Proceedings of the 7th International
Scientific and Practical Conference
«Innovative Development in the
Global Science»

(May 26-28, 2026).
Boston, USA

No
296

INTERCONF
Scientific Publishing Center

RADIO ENGINEERING, ELECTRONICS AND ELECTRICAL ENGINEERING

Development of a Self-learning and Adaptation Algorithm for Microclimate Control System Using Sensor Networks

Yevsieiev Vladyslav Viacheslavovych[1], Holod Ihor Viktorovych[2]

[1] Professor of the Department of Computer-Integrated
Technologies and Robotics (CITAR),
Academic Secretary of the Specialized Academic Council,
Doctor of Technical Sciences, Professor;
Kharkiv National University of Radio Electronics; Ukraine

[2] PhD student, Department of Computer Integrated Technologies,
Automation and Robotics;
Kharkiv National University of Radio Electronics; Ukraine

Abstract. The paper presents an algorithm for self-learning and adaptation of an intelligent microclimate control system for industrial premises, operating based on a cyber-physical architecture with the use of a distributed sensor network. The mechanism of incremental retraining of an NNARX neural network model during operation is described, ensuring gradual refinement of the model's predictive properties considering real production conditions. The architecture of the sensor subsystem is presented, including sensors for temperature, humidity, gas concentration, and differential pressure, integrated via industrial interfaces RS-485 and Modbus RTU/TCP protocols. The results of experimental studies are provided, confirming the effectiveness of the developed algorithm: periodic retraining of the model based on accumulated operational data ensures a reduction in the mean absolute prediction error by 12-15%, while the system maintains temperature with a deviation of no more than 0.5 °C from the setpoint under external temperature fluctuations of 5-7 °C. It is shown that adaptive tuning of the fuzzy logic controller parameters, performed in parallel with neural network retraining, provides an additional improvement in transient response quality and a reduction in stabilization time.

Keywords: *self-learning, adaptation, sensor network, microclimate, NNARX, fuzzy controller, cyber-physical system, Modbus, predictive control.*

The development of adaptive microclimate control systems for industrial premises is one of the key directions in the advancement of industrial automation under conditions of digital transformation of production. Traditional control systems based on PI and PID controllers with fixed tuning parameters demonstrate acceptable control quality under conditions of stability of the controlled object characteristics and external disturbances.

However, in real operating conditions, the parameters of the production environment undergo continuous changes caused by seasonal temperature fluctuations, equipment wear, changes in technological process modes, modifications of ventilation channel configurations, and other factors, which inevitably lead to a gradual decrease in control accuracy. These circumstances determine the relevance of developing self-learning and adaptation algorithms that ensure automatic adjustment of control system parameters during operation without operator intervention [1].

The conceptual basis of the developed algorithm is the principle of incremental retraining of an NNARX neural network forecasting model based on operational data continuously received from the sensor network. The NNARX model, which serves as the predictive core of the control system, represents the relationship between current and previous values of microclimate parameters and generates a forecast of air temperature for the next time step. Formally, the model is described by the following relation:

$$y(t+1) = F(y(t), y(t-1), \dots, y(t-ny), u(t), u(t-1, \dots, u(t-nu)) \qquad (1)$$

where ***y*** *— predicted microclimate parameter,* ***u*** *— vector of exogenous input variables,* ***ny*** *and* ***nu*** *— delay orders of the output and input variables, respectively,* ***F*** *— a nonlinear function implemented by a neural network. Initial training of the model is performed on a prepared dataset using the Adam optimizer and the mean squared error loss function, after which the trained weights are saved in .h5 format for deployment on an industrial controller.*

The architecture of the sensor subsystem of the developed hardware-software module ensures continuous monitoring of microclimate parameters with high accuracy and reliability. The sensor network includes air temperature sensors with a measurement range from -30 to +60 °C and an accuracy class not worse than 0.5 °C, relative humidity sensors with a range from 0 to 100% and an error not exceeding 3%, carbon dioxide concentration sensors with a range up to 5000 ppm and an accuracy of 50 ppm, as well as differential pressure sensors for airflow control and optional solar radiation sensors for glazed помещений. All sensors have an enclosure protection rating of at least IP65 and standard analog output signals of

4-20 mA or 0-10 V, ensuring compatibility with common industrial data acquisition systems [2].

Data exchange between the components of the sensor network and the controller is carried out via the industrial serial interface RS-485 using the Modbus RTU protocol, which ensures reliable data transmission in industrial environments with electromagnetic interference. Integration with higher-level automation systems such as SCADA and MES is implemented via the Ethernet interface using the Modbus TCP protocol. The MR100-24.02.2 data acquisition module performs analog-to-digital conversion of sensor signals, their filtering and normalization, after which the processed values are transmitted to the KSP-08.L controller running a Linux operating system that supports Python script execution and ensures interaction between all software modules of the system [3].

The self-learning algorithm is implemented as a background process in the Linux environment of the controller and does not interfere with the main real-time control loop. During operation, the system continuously accumulates data from the sensor network, storing it in an internal SQLite database with timestamps. The accumulated data include temperature, humidity, gas concentration values, actuator states, and model prediction results. When a defined volume of new data is reached or a specified time interval elapses, a retraining cycle is initiated.

The retraining mechanism is based on the backpropagation algorithm using a small learning rate, which ensures gradual refinement of the weight coefficients without disrupting the stability of previously formed relationships. The weight update is performed according to the following rule:

$$w_{new} = w_{old} - \eta * {}^{\partial E}/_{\partial w} \tag{2}$$

where η — is a small learning rate, E — is the mean squared error loss function. This approach allows the model to adapt to gradual changes in the dynamics of the controlled object, including seasonal variations in the external environment, equipment wear, or modifications in the characteristics of ventilation channels, without the need for a full retraining phase [4].

In parallel with the retraining of the neural network model, a mechanism for adaptive tuning of the fuzzy logic controller parameters has been implemented. The scaling coefficients of the membership functions are automatically adjusted depending on the magnitude of the mean error between the predicted and actual temperature values. In the presence of large deviations, the system activates a high-sensitivity mode of the fuzzy controller, ensuring a more intensive response to changes in microclimate parameters. Under stable operation and low error values, the system reduces the intensity of corrections, switching to an energy-efficient control mode, which decreases actuator wear and reduces energy consumption.

The operation of the developed algorithm is implemented within a three-level modular software architecture. The data acquisition module performs cyclic reading of sensor data with a sampling period of 10 seconds, applies filtering and normalization of measurement data, and stores the results in an SQLite database. The prediction module loads the trained NNARX model in .h5 format, forms the input vector based on recent observations considering the autoregressive component, and generates a temperature forecast for the next time step. The control action module generates decisions based on a combination of NNARX predictions and fuzzy logic controller rules and transmits commands to actuators via the pymodbus and minimalmodbus libraries. Interaction between modules is ensured through a shared SQLite database, which functions as an inter-process communication mechanism [5].

The results of experimental studies confirm the effectiveness of the developed self-learning and adaptation algorithm. Initial training of the NNARX model on real-world data yielded a mean squared error of 0.091, a root mean squared error of 0.302 °C, and a mean absolute error of 0.248 °C. After several retraining cycles based on operational data accumulated over several days of system operation, a reduction in the mean absolute prediction error by 12–15% was observed. The summarized results of the comparative analysis are presented in Table 1.

As shown in the table, the greatest effect is achieved by combining neural network model retraining with adaptive tuning of the fuzzy logic controller parameters. This combination provides a reduction in the mean absolute prediction error from 0.248 to 0.210 °C, improves setpoint tracking accuracy from 0.5 to 0.35 °C, and reduces the stabilization time to 2–4 minutes. The absence of overshoot is maintained at all stages of adaptation, indicating the stability and safety of the algorithm's operation. An increase in energy efficiency by 15-18% is achieved due to more accurate forecasting, which allows control actions to be generated in advance and avoids excessive activation of actuators.

Table 1

Comparative characteristics of control systems with different levels of adaptability

Indicator	System without adaptation	System with retraining NNARX	Full adaptation (NNARX + adaptive FLC)
MAE forecast, °C	0.248	0.215	0.210
Setpoint maintenance accuracy, °C	0.5	0.4	0.35
Stabilization time, min	3-5	2.5-4.5	2-4
Seasonal adaptation	None	Retraining of the model	Further learning + adaptive FLC
Overshoot	None	None	None
Energy efficiency	Basic	Increased by 10-12%	Increased by 15-18%

An important feature of the developed algorithm is its full autonomy: retraining and adaptation cycles are initiated by the system independently without operator intervention. After each retraining cycle, the updated model weights are automatically saved in a .h5 file and connected to the prediction module, ensuring continuous improvement of forecasting quality. The event log maintained in the SQLite database records all stages of adaptation and enables tracking of the model accuracy dynamics over time, which is essential for diagnostics and performance analysis of the system [6].

Conclusions. The paper presents an algorithm for self-learning and adaptation of an intelligent microclimate control system for industrial premises, based on incremental retraining of an NNARX neural network model and adaptive tuning of fuzzy logic controller parameters using data from a distributed sensor network. It is shown that the combination of these two adaptation mechanisms provides a reduction in the mean absolute prediction error by 12-15%, improves temperature control accuracy to 0.35 °C from the setpoint, and reduces stabilization time to 2-4 minutes under external temperature fluctuations of 5–7 °C. The full autonomy of the algorithm eliminates the need for manual system retuning and ensures its continuous self-improvement during operation.

Further research should be focused on developing criteria for automatic determination of the optimal moment to initiate the retraining cycle based on the analysis of prediction error dynamics, implementing ensemble forecasting methods to increase robustness to anomalous measurements in the sensor network, and extending the adaptation algorithm for simultaneous control of multiple microclimate parameters, in particular humidity and gas concentration.

References:

[1] Nevliudov, I., Yevsieiev, V., Baker, J. H., Ahmad, M. A., & Lyashenko, V. (2020). Development of a cyber design modeling declarative Language for cyber physical production systems. *J. Math. Comput. Sci.*, *11*(1), 520-542. https://doi.org/10.28919/jmcs/5152

[2] Bouzeffour, F., & Khelidj, B. (2023). An application of nonlinear autoregressive (NARX) model to predict adsorbent bed temperature of solar adsorption refrigeration system. Journal of Systems Science and Systems Engineering, 32(6), 687-707. https://doi.org/10.1007/s11518-023-5578-4

[3] Nevliudov, I., Omarov, M., Yevsieiev, V., Bronnikov, A., & Lyashenko, V. (2020). Method of Algorithms for Cyber-Physical Production Systems Functioning Synthesis. https://doi.org/10.30534/ijeter/2020/1278102020

[4] Bag, S., Gupta, S., & Kumar, S. (2021). Industry 4.0 adoption and 10R advance manufacturing capabilities for sustainable development. International Journal of Production Economics, 231, 107844. https://doi.org/10.1016/j.ijpe.2020.107844

[5] Lasi, H., Fettke, P., Kemper, H. G., Feld, T., & Hoffmann, M. (2014). Industry 4.0. Business & Information Systems Engineering, 6, 239-242. https://doi.org/10.1007/s12599-014-0334-4

[6] Ogundiran, J., Asadi, E., & Gameiro da Silva, M. (2024). A systematic review on the use of AI for energy efficiency and indoor environmental quality in buildings. Sustainability, 16(9), 3627. https://doi.org/10.3390/su16093627