USING HISTORICAL DATA IN THE NNARX MODEL TO IMPROVE THE ACCURACY OF MICROCLIMATE PARAMETER FORECASTING

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***Annotation*:** The paper considers an approach to forecasting microclimate parameters in industrial premises based on a neural network of the NNARX type using historical data. The feasibility of incorporating time delays of input and output parameters is substantiated, taking into account the inertial nature of microclimate processes. The role of the autoregressive component in forming the internal "memory" of the model and ensuring temporal consistency of forecasts is demonstrated. The proposed approach establishes methodological prerequisites for the application of NNARX in intelligent microclimate control systems operating under dynamic industrial conditions.

Key words: NNARX neural network, historical data, microclimate forecasting, autoregressive model, intelligent control.

ВИКОРИСТАННЯ ІСТОРИЧНИХ ДАНИХ У МОДЕЛІ NNARX ДЛЯ ПІДВИЩЕННЯ ТОЧНОСТІ ПРОГНОЗУВАННЯ ПАРАМЕТРІВ МІКРОКЛІМАТУ

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***Анотація*.** У роботі розглянуто підхід до прогнозування параметрів мікроклімату у промислових приміщеннях на основі нейронної мережі типу NNARX з використанням історичних даних. Обґрунтовано доцільність урахування часових затримок вхідних та вихідних параметрів з огляду на інерційний характер мікрокліматичних процесів. Показано роль авторегресивної складової у формуванні внутрішньої «пам'яті» моделі та забезпеченні часової узгодженості прогнозів. Запропонований підхід створює методологічні передумови для застосування NNARX у інтелектуальних системах керування мікрокліматом, що функціонують у динамічних промислових умовах.

***Ключові слова*:** нейронна мережа NNARX, історичні дані, прогнозування мікроклімату, авторегресивна модель, інтелектуальне керування.

The task of intelligent microclimate control in industrial premises is closely associated with the need to forecast the behavior of key environmental parameters [1], including temperature, humidity, and air composition. Within this study, the primary focus is placed on forecasting the value of a microclimate parameter for the next time step [2] in order to enable the formation of proactive control actions. To address this task, a neural network of the NNARX type is employed, which allows the construction of a nonlinear predictive model based on available sensor data.

The processes governing microclimate formation in industrial environments exhibit a pronounced dynamic nature and are characterized by inertia caused by the thermal capacity of building structures, air masses, and technological equipment. Changes in control actions or external disturbances do not lead to an instantaneous change in the system state but manifest themselves with a certain time delay. Consequently, the current values of microclimate parameters do not contain complete information about the future behavior of the system, while its state is largely determined by previous values of both input and output variables.

Under such conditions, forecasting microclimate parameters based solely on current measurements is insufficient to ensure the required accuracy and stability. This substantiates the feasibility of using historical data that reflect the temporal evolution of the process and allow accounting for accumulative and inertial effects. The integration of previous parameter values into the structure of the predictive model is therefore a key prerequisite for improving forecasting accuracy and enhancing the effectiveness of subsequent intelligent microclimate control.

A key feature of the NNARX neural network is the use of input data with an explicit temporal structure, including delayed values of both exogenous parameters and the model output variable. This approach enables the formation of a nonlinear dynamic model capable of capturing the inertial properties of microclimate formation processes in industrial premises. Unlike static models, NNARX is not limited to analyzing the current state of the system but exploits information about its past behavior.

Within the NNARX model structure, delayed input signals represent the influence of external and control factors at previous time instants, while delayed values of the output parameter implement the autoregressive mechanism. It is the autoregressive component that ensures the formation of the model's internal "memory," allowing the neural network to reproduce the dynamics of the controlled object and to account for the accumulative nature of thermal processes. This is critically important for microclimate forecasting tasks, since the system state at a given time is largely determined by its previous states.

Formally, the model for forecasting a microclimate parameter in the form of a nonlinear autoregressive neural network with exogenous inputs is described by the following relation [3]:

$$y\hat{}(t) = f(y(t-1), y(t-2), \dots, u_1(t-1), u_2(t-1), \dots) \quad (1)$$

where the predicted value of the parameter at time t is determined based on the previous values of the same parameter as well as delayed exogenous input variables. The input variables characterize the current and past values of factors influencing the microclimate, whereas the delayed values of the output variable $y(t-k)$ implement the autoregressive effect and ensure that inertia and energy accumulation in the system are taken into account.

The engineering rationale for employing time delays lies in the physical nature of microclimate processes. Thermal systems do not respond instantaneously to changes in control actions or external conditions; instead, they exhibit gradual state variations caused by the thermal capacity of the environment and surrounding structures. Accounting for historical parameter values enables the NNARX model to accurately represent these processes, which directly contributes to improved forecasting accuracy and enhanced stability of the intelligent control system.

The formation of the input vector of the NNARX neural network represents a key stage in the development of the predictive model, as it determines the amount of information about the current and previous states of the system supplied to the neural network. The input vector is constructed by combining the current values of exogenous microclimate parameters with their delayed values, as well as with delayed values of the output parameter that implement the autoregressive component of the model. This approach allows the neural network to capture both the instantaneous state of the environment and its temporal evolution.

The inclusion of both current and historical parameter values in the input vector is justified by the dynamic nature of microclimate formation processes. Current values reflect the actual state of the system, whereas historical values contain information about prior influences and system responses, which is essential for reproducing inertial and accumulative effects. As a result, the formed input vector enables the NNARX model to describe the dynamics of the controlled object more comprehensively and to provide accurate forecasting of microclimate parameters for the next time step.

An important aspect of input vector design is the selection of the number of time delays. Increasing the number of delayed values does not necessarily lead to improved forecasting quality. On the one hand, a larger number of delays allows a longer history of parameter variations to be taken into account and may potentially enhance model accuracy. On the other hand, excessive expansion of the input vector increases the number of neural network parameters, complicates the training process, and raises the risk of overfitting.

Thus, a trade-off exists between forecasting accuracy and model complexity, which must be considered when selecting the number of time delays. An inappropriate choice of this parameter may have adverse effects: an insufficient number of delays limits the model's ability to capture the dynamic properties of the system and reduces forecasting accuracy, whereas an excessive number of delays promotes memorization of random data fluctuations and leads to overfitting. Therefore, optimal input vector structuring is a critical factor for the effective operation of the NNARX model in microclimate forecasting tasks.

The structure of the data flow in the microclimate parameter forecasting system defines the sequence of data formation, processing, and transmission to the NNARX neural network. The general logic of interaction between the functional blocks of the system is illustrated in Figure 1, which demonstrates the integration of sensor data acquisition, preprocessing, and the predictive core of the model.

The formation of historical data takes place at the stage of processing primary measurements received from sensor systems. Current values of microclimate parameters are stored in time buffers, where their sequential accumulation and temporal shifting are performed. Thus, for each new system operation cycle, a set of delayed values of both exogenous parameters and the predicted output parameter is formed. It is at this stage that the informational basis for implementing the autoregressive structure of the NNARX model is created.

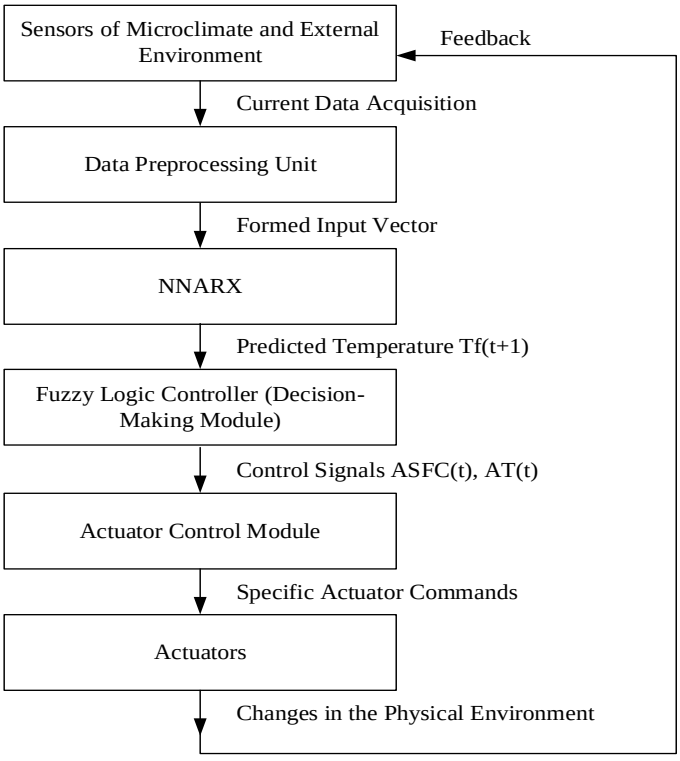

Figure 1 – Block diagram of data flow and control with NNARX.

The generated historical data, together with the current parameter values, are transmitted to the input layer of the NNARX neural network in the form of a structured input vector. Data transmission

is carried out in a streaming mode, which ensures continuity of forecasting and temporal consistency between input and output variables. As a result, the neural network receives complete information about the system dynamics rather than only its instantaneous state.

It is important to emphasize that, within this structure, historical data do not serve an auxiliary or secondary role. On the contrary, they form the foundation of the predictive capability of the NNARX model by enabling the consideration of inertial and accumulative properties of microclimate processes. Owing to the integration of temporal information into the overall data flow, the model is able to provide stable and accurate forecasting of microclimate parameters under dynamic industrial conditions.

An analysis of the structure and operating principles of the NNARX model makes it possible to assess the impact of using historical data on the quality of microclimate parameter forecasting. A comparison of approaches based solely on current parameter values with models that incorporate time delays demonstrates a significant advantage of the autoregressive structure when dealing with dynamic processes.

Forecasting models without an autoregressive component exhibit a limited ability to reproduce the dynamics of microclimate processes. In the presence of system inertia and delayed responses, such models react to changes in conditions with a lag, which manifests itself in increased fluctuations of predicted values and reduced forecast stability. This effect is particularly pronounced under external or internal disturbances, when current measurements do not fully reflect the actual system state.

In contrast, the incorporation of an autoregressive component in the NNARX model ensures more stable forecasting by accounting for previous system states. Historical data enable the model to smooth random measurement fluctuations, reduce forecast oscillations, and more adequately represent the inertial properties of microclimate processes. As a result, the model demonstrates improved adaptability to disturbances and changes in operating modes while maintaining temporal consistency of forecasts.

Thus, the use of historical data shifts the NNARX model from a reactive mode of operation to a proactive one [4], in which forecasting is performed not only on the basis of the current state but also by considering trends in process development. This is of fundamental importance for intelligent microclimate control tasks in industrial environments.

The considered structure of the NNARX model demonstrates the fundamental feasibility of using historical data for forecasting microclimate parameters under dynamic industrial conditions. The inclusion of delayed values of input and output parameters in the formation of the input vector makes it possible to account for inertial and accumulative properties of microclimate processes that cannot be adequately described using only current measurements.

The autoregressive component of the model plays a key role in forming the internal “memory” of the system and creates prerequisites for improving forecast stability under varying operating modes and the presence of disturbances. This approach ensures temporal consistency of forecasts and contributes to reducing the sensitivity of the model to random measurement fluctuations.

Therefore, the use of historical data in the structure of the NNARX model should be regarded not as an auxiliary element but as a fundamental principle for constructing predictive models intended for subsequent application in intelligent microclimate control systems [5]. The presented considerations form a methodological basis for further integration of predictive models with decision-making and control algorithms.

CONCLUSIONS. This paper considers an approach to forecasting microclimate parameters based on a neural network of the NNARX type using historical data. It is shown that the dynamic nature of microclimate processes and their inherent inertia necessitate accounting for previous values of both input and output parameters. The autoregressive structure of the model enables the formation of an

internal system “memory” and creates prerequisites for a more accurate representation of the temporal evolution of microclimate formation processes.

The incorporation of historical data into the input vector structure of the NNARX model contributes to improved forecast stability and reduced sensitivity to random measurement disturbances. This approach should be regarded as a fundamental principle for constructing predictive models for intelligent microclimate control systems in industrial environments and as a methodological basis for further integration of forecasting models with control decision-making algorithms.

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