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INTELLIGENT MICROCLIMATE CONTROL IN INDUSTRIAL PREMISES USING HYBRID NEURAL–FUZZY MODEL

ІНТЕЛЕКТУАЛЬНЕ КЕРУВАННЯ МІКРОКЛІМАТОМ У ПРОМИСЛОВИХ ПРИМІЩЕННЯХ З НЕЙРО-НЕЧІТКОЮ МОДЕЛЛЮ

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Abstract. *Purpose*. The article considers the problem of intelligent microclimate control in industrial premises, which plays a decisive role in maintaining the stability of technological processes, ensuring product quality, reducing energy consumption, and guaranteeing occupational safety. The purpose of this research is to develop and validate a hybrid predictive and control system capable of adapting to dynamic industrial conditions and maintaining stable operating parameters under uncertainty.
Method. The methodology of the study is based on combining a nonlinear autoregressive neural network with exogenous inputs (NNARX) for forecasting key microclimate indicators with a fuzzy logic controller (FLC) for generating effective control actions. The system was implemented in the Python environment using the Keras library, which allowed flexible tuning of the network structure, adjustment of the number of layers and neurons, and testing of different architectural configurations. To improve robustness and generalization ability, regularization, dropout, complexity control, and artificial variation of input data within physical ranges were applied.
Results. The results of modeling confirmed that the developed system provides accurate forecasting of temperature and humidity, ensures stable control performance, and reduces prediction errors even under variable conditions. Comparative analysis demonstrated that the integration of NNARX prediction with fuzzy logic outperforms classical methods by combining forecasting accuracy with adaptive decision-making.
Scientific novelty. The scientific novelty of the work lies in the integration of predictive neural modeling and fuzzy logic control into a single architecture for intelligent microclimate regulation in production.
Practical importance. The practical significance is defined by the possibility of implementing the proposed approach in industrial cyber-physical systems to optimize energy use, increase the reliability of technological processes, and reduce human influence on decision-making. Future research directions include validation of the model with real production data and adaptation of the proposed architecture to various industrial domains requiring precise and energy-efficient microclimate control.
Key words: intelligent control; microclimate; cyber-physical systems; nnarx; fuzzy controller.

Анотація. *Мета*. У статті розглянуто проблему інтелектуального керування мікрокліматом у промислових приміщеннях, що має ключове значення для забезпечення стабільності технологічних процесів, підтримання якості продукції та зниження енергетичних витрат. Метою дослідження є створення гібридної системи прогнозування та керування, яка забезпечує адаптивність і стійкість у динамічних промислових умовах.
Методика. Методика дослідження ґрунтується на поєднанні нейромережевої моделі типу NNARX для прогнозування ключових параметрів та нечіткого логічного контролера для прийняття керуючих рішень. Реалізація виконана у середовищі Python із використанням бібліотеки Keras, що дозволило налаштовувати архітектуру мережі, варіювати кількість шарів і нейронів та оцінювати різні конфігурації. Для підвищення точності та узагальнюючої здатності застосовано регуляризацію, Dropout, контроль складності моделі та штучне варіювання вхідних даних.
Результати. Результати моделювання підтвердили здатність системи з високою точністю прогнозувати температуру та вологість, забезпечувати стабільність регулювання й знижувати похибку навіть в умовах невизначе-

ності. Порівняння з класичними методами продемонструвало переваги інтеграції прогнозної нейромережевої моделі з нечіткою логікою, що забезпечує гнучкість реагування на змінні фактори.
Наукова новизна. Наукова новизна роботи полягає у створенні комбінованої архітектури NNARX+FLC, яка поєднує прогнозування та адаптивне керування в єдиній системі.
Практична значимість. Практична значимість визначається можливістю впровадження запропонованого підходу у промислові кіберфізичні комплекси для оптимізації енергоспоживання, підвищення надійності технологічних процесів і зменшення впливу людського фактора. Перспективним напрямом є перевірка моделі на реальних даних і її адаптація до різних галузей промисловості.
Ключові слова: інтелектуальне керування; мікроклімат; кіберфізичні системи; nnarx; нечіткий контролер.

TASK STATEMENT

Ensuring a stable microclimate in industrial premises is a critical condition for the efficiency of technological processes, rational use of energy, and personnel safety. Classical control systems based on simplified linear models are unable to fully account for the nonlinearity and multifactorial nature of processes, which leads to reduced accuracy and reliability of control. The microclimate is formed under the influence of a complex of interrelated factors: internal environmental parameters, external disturbances, and the history of previous system states. This creates a high level of uncertainty that makes it impossible to rely solely on traditional approaches. Under such conditions, there is a need for intelligent methods capable of adaptively modeling dynamics and making effective decisions.

This study considers an approach based on a neural network with autoregressive connections combined with fuzzy logic, which makes it possible to integrate the advantages of forecasting and adaptive control. The main task is to verify the effectiveness of such an architecture for stabilizing microclimate parameters in industrial conditions and to assess its practical applicability for implementation in cyber-physical systems.

ANALYSIS OF RECENT RESEARCH AND PUBLICATIONS

In [1], the directions of artificial intelligence application in climate research and energy systems are summarized, confirming the relevance of intelligent methods for optimizing microclimate processes. Study [2] demonstrates the role of digital twins in smart manufacturing and emphasizes the integration of sensor systems, IoT, and AI, which corresponds to the concept of cyber-physical systems. In [3], the implementation of intelligent HVAC solutions aimed at reducing energy consumption through sensors and AI algorithms is considered, which confirms the relevance of the chosen approach for industrial conditions.

Article [4] focuses on the cybersecurity of SCADA/HMI through user authentication in unprotected networks, which is important for the secure implementation of intelligent control systems. Work [5] confirms the effectiveness of NNARX in time series forecasting tasks, which is a key element in building the predictive subsystem of our model. In [6], the feasibility of using type-2 fuzzy systems for handling uncertainty is demonstrated, which determines a promising direction for improving the fuzzy controller.

Review [7] highlights the application of hybrid AI–fuzzy logic models in photovoltaic systems, confirming the effectiveness of combined approaches in other fields as well. In [8], the use of hybrid methods in smart grids to enhance real-time energy efficiency is analyzed, which resonates with our task of adaptive microclimate regulation.

In [9], a sensor system for mobile robot navigation is developed, emphasizing the role of multisensory monitoring and real-time data processing — an approach also important for our microclimate model. Study [10] compares neural networks and MPC in energy flow control tasks, proving the adaptability and flexibility of AI-based approaches. In [11], approaches to building industrial CPS are systematized, with emphasis on cybersecurity, which is a necessary condition for implementing intelligent systems.

Article [12] describes a method for synthesizing CPS operation algorithms that ensures coordination and optimization of their work, which directly correlates with the algorithmic part of our system. Review [13] is devoted to neuro-fuzzy architectures in the context of interpretable AI, confirming the importance of decision-making transparency. In [14], aspects of cyber resilience and protection in CPS are emphasized, which are critically important for industrial control systems. In [15], a declarative CPS modeling language is developed, which directly correlates with our task of parameter formalization and construction of a decomposition model of the microclimate.

Thus, the analyzed studies demonstrate the intensive development of intelligent methods in climate optimization tasks, the implementation of hybrid models, and their integration into cyber-physical systems. They confirm the feasibility of the selected NNARX+FLC architecture for the industrial environment, which combines forecasting and fuzzy logic to ensure adaptability and efficiency of microclimate control.

SEPARATION OF PREVIOUSLY UNRESOLVED PARTS OF THE OVERALL PROBLEM

Despite advances in intelligent control, many issues remain. Traditional methods cannot fully handle multifactor influences, and neural networks often struggle under uncertainty, noise, and rapid changes. Most research addresses forecasting or optimization separately, without combining predictive accuracy and adaptive control. The integration of NNARX models with fuzzy controllers into unified adaptive systems for industrial microclimate regulation is still underexplored, creating the need for hybrid solutions that ensure forecasting, adaptation, and robustness in real production environments.

PURPOSE OF THE STUDY

The aim of this study is the development and validation of an intelligent microclimate control system for industrial premises based on the integration of a predictive neural network model of the NNARX type and a fuzzy logic controller. The proposed system is designed to ensure high accuracy in forecasting environmental parameters, adaptability to external disturbances, and stability of technological processes, while simultaneously optimizing energy consumption and enhancing the efficiency of industrial cyber-physical systems.

METHODS, OBJECT, SUBJECT AND METHODS OF RESEARCH

Methods. Observation, analysis and synthesis, mathematical modeling, methods of artificial neural networks, fuzzy logic, and experimental modeling in Python using the Keras library.

Object of the study – microclimate control processes in industrial premises under conditions of variable external and internal factors.

Subject of the study – development and integration of a hybrid neural network model of the NNARX type with a fuzzy logic controller into the intelligent microclimate control system of industrial cyber-physical complexes.

THE MAIN MATERIAL

Maintaining optimal microclimate parameters in industrial production facilities is one of the key factors in ensuring the stability of technological processes, preserving product quality, and safeguarding personnel. In modern production environments, particularly in industries with strict requirements for temperature-humidity regimes, air composition, and airflow rates, even minor deviations from the set parameters can lead to significant economic losses, reduced productivity, and deterioration of the final product's quality.

Traditional automatic microclimate control systems, based on rigidly predefined algorithms or PID controllers, often prove insufficiently effective in cases where the production environment is characterized by high inertia, nonlinearity, and a large number of interrelated factors. Such systems can maintain an acceptable regime under stable conditions; however, their adaptability to abrupt external changes (e.g., fluctuations in outdoor air temperature, variations in equipment performance, or changes in system load) remains limited. As a result, they are not always able to provide fast and accurate responses to unpredictable changes in microclimate parameters, which reduces overall energy efficiency and production stability.

In the context of the growing integration of production processes into digital ecosystems, intelligent control methods capable of combining monitoring, forecasting, and adaptive optimization functions gain special importance. Within the development of cyber-physical systems (CPS) equipped with networks of distributed sensors and actuators, there arises the possibility of performing a comprehensive analysis of current and predictive data, thereby enhancing the accuracy and stability of regulation. Intelligent approaches, particularly those based on artificial neural networks and fuzzy logic, provide the ability for self-organization and automatic adjustment of control algorithms depending on changing conditions.

The key scientific problem addressed in this work is the creation of an adaptive microclimate control system capable of functioning under the complex dynamics of industrial environments. The distinctive feature of the proposed approach is the combination of an NNARX-type model for predicting microclimate parameters with a FLC. This combination makes it possible to account for process nonlinearity, anticipate future system states, and implement more flexible control of actuators.

The choice of the NNARX architecture is driven by its ability to reproduce complex temporal dependencies arising in microclimate dynamics, while the use of FLC enables the formalization of expert knowledge and the handling of fuzzy boundaries between "normal" and "critical" modes. This integration provides the foundation for an adaptive system capable of improving prediction accuracy and reducing the need for manual intervention.

Further analysis showed that among the available architectures, it was the NNARX combined with fuzzy logic that proved to be the most suitable for solving the stated problem. To confirm this, several commonly used approaches were considered — multilayer perceptrons (MLP), recurrent neural networks (RNN), and other alternatives. The choice in favor of NNARX+FLC is based on a comparative assessment of their capabilities in forecasting and accounting for external factors that create complex and nonlinear dynamics of industrial processes.

MLP is a classical example of a fully connected neural network that effectively approximates complex nonlinear dependencies. However, in time series forecasting tasks, it demonstrates limited ability to account for the temporal structure of data. To reproduce process dynamics, it is necessary either to artificially expand the input vector with values from previous time steps or to integrate external memory modules. In the context of microclimate control, this means that although MLP can accurately approximate static dependencies, it does not always respond adequately to rapid changes and does not account for the inertial properties of production systems.

RNNs, by contrast, are distinguished by their internal feedback loops, which provide them with the ability to handle temporal dependencies without explicitly duplicating input data. They can store previous states, making them useful for predicting dynamic processes. At the same time, in practical industrial conditions, RNNs often suffer from the problem of vanishing or exploding gradients during training, which complicates their application over long time intervals. Furthermore, their high computational complexity and demand for large training datasets make them less attractive for systems where the model must be updated quickly or work with a limited amount of data.

NNARX architectures represent a natural extension of autoregressive modeling ideas. They use both past values of the target variable and exogenous input factors, which allows the model to effectively account for the influence of both the system's internal dynamics and external conditions. For the task of microclimate control, this is particularly important, since the state of the indoor environment is simultaneously affected by controlled technological parameters and uncontrollable external disturbances. The advantage of NNARX is its ability to operate with relatively small datasets while maintaining high forecasting accuracy.

The combination of NNARX with a FLC makes it possible to merge the strengths of both approaches. The NNARX model generates forecasts of key microclimate parameters based on historical and current data, while the FLC provides adaptive control using a set of rules that reflect expert knowledge and account for fuzzy boundaries between acceptable and critical system states. Such integration enables the system to respond to predicted changes before they manifest in measured values, thereby reducing inertia and improving stability.

The comparative analysis shows that although MLP and RNN offer advantages in reproducing complex dependencies, they have significant limitations in industrial environments characterized by high inertia and the influence of numerous exogenous factors. NNARX, due to its structure, is better suited to such conditions, and the addition of FLC provides the system with the ability to perform adaptive optimization based on fuzzy rules. As a result, a hybrid system is obtained that combines forecasting and control, ensuring high accuracy, robustness under uncertainty, and efficient energy use.

The developed intelligent microclimate control system is implemented as a multilayer architecture that integrates the NNARX neural network model with the FLC. This approach allows for both accurate time series–based forecasting and adaptive decision-making under uncertainty. Each level of the architecture performs specific functions and interacts with other elements within a closed-loop control system.

At the first level, a set of sensors continuously collects environmental data such as temperature, humidity, gas concentrations, and other key indicators. The sensor data are transmitted to a preprocessing module, where they undergo noise filtering and normalization to a specified range, ensuring the stability of the forecasting model. At this stage, historical parameter values are also taken into account, forming the autoregressive structure of the input data.

The second level is represented by the NNARX neural network, which performs forecasting of future microclimate parameters. A key feature of this architecture is its ability to incorporate exogenous signals, meaning that it accounts for the influence of both internal factors (system states) and external ones (environmental changes, operation of technological equipment). The model consists of an input layer that receives both current and past values of the parameters, one or more hidden layers that detect nonlinear dependencies, and an output layer that generates forecasts for a specified time horizon.

Figure 1 demonstrates the sequence and interconnections between components: from data collection by sensors to processing by the neural network, transmission of predictions to the fuzzy logic controller, and generation of control signals for actuators. This visualization helps to clarify the logic of information flow and feedback.

The third level is represented by the FLC module, which receives predicted parameters from the neural network and, based on a set of fuzzy rules, transforms them into specific control actions. The use of fuzzy logic makes it possible to account for measurement inaccuracies and incomplete data, while maintaining stability of control even in situations where an exact mathematical model of the process is complex or infeasible.

The fourth level consists of actuators that implement the regulator's commands: ventilation systems, heating and cooling elements, humidifiers, and other equipment. Their operation is controlled in real time, and the results of their actions are directly reflected in sensor measurements, forming the feedback loop for closed-loop control.

To ensure the proper functioning of the NNARX model, careful selection of input parameters is crucial. These parameters must reflect both the current state of the microclimate and its dynamics over time. Particular attention is given to combining direct measurements with autoregressive components, which provide the network with «memory» of the system's previous states.

Table 1 presents a generalized description of the input signals, their type, a short explanation, and justification for their inclusion in the model. These parameters form a multidimensional feature space in which the neural network performs forecasting. Such an approach allows the system to take into account process inertia, the influence of exogenous factors, and ensures improved prediction accuracy.

The information in the table demonstrates that each signal has a clearly defined role in modeling: from target controlled variables (e.g., indoor temperature) to external influences and the system's memory of its own previous

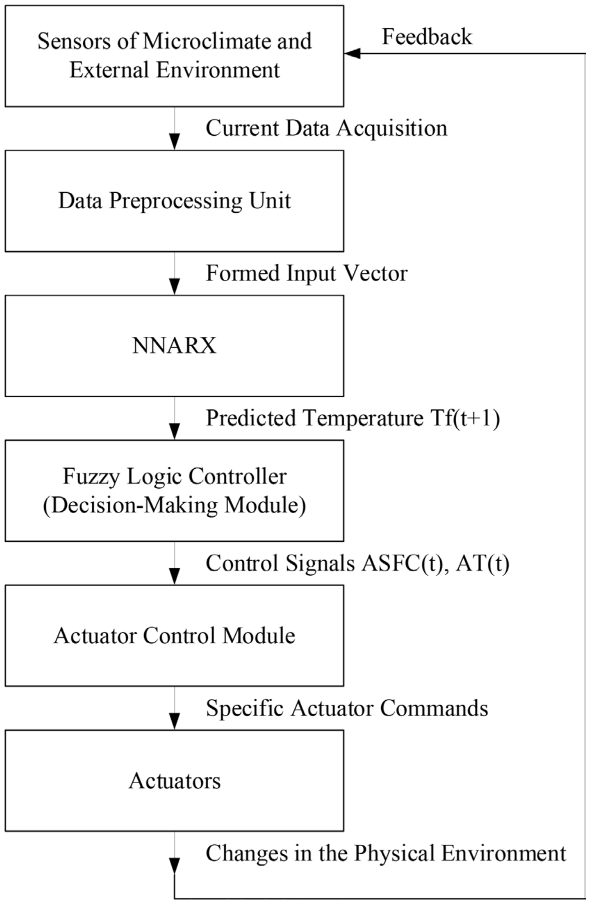

Fig. 1. Block diagram of data flow and control with NNARX

states. This combination enables the NNARX model to capture complex nonlinear dependencies and interactions of factors that determine the microclimate in industrial premises, while maintaining forecast stability even under significant environmental variability.

Thus, the use of the hybrid NNARX+FLC architecture combines forecasting accuracy with adaptive control. This ensures the system's ability to maintain optimal microclimate parameters under changing conditions, avoid excessive energy consumption, and account for production constraints. An additional advantage is the possibility of integrating the solution into industrial cyber-physical systems, which makes the approach scalable and reliable.

At the next stage of the study, the focus was on the practical implementation and training of the model. For this purpose, a training dataset was formed, preliminary parameter tuning was carried out, and a series of experiments was organized, the results of which made it possible to evaluate the architecture's ability to reproduce the dynamics of real microclimate processes.

Training was conducted within the paradigm of supervised learning, where both input data and target output values are known. The main objective was to minimize the difference between predicted and actual temperature values, which is formalized through the Mean Squared Error (MSE) function:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2, \tag{1}$$

where: n – number of observations, y_i – actual value, a $\hat{y}_i$ – predicted value.

To interpret the error in the same units as the predicted parameter, the Root Mean Squared Error (RMSE) was also used:

$$RMSE = \sqrt{MSE}. \tag{2}$$

The adaptation of the network's weight coefficients was carried out using the backpropagation method in combination with the Adam optimizer, which provides automatic adjustment of the learning rate for each parameter. This made it possible to achieve fast convergence even in the presence of a large number of input features and time delays inherent to the NNARX

Table 1. NNARX Input Parameters and Justification

Parameter	Type	Short Description	Justification
$Ti(t)$	Current	Indoor Air Temperature	The main indicator of the internal microclimate and the target parameter for control
$Ta(t)$	Current	Outside Air Temperature	A key exogenous factor influencing the building's thermal balance
$RH(t)$	Current	Indoor Relative Humidity	An important factor for comfort and its impact on production processes
$S(t)$	Current	Solar Radiation Intensity	A significant external factor affecting heat gain
$Ti(t-k)$	Historical	Previous indoor temperature values	Allows accounting for inertia and dynamics of internal thermal processes
$Ta(t-k)$	Historical	Previous outdoor temperature values	Allows accounting for the dynamics of external temperature changes and their impact
$RH(t-k)$	Historical	Previous indoor humidity values	Allows accounting for the dynamics of humidity changes and their impact on the microclimate
$S(t-k)$	Historical	Previous solar radiation values	Allows accounting for the cumulative effect of solar radiation
$Tf(t-1)$, $Tf(t-2)$,...	Historical	Allows incorporating predictive correction and assessing model accuracy over time	A key autoregressive component that provides the network with «memory» of its previous states and the system's inertia.

model. The training process was accompanied by continuous monitoring of the error on the validation set in order to promptly detect signs of overfitting.

To enhance the generalization ability and robustness of the model, several complementary approaches were applied. The optimal architecture configuration was determined in such a way as to avoid excessive depth or an excessive number of parameters that could lead to overfitting. Overfitting prevention mechanisms included L2 regularization (weight decay), which limited excessive growth of weights, and Dropout in the hidden layers, which reduced correlations between neurons and increased the diversity of internal data representations. Additionally, early stopping was applied when the validation set performance stabilized or started to deteriorate, thus preventing excessive adaptation of the model to the training examples. In cases of insufficient real data, artificial dataset augmentation was carried out by varying the input signals within admissible physical ranges. To further improve result stability, ensemble learning was occasionally used, combining several network variants with different initial weights and hyperparameter settings.

The combination of these methods ensured a balance between forecasting accuracy and the model's ability to adapt to variable industrial conditions. As a result, the obtained NNARX configuration demonstrated not only high accuracy but also stable performance under noisy, incomplete, or changing input data — a feature critically important for an intelligent microclimate control system.

The experimental part of the study was aimed at verifying the operability and effectiveness of the constructed NNARX forecasting model in the context of intelligent microclimate control tasks in industrial premises. The main objective was to determine the model's ability to reproduce the dynamics of temperature changes based on the history of previous values and external factors, thereby enabling timely generation of control actions. The experimental tasks included testing the adequacy of the model's architecture, assessing its robustness to noise and variable conditions, and evaluating prediction accuracy under conditions of limited data availability.

To achieve these objectives, a synthetically generated dataset was used, which allowed full control over the influence of each parameter and avoided uncontrolled external disturbances typical of real industrial facilities. This approach had several advantages: first, it provided the ability to vary ranges and combinations of values without the risk of obtaining distorted dependencies; second, it ensured a sufficient number of training examples without the need for long-term field data collection; third, it created conditions for testing the model under edge cases, which occur rarely in real data but are critical for the system's stability.

The dataset structure was designed in accordance with the requirements of the NNARX model and included a time stamp along with parameters representing internal and external microclimate conditions. The input features comprised the indoor air temperature T_{in}, outdoor air temperature T_{out}, indoor air humidity H_{in}, carbon dioxide concentration CO_2, fan operation intensity$Fans_{reg}$, and the level of heating influence *Heat*. The output variable was the predicted indoor temperature, which had a direct impact on the formation of control actions. To ensure training stability, all numerical parameters were normalized to the range [0,1], which reduced the influence of scale differences and accelerated the convergence of the optimization algorithm.

Special attention was paid to the formation of training samples using the sliding window method. This approach assumed that, in order to predict the value at time *t*, a certain number of previous observations within a fixed-length time window were used. Such a method captures temporal dependencies between observations and reflects the inherent inertia of microclimate systems. The optimal window length was determined experimentally by comparing prediction accuracy across different values of this parameter.

The model was implemented in Python using the Keras library, which provided flexibility in configuring the architecture and enabled rapid testing of various configurations. The architecture included an input layer receiving values from the sliding window, one or several hidden layers with ReLU activation, and an output layer with linear activation generating the temperature forecast. The number of neurons in hidden layers and the delay parameters of input signals were determined experimentally, ensuring a balance between predictive accuracy and computational complexity.

An important element of the experiment was the proper division of the dataset into training, validation, and test sets, which allowed for an objective evaluation of the model's generalization capability. Training was accompanied by monitoring the validation error and applying early stopping if no improvement was observed over a predefined number of epochs. This helped to avoid overfitting and ensured robustness of the model under noisy or partially incomplete input data.

Thus, the designed experimental plan allowed us to verify the key research hypothesis, namely, that the NNARX model is capable of accurately predicting the dynamics of indoor temperature in production facilities using a limited set of measured parameters while accounting for temporal dependencies of the process. The results obtained during modeling confirmed the effectiveness of the chosen architecture and training methods, as well as its potential for deployment in real intelligent microclimate control systems.

After the training stage was completed, an evaluation of the NNARX predictive model integrated with the FLC was conducted. The aim of the analysis was to determine the forecasting accuracy of microclimate parameters and to verify the stability of the model under input variability.

In addition to visual analysis, the model's performance was quantitatively assessed using classical forecasting metrics – Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). On the test set, the NNARX model achieved the following results: MAE = 0.5766; RMSE = 0.7107. These values indicate acceptable accuracy for short-term forecasting of microclimate parameters based on synthetic data. The presence of noise and variability in the input parameters reproduces the conditions of industrial environments, where ideal data are unattainable. In real scenarios, further error reduction may be achieved by expanding the dataset, improving the network architecture, or applying more advanced models such as LSTM or ensemble approaches.

The visualization of model performance (Figure 2) demonstrates a strong correlation between predicted and actual temperature values. The plot shows that the model is capable of accurately reproducing both general trends and local fluctuations, while maintaining forecast stability even under varying external factors. Minor discrepancies occur mainly in peak values, which can be explained by the limited number of training examples available for extreme operating conditions.

Figure 3 shows the dynamics of the mean squared error (MSE) changes for the training and validation datasets over 25 training epochs of the NNARX model. A rapid decrease in error is observed at the initial stages, followed by stabilization, which indicates effective training without significant overfitting. The close MSE values for the training and validation datasets demonstrate good model consistency and the ability to generalize knowledge to new data.

The obtained results confirm that the proposed hybrid NNARX+FLC architecture provides accurate and adaptive forecasting of microclimate parameters, surpassing classical regression methods in its ability to capture nonlinear dependencies and dynamic changes. The combination of the neural network component for forecasting and the fuzzy logic controller for decision-making enables the system to operate stably under conditions of uncertainty and incomplete input data.

In summary, the experimental implementation validated the effectiveness and practical applicability of the NNARX+FLC architecture in intelligent microclimate control systems for industrial facilities. Prospects for further research are associated with testing the model on real production data and expanding the scope of its application.

DISCUSSION OF THE RESULTS OBTAINED

The conducted experiments demonstrated that the hybrid NNARX + FLC architecture provides a significant

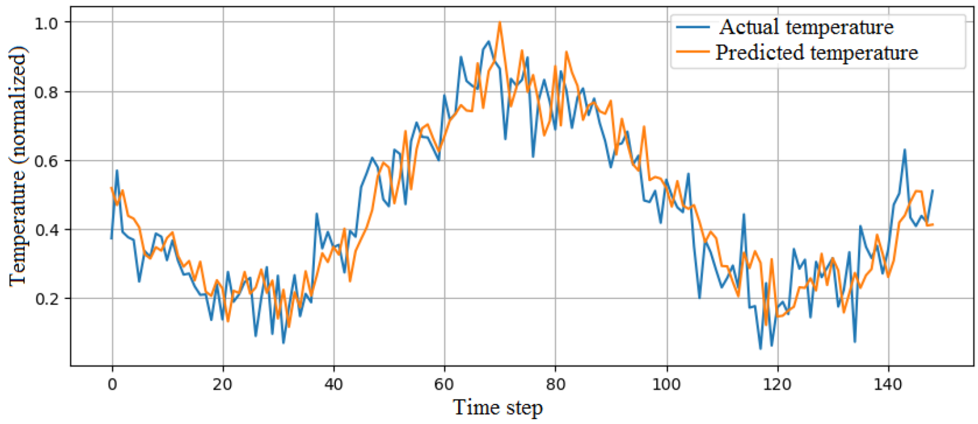

Fig. 2. Comparison of actual and predicted temperature on the test dataset

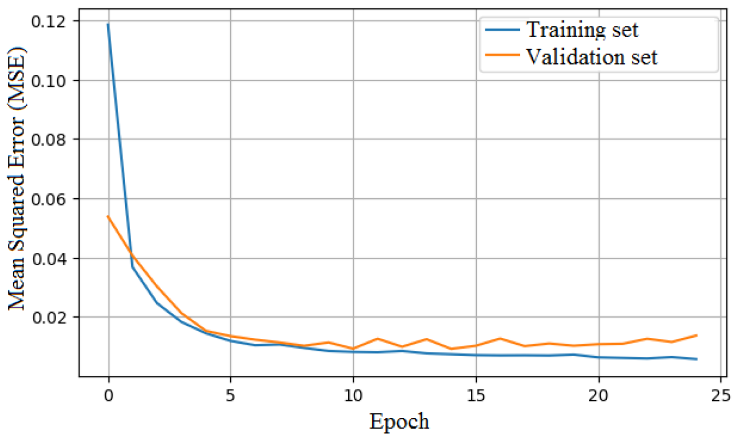

Fig. 3. NNARX training loss dynamics

improvement in forecasting accuracy and adaptability compared to traditional control methods. The system successfully maintained stable microclimate parameters under varying external influences and noise, confirming its robustness and practical applicability.

The results also showed that combining predictive neural network modeling with fuzzy logic rules enables not only accurate short-term forecasting but also flexible adaptation of control actions to production constraints. Such integration contributes to reducing energy consumption and minimizing the need for manual intervention, making the proposed solution particularly relevant for implementation in modern industrial cyber-physical systems.

CONCLUSIONS

The conducted study confirmed the effectiveness of the proposed hybrid NNARX + FLC architecture for intelligent microclimate control in industrial facilities. The model demonstrated the ability to predict the dynamics of key parameters with sufficient accuracy while maintaining adaptability to external influences and production constraints. This made it possible to achieve a balance between the stability of technological processes and rational energy consumption.

The results of experimental modeling in Python using the Keras library showed that the application of autoregressive structures with historical data combined with fuzzy logic decision-making provides a flexible control mechanism. This approach allows not only predicting changes in environmental parameters but also implementing control actions adapted to production constraints, ensuring the system's reliability under uncertainty.

The obtained results indicate the feasibility of integrating the proposed architecture into cyber-physical systems of industrial enterprises. Further research will focus on testing the model with real production data, expanding the range of controlled parameters, and adapting the developed approach to various industrial scenarios requiring precise and energy-efficient microclimate regulation.

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