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Methods for preventing overfitting in microclimate forecasting tasks

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Abstract. The paper addresses the problem of overfitting in neural network models used for forecasting microclimate parameters in industrial facilities. It is shown that in microclimate control systems overfitting leads not only to reduced forecasting accuracy, but also to unstable control actions, increased energy consumption, and accelerated wear of actuators. The main focus is on NNARX-type neural network models, which use historical values of input and output parameters and are sensitive to limited and uneven training data. Practical methods for preventing overfitting are analyzed, including Dropout, weight regularization, and training data variation. The applicability of Dropout in the hidden layer of NNARX without violating autoregressive relationships is substantiated. It is shown that the combined use of these methods makes it possible to improve forecast stability, ensure smoother control signals, and enhance the reliability of intelligent microclimate control systems under real industrial operating conditions.
Keywords: *neural network forecasting, NNARX, overfitting, Dropout, regularization, microclimate.*

Microclimate control systems in industrial premises operate under conditions of constant instability and process nonlinearity [1]. Changes in external climatic factors, fluctuations in thermal loads, equipment operating modes, and the influence of the human factor form complex environmental dynamics that cannot be effectively described by simple linear models. Under such conditions, ensuring a stable microclimate requires the use of predictive models capable of accounting for temporal dependencies and nonlinear relationships between parameters.

Forecasting microclimate parameters in industrial systems makes it possible to move from purely reactive control to proactive decision-making aimed at preventing deviations of environmental parameters [2]. Reliable forecasting enables smoother formation of control actions, reduces the number of abrupt corrections, and contributes to improved energy efficiency of the system. At the same time, the use of neural network models for time-series analysis is associated with the risk of overfitting, in which the model demonstrates high accuracy on training data but loses the ability to operate stably under changing operating conditions, which is critical for control systems.

Forecasting microclimate parameters in industrial premises differs significantly from classical regression tasks, as it deals with time series characterized by inertia, nonlinearity, and dependence on previous system states [3]. The values of temperature, humidity, or air gas composition at a given moment depend not only on instantaneous external influences but also on the history of changes, accumulated thermal effects, and control system actions. This necessitates the use of models capable of accounting for temporal dependencies, in particular NNARX-type neural network models, in which historical delays of input and output signals play an important role.

At the same time, the use of historical delays significantly complicates the model structure and increases the number of parameters to be learned. In the absence of sufficiently representative data, this creates prerequisites for overfitting, when the model begins to memorize specific features of the training dataset instead of identifying generalized patterns. Unlike classical regression tasks, where overfitting mainly affects forecast accuracy, in microclimate control tasks its consequences are more critical.

Sensor measurement noise manifests itself in short-term fluctuations of forecasted parameters, leading to unstable control actions and frequent corrections of actuator operating modes.

Limited and uneven training datasets result in correct model performance only in typical operating modes and unstable forecast behavior when transitioning to atypical or emergency states. Excessive model architecture complexity manifests itself in increased sensitivity of the forecast to small changes in input signals and the formation of sharp oscillations in control actions.

The practical consequences of overfitting in industrial microclimate control systems manifest themselves in the formation of unstable control actions. Forecast oscillations can lead to frequent and abrupt changes in control signals, causing excessive energy consumption, accelerated wear of actuators, and reduced overall system efficiency. In critical cases, incorrect forecasting can create prerequisites for emergency modes, especially in facilities with strict requirements for maintaining environmental parameters.

One of the simplest yet most effective methods for reducing overfitting in neural network models is Dropout. Its practical value lies in the fact that the method does not require changes to the model architecture or complex algorithmic solutions and can be easily integrated into existing neural network-based microclimate forecasting systems.

The principle of Dropout is based on randomly and temporarily disabling a portion of neurons during the training process. At each training iteration, a certain fraction of neurons in the hidden layer does not participate in computations, forcing the model to form predictions not on the basis of individual strong connections, but through a more evenly distributed representation of features. As a result, neuron co-adaptation is reduced and the generalization capability of the model is improved.

In microclimate forecasting tasks that use NNARX-type models, the application of Dropout requires a careful approach. Since the autoregressive structure of the model relies on historical values of input and output parameters, applying Dropout in the input or output layers may disrupt the temporal integrity of information. Therefore, in practice, Dropout should be applied only in the hidden layer of the neural network, where it performs a regularization function without distorting autoregressive relationships. The choice of the Dropout rate is also important: excessive neuron deactivation may lead to a loss of forecasting accuracy, while too small a value does not produce a noticeable reduction in overfitting.

The practical effect of using Dropout in microclimate forecasting tasks is primarily manifested in a reduced sensitivity of the model to sensor measurement noise. Due to random neuron deactivation, the model becomes less responsive to individual random data fluctuations, producing a smoother and more stable forecast. This is especially important in industrial environments, where sensor data often contain short-term distortions or anomalous values.

A more stable forecast directly affects the quality of controller operation, in particular a fuzzy logic controller (FLC), which uses forecasted values to generate control actions [4]. Reducing sharp forecast oscillations makes it possible to avoid frequent changes in control signals, resulting in more predictable system behavior. In practical terms, this means reduced fluctuations in fan speed, smoother operation of heating or cooling systems, and lower dynamic loads on actuators [5].

At the same time, the use of Dropout involves a certain trade-off between accuracy and forecast stability. In some cases, a model with Dropout may demonstrate a slightly higher average error compared to a model without regularization; however, its behavior in variable or atypical operating modes is significantly more robust. For industrial control systems, this property is an advantage, since stability and operational reliability have a higher priority than minimizing error in individual data segments.

Thus, Dropout can be considered the first practical engineering tool for preventing overfitting in neural network models for microclimate forecasting. Its use makes it possible to increase forecast robustness and predictability of control system behavior without significantly complicating the model, which makes this method suitable for application in real industrial conditions.

Weight regularization is one of the basic and at the same time most effective approaches to reducing overfitting in neural network models intended for operation in real industrial environments. Unlike methods that modify the structure of training data or network architecture, regularization directly affects model behavior by limiting excessive complexity and preventing the formation of sharp, unstable dependencies in the forecast.

In practical microclimate forecasting tasks, L1 and L2 regularization approaches are most commonly used. Although they differ in the nature of their impact on weight coefficients, they share a common goal—restraining excessive weight growth. L1 regularization promotes the formation of more sparse models by reducing the influence of secondary connections, whereas L2 regularization provides smooth constraints on all weight coefficients. In the context of microclimate control, both approaches are used primarily as tools for stabilizing forecasts rather than for optimizing network structure.

Weight regularization ensures smoother time-series forecasts, which directly reduces abrupt changes in control signals such as *Fans_reg* and *Heat*, contributing to smoother actuator operation and reduced dynamic loads in microclimate control systems.

An additional effect of regularization is improved energy efficiency of the system. Smoother control signals reduce peak loads and inefficient energy consumption, which is particularly important for industrial facilities with long operating cycles. Moreover, a more stable forecast reduces the likelihood of erroneous control decisions that may arise from the model's response to random noise or anomalous input data.

At the same time, the effectiveness of regularization largely depends on the choice of the regularization coefficient, which cannot be determined universally under real operating conditions. Too weak regularization does not provide a noticeable reduction in overfitting, while excessive weight constraints lead to a loss of model sensitivity to actual changes in the microclimate. In industrial systems, the selection of the regularization coefficient is usually performed experimentally, taking into account the trade-off between forecast accuracy and control stability.

Thus, weight regularization in microclimate forecasting tasks can be regarded as a practical engineering tool aimed at improving the stability and predictability of control system operation.

One of the characteristic features of microclimate forecasting tasks in industrial environments is the limited availability of historical data. In most cases, training datasets are formed based on long periods of normal equipment operation, whereas transitional, atypical, or emergency modes are represented by a much smaller number of observations. Such data imbalance creates prerequisites for overfitting of neural network models and reduces their ability to operate correctly under conditions that differ from typical ones.

An additional complicating factor is the seasonality of microclimate processes. Changes in external temperature, humidity, and solar activity lead to significantly different control system operating modes throughout the year. If the training dataset does not cover the full range of such regimes, the model may demonstrate high accuracy within a particular season but lose adequacy when transitioning to other conditions. A similar situation arises for rare emergency or pre-emergency modes, which are critical for the reliability of industrial systems but are scarcely represented in real data.

Under such conditions, an effective practical approach is the variation and augmentation of training data aimed at artificially expanding the dataset and increasing the diversity of input scenarios. One of the simplest methods is adding small random noise to input time series, which simulates sensor measurement errors. This allows the model to learn to ignore minor fluctuations and focus on stable patterns of microclimate parameter changes.

Another common approach is input data scaling, which involves proportional increases or decreases in parameter amplitudes within permissible limits. This method makes it possible to model variations in thermal loads or air exchange intensity characteristic of different operating modes. Time shifts represent another effective augmentation tool, involving shifting input and output time series relative to the time axis. This enables the generation of additional training examples without violating the physical meaning of the processes.

The practical effect of data variation and augmentation is manifested in improved generalization capability of the neural network model. A model trained on a more diverse dataset demonstrates more stable behavior under changing operating conditions and is able to operate more reliably in atypical or transitional modes. In the context of microclimate control systems, this means a reduced likelihood of abrupt forecasting errors and improved overall system reliability.

At the same time, data augmentation requires careful application. Excessive addition of noise or artificial variations may lead to oversaturation of the training dataset with incorrect or physically unjustified scenarios. In such cases, the model loses sensitivity to real changes in microclimate parameters, which negatively affects forecasting accuracy. Therefore, in industrial environments, data augmentation methods should be applied with consideration of the physical constraints of the process and in combination with other overfitting prevention techniques.

To assess the feasibility of applying different overfitting prevention methods in microclimate forecasting tasks, a comparative analysis from the perspective of practical use in industrial systems is advisable. Since neural network models are components of control systems, key performance criteria include not only formal forecasting accuracy, but also control action stability, computational cost, and suitability for implementation under real operating conditions. The generalized results of such an analysis are presented in Table 1.

Table 1

Practical impact of overfitting prevention methods in microclimate forecasting

Criterion	Dropout	Regularization (L1/L2)	Data augmentation
Impact on prediction accuracy	Slight reduction of peak accuracy on training data	Minor smoothing of predictions without critical loss of accuracy	Improved generalization accuracy, especially outside typical regimes
Impact on control stability	Significant reduction of prediction oscillations and control signal fluctuations	Smoother control actions, reduced abrupt changes of Fans_reg and Heat	More stable behavior in transitional and atypical operating conditions
Computational cost	Low, no increase in model size during inference	Very low, minimal additional computational overhead	Moderate, due to increased training data volume
Practical suitability in industrial systems	High, easy to integrate without changing model architecture	High, effective engineering tool for stabilizing control systems	High when historical data are limited or unevenly distributed

The analysis shows that none of the considered methods is a universal solution; however, each of them effectively addresses specific practical aspects of the overfitting problem. Dropout and regularization are primarily aimed at stabilizing model behavior and reducing abrupt control actions, whereas data variation improves the model's ability to operate correctly under conditions that differ from typical ones. In industrial systems, the most appropriate approach is the combined use of these methods, which makes it possible to achieve a compromise between forecasting accuracy, control stability, and computational efficiency, thereby creating prerequisites for reliable operation of intelligent microclimate control systems.

Based on the conducted analysis, it is advisable to recommend the combined application of overfitting prevention methods for NNARX-type neural network models used in microclimate forecasting systems. Practical experience shows that the best results are achieved through the simultaneous use of weight regularization, Dropout in the hidden layer, and moderate augmentation of training data. Such an approach allows balancing forecasting accuracy, stability, and the model's ability to operate correctly under variable operating conditions.

When implementing neural network models in real cyber-physical systems, special attention should be paid not to maximizing formal accuracy metrics, but to ensuring predictable and stable control system behavior. In industrial environments, a slight increase in average forecasting error is acceptable if it is accompanied by reduced control signal oscillations, lower loads on actuators, and improved overall system reliability.

The integration of NNARX models into control systems based on fuzzy logic controllers (FLC) and SCADA systems requires particular attention to the quality of forecast signals [6]. A stable and smoothed forecast ensures correct control logic operation, reduces the number of erroneous or excessive control actions, and simplifies controller tuning. From this perspective, regularization and Dropout play a key role as engineering tools for improving overall system reliability.

Thus, in practical industrial systems, the primary criterion for the effectiveness of neural network forecasting should be operational stability and control predictability, rather than achieving the minimum RMSE value on training or test datasets.

Conclusions. The paper examines the problem of overfitting in neural network models used for forecasting microclimate parameters in industrial control systems. It is shown that for time series of microclimate parameters, overfitting has a direct impact on the stability of control actions, energy efficiency, and overall system reliability under real operating conditions [7].

Practical methods for preventing overfitting, including

Dropout, weight regularization, and training data variation, are analyzed and compared. It is established that their combined use in NNARX-type models makes it possible to reduce forecast sensitivity to noise, ensure smoother changes in control signals, and improve the stability of microclimate control systems.

Further research should focus on the adaptive selection of regularization and Dropout parameters taking into account the current operating mode of the object, as well as on the integration of neural network forecasting models with online learning algorithms within cyber-physical control systems.

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