant to non-stationary perturbations. This is especially important for processes with variable modes and long operating time, where the degradation of sensitive elements is inevitable. Cognitive self-control complements neural compensation, forming a mechanism for early warning of failures.

The practical consequence is the transfer of a portion of computational functions from the TP ASU level to the sensor level, which reduces network load and increases the system's overall fault tolerance. At the same time, the implementation of intelligent control tools requires consideration of interface standardization, cybersecurity, and compatibility with existing infrastructure.

From a methodological point of view, the balance between the complexity of the model and the computational resources is important. It has been shown that compact neural networks with a limited number of parameters provide sufficient accuracy with low energy consumption, which is critical for industrial applications.

CONCLUSIONS AND SUGGESTIONS

The work developed and expandedly substantiated the concept of intellectualizing technical means of controlling technological processes based on neural and cognitive models. For the first time, mathematical modeling of errors, neural compensation of nonlinearities, and metrological self-control algorithms have been combined within a single architecture.

The main scientific results include: formalization of the measurement channel model taking into account external influences; development of a neural model for compensation of drift and nonlinearity; self-control algorithm with early detection of degradation; self-calibration method without removing the device from operation. The practical significance lies in increasing the accuracy and reliability of measurements, increasing the calibration interval, and reducing operating costs. The proposed solutions can be used in the design of intelligent sensors and integration into ATPCS, as well as in the creation of digital counterparts and cyber-physical production systems.

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