Comparative Analysis of Neural Network Architectures for Intelligent Microclimate Control in Production

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Abstract: A comparative analysis of neural network architectures (MLP, RNN, NNARX) for predicting microclimate parameters in industrial cyber-physical systems has been carried out. The advantages of NNARX in reproducing environmental dynamics are demonstrated, and its application for intelligent control is substantiated.

Keywords: microclimate, neural networks, NNARX, forecasting, control.

I. INTRODUCTION

Maintaining optimal microclimate parameters in industrial premises is a key condition for the stability of technological processes, ensuring high product quality, and creating safe and comfortable working conditions for personnel. Deviations in temperature, humidity, or air composition lead to reduced productivity, energy losses, and deterioration of equipment performance.

Traditional automatic control systems are mostly based on reactive principles and threshold algorithms, which activate actuators only after exceeding permissible limits. Such an approach often causes oscillations of parameters around the set values, delayed responses to changing conditions, and reduced energy efficiency. In addition, the interdependence between microclimate parameters and the presence of external disturbances (weather factors, heat from equipment, human presence) makes the control process even more complex and unpredictable [1].

The integration of cyber-physical systems opens new opportunities for intelligent microclimate control. The combination of sensor networks, actuators, and computational methods within a unified architecture enables data collection and analysis in real time. The use of neural networks as part of such systems allows a transition from static, reactive regulation to predictive and adaptive control, which increases the accuracy of parameter stabilization and ensures optimal use of energy resources [2].

The aim of this study is to improve the efficiency of intelligent microclimate control in industrial cyber-physical systems by performing a comparative analysis of neural network architectures (MLP, RNN, NNARX) and substantiating the choice of the most suitable model for forecasting and optimization of environmental parameters.

II. DECOMPOSITION OF THE MICROCLIMATE FORECASTING AND CONTROL PROBLEM

The task of intelligent microclimate control in industrial premises is complex due to the multifactorial and nonlinear nature of the processes. Environmental parameters (temperature, humidity, air composition, air velocity) are interdependent and are highly sensitive to both external influences (weather conditions, seasonal variations, solar radiation) and internal factors (heat emissions from equipment, human presence, disturbances from production operations) [3].

For effective forecasting and control, the problem should be considered as two interrelated sub-tasks. The first concerns forecasting future microclimate states based on historical data and current measurements. The second involves forming control actions based on the forecasts to maintain parameters within permissible limits.

The general model of the microclimate can be represented as a multifactorial dependence:

$$MicroC\,lim = f(T_{in}, T_{out}, H_{in}, H_{out}, Gas, N_{pip}, Act, Dist), \quad (1)$$

where T_{in}, T_{out} – indoor and outdoor temperature, H_{in}, H_{out} – indoor and outdoor humidity, Gas – concentration of the gas mixture, N_{pip} – number of people in the room, Act – state of actuators (heaters, fans, humidifiers), $Dist$ – disturbances (solar radiation, open doors, etc.).

Such a decomposition makes it possible to combine the tasks of time series forecasting with control tasks, where the key role is played by the choice of neural network architecture capable of accounting for both temporal dependencies and system nonlinearity [2].

III. FORMULATION AND MATHEMATICAL MODEL OF MICROCLIMATE FORECASTING

The problem of forecasting the microclimate in industrial premises is reduced to determining future values of environmental parameters based on their previous states and the influence of external and internal factors. This task can be formalized as a time series forecasting problem [4]

Let $y(t)$ denote the vector of output microclimate parameters (e.g., temperature, humidity), and $u(t)$ – the vector of control actions and external factors (actuators, disturbances, changes in the external environment). Then, the general forecasting equation can be expressed as:

$$y(t+1) = F(y(t), y(t-1), \ldots, u(y), u(t-1), \ldots), \quad (2)$$

where $F(\bullet)$ – is a nonlinear function of the previous values of outputs and inputs.

In the classical NNARX (Nonlinear AutoRegressive with eXogenous inputs) architecture, this function is approximated by a neural network, which takes into account both the autoregressive dependence on past states and the influence of exogenous variables. Such an approach allows the model to reproduce the inertia of the system and the interdependence between microclimate parameters.

In fact, the forecasting task in a cyber-physical system can be formulated as building the following mapping:

$$F:(Y_t,U_t)\rightarrow y(t+1), \tag{3}$$

where $Y_t=\{y(t),y(t-1),...,y(t-n)\}$ – is the vector of past system states, $U_t=\{u(t),u(t-1),...,u(t-m)\}$ – is the vector of exogenous inputs, $y(t+1)$ – is the predicted future state.

Thus, the mathematical model of microclimate forecasting is defined as the problem of approximating a nonlinear mapping between historical data and predicted values, where the key role is played by the choice of the neural network architecture.

IV. COMPARATIVE ANALYSIS OF NEURAL NETWORK ARCHITECTURES

To address the problem of forecasting microclimate parameters in industrial conditions, three main neural network architectures are considered: multilayer perceptron (MLP), recurrent neural networks (RNN), and neural networks of the NNARX type. Each of these approaches represents a different paradigm of neural modeling and has its own advantages and limitations that determine their applicability in dynamic and nonlinear industrial systems [5].

The MLP is one of the most widely used neural architectures due to its conceptual simplicity and universal approximation capability. It can successfully model nonlinear relationships between input and output variables, which makes it useful in many engineering applications. However, MLPs are static models that do not possess an inherent mechanism for handling temporal dependencies. For this reason, when applied to microclimate forecasting, MLPs require explicit construction of input vectors that include lagged variables or statistical features derived from time series. This preprocessing increases model complexity and reduces flexibility, especially when system dynamics change rapidly.

The RNN architecture was introduced as a natural extension of feedforward networks to sequential data. Through recurrent connections, RNNs are able to preserve internal states and thus capture temporal dependencies in dynamic processes. This makes them theoretically more powerful for time series forecasting tasks. Nevertheless, in practice, RNNs often face significant training difficulties. The vanishing and exploding gradient problems limit their ability to model long-term dependencies, which are essential for accurate forecasting of industrial microclimates influenced by both short-term fluctuations and long-term trends. Advanced variants such as LSTM or GRU partially solve these issues, but they introduce additional complexity and computational overhead.

The NNARX (Nonlinear AutoRegressive with eXogenous inputs) model is specifically designed for systems where both autoregressive terms and external factors play a crucial role. By explicitly incorporating past values of the system outputs along with exogenous inputs, NNARX networks are particularly well suited for modeling the inertia and multi-factor interactions inherent to industrial environments. This architecture allows the system to take into account both the history of microclimate variables (e.g., temperature, humidity) and external influences such as outdoor conditions, equipment operation, or human activity. As a result, NNARX provides higher forecasting accuracy and robustness in dynamic, nonlinear production settings.

While MLPs and RNNs can serve as baseline forecasting models, NNARX is the most suitable for intelligent microclimate control in industrial cyber-physical systems. By integrating autoregressive dynamics with external inputs, it ensures accurate prediction and compatibility with adaptive control strategies.

Table 1 summarizes the comparison of these architectures and highlights their main strengths and weaknesses in the context of microclimate forecasting.

Table 1 – Comparison of Neural Network Architectures for Microclimate Forecasting

Architecture	Advantages	Disadvantages	Applicability to the microclimate task
MLP	Simple implementation, universality, high accuracy for static data	Lacks internal memory, requires formation of input vectors with delays	Can be applied for basic forecasts after special data preprocessing
RNN	Models temporal dependencies, ability to work with sequential data	Training instability (vanishing/exploding gradients), complex tuning	Suitable for short-term parameter forecasting
NNARX	Oriented towards time series, accounts for exogenous inputs, high forecasting accuracy, adaptability	Requires large amounts of training data, more computationally intensive	Most effective for dynamic and nonlinear industrial conditions

V. RATIONALE FOR CHOOSING NNARX

Among the analyzed neural network architectures, the most promising for forecasting microclimate parameters in industrial cyber-physical systems is the NNARX (Nonlinear AutoRegressive with eXogenous inputs) model. Its key feature is the ability to account simultaneously for both past system states and external factors, which makes it naturally suited for modeling dynamic and nonlinear processes [6].

Practical studies have demonstrated the high accuracy of NNARX-like models in microclimate forecasting. For example, Caixia Yan et al. reported coefficients of determination of R^2 =0.997, for temperature and R^2 =0.996 for humidity [7], confirming the architecture's ability to capture complex interdependencies between environmental parameters.

Another important advantage of NNARX is its adaptability to real production conditions. The autoregressive structure reflects system inertia, while exogenous inputs allow consideration of both external (outdoor temperature, solar radiation) and internal factors (heat emissions from equipment, human presence, actuator states). This ensures forecasts that more accurately reflect the real behavior of the production environment.

In the context of cyber-physical systems, NNARX can also be integrated with other intelligent approaches, such as fuzzy logic. This combination allows precise neural forecasts to be transformed into control actions understandable to actuators, enabling a shift from reactive to proactive microclimate control.

Thus, NNARX is a justified choice for intelligent microclimate control, as it combines high forecasting accuracy, the ability to consider multiple factors, and flexibility under industrial conditions.

VI. CONCLUSION

This study presents a comparative analysis of neural network architectures for forecasting microclimate parameters in industrial cyber-physical systems. It has been demonstrated that multilayer perceptrons (MLP) are suitable for approximating nonlinear dependencies between environmental variables; however, their effectiveness decreases when applied to tasks with pronounced temporal dynamics. Recurrent neural networks (RNN), on the other hand, are able to capture short-term dependencies and sequential patterns, yet they suffer from issues of training stability and limited scalability when applied to long-term or highly nonlinear processes.

The most promising architecture identified is NNARX, which integrates both autoregressive dynamics and exogenous inputs. This dual structure enables the model to accurately reproduce complex dependencies, capture system inertia, and reflect the influence of external factors such as outdoor temperature or human activity. NNARX-based models have already demonstrated strong performance in practical studies of microclimate forecasting, which confirms their suitability for solving industrial challenges where precision and adaptability are critical.

Therefore, the choice of NNARX as the baseline architecture is well justified for the development of intelligent microclimate control systems in industrial environments. Beyond forecasting, NNARX provides a foundation for creating predictive and adaptive control strategies that move beyond reactive approaches. Future research should focus on combining NNARX with fuzzy logic controllers, optimization algorithms, and online adaptive learning methods, in order to enhance energy efficiency, reduce operational costs, and ensure the stability of technological processes under varying production conditions.

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