ISSN 2071-1077(print)
ISSN 2663-2411(online

**doi: 10.32620/oikit.2026.107.07**

UDC 004.896.032.26:[681.536.5:004.94]
Vladyslav Yevsieiev, Ihor Holod

# Evolution of approaches to intelligent microclimate control in industrial environments: A review of models for cyber-physical systems

*Kharkiv National University of Radio Electronics, Ukraine*

This article presents a systematic review of modern approaches to intelligent forecasting and control of microclimate parameters in industrial environments within the context of cyber-physical systems (CPS) development. The analysis covers classical control methods (PID), heuristic techniques (Fuzzy Logic), machine-learning-based approaches, as well as neural network architectures of varying complexity, including multilayer perceptrons (MLP), recurrent models (RNN, LSTM, GRU), and nonlinear autoregressive neural networks with exogenous inputs (NNARX). Special attention is given to the NNARX model as one of the most promising solutions for short-term forecasting of microclimate parameters in inertial industrial ventilation and thermal regulation systems.

The article highlights the specific aspects of integrating forecasting models into CPS structures, where the combination of sensors, actuators, and the computational cyber layer forms an adaptive real-time control loop. A comparative analysis of the main neural network architectures is conducted based on accuracy, dynamic modeling capability, incorporation of external factors, and suitability for CPS implementation.

The literature review reveals several research gaps, including an insufficient number of studies addressing complex microclimate interactions ($T, H, CO_2$), the lack of universal parametric models, limited availability of real industrial datasets, and the challenges of ensuring real-time operation of forecasting models. Promising future research directions are outlined, such as the development of microclimate digital twins, the adoption of Edge AI solutions, hybrid NNARX+FLC control strategies, and the adaptation of microclimate control systems to the principles of Industry 5.0.
***Key words:*** intelligent microclimate control; cyber-physical systems; neural networks; RNN; NNARX.

## Introduction

A stable microclimate is one of the key factors determining the efficiency of modern industrial processes, as it directly influences product quality, the safety of technological operations, working conditions for personnel, and the overall energy efficiency of an enterprise. In many industrial sectors deviations in temperature, humidity, or gas composition from optimal values lead to reduced product output, accelerated equipment wear, and increased energy consumption. Therefore, maintaining stable microclimate parameters is considered not only a technical task but also an essential component of strategies aimed at improving production quality and competitiveness [1-12].

The emergence of new technological paradigms within the Industry 4.0 concept has transformed approaches to automation. Cyber-physical systems (CPS), integrating sensors, actuators, computational models, and network infrastructure into a unified intelligent control loop, have become the foundation for flexible and adaptive production processes. In such systems the microclimate is viewed as a complex dynamic object interacting with technological equipment, personnel, and the external environment, which significantly increases the requirements for the accuracy and responsiveness of control algorithms [13-22].

ISSN 2071-1077(print)
ISSN 2663-2411(online

Traditional regulation methods, including PID controllers and fuzzy-logic-based systems, demonstrate limited effectiveness when the controlled object is highly nonlinear, inertial, and influenced by numerous internal and external disturbances. These methods are difficult to adapt to rapidly changing real-time conditions, and their capacity to model multifactor dependencies is insufficient for modern industrial environments [23-32]. This creates the need for intelligent forecasting and adaptive control tools capable of capturing nonlinear relationships and generating optimal control actions based on time-series analysis and exogenous factors.

Thus, the application of intelligent, data-driven, and predictive models capable of improving microclimate regulation accuracy, ensuring adaptation to environmental changes, and integrating into cyber-physical system architectures becomes increasingly relevant. In this context, neural network models occupy a prominent place due to their ability to reproduce complex system dynamics and forecast behavior based on measurements and predictive signals [33-40].

The purpose of this article is to conduct a systematic review of modern approaches to intelligent microclimate control in industrial environments, analyze machine-learning and neural-network methods, compare their capabilities and limitations, and evaluate the prospects for implementing these models within industrial cyber-physical systems. The article aims to identify trends, shortcomings of existing approaches, and scientific prerequisites for further development of microclimate forecasting and control models.

## 1. Systematic Review Methodology for Intelligent Microclimate Control Models in Industrial Cyber-Physical Systems

The systematic review methodology conducted in this study was based on the principles of transparency, scientific objectivity, and representativeness in order to ensure the reliability of the conclusions regarding the evolution of approaches to intelligent microclimate control in industrial environments within the frameworks of Industry 4.0 and cyber-physical systems. The primary objective is to identify, classify, and compare models for forecasting and regulating microclimate parameters (temperature, humidity, gas composition) used in industrial technological processes, as well as to evaluate their suitability for integration into CPS architectures. To achieve this goal, leading scientometric databases – Scopus, Web of Science, IEEE Xplore [40-51], SpringerLink – and the academic search platform Google Scholar were utilized, enabling broad coverage of interdisciplinary research in automation, machine learning, energy systems, and intelligent manufacturing technologies.

Source selection was performed using several inclusion criteria, such as: publications from 2010 to 2025; the presence of theoretical or applied models for microclimate control or forecasting; descriptions of intelligent methods (MLP, SVM, LSTM, GRU), mathematical models (ARX/ARMAX), hybrid systems, and neural network architectures including NNARX; relevance to industrial or building environments; peer review; and technological novelty. Exclusion criteria included: publications unrelated to microclimate or addressing it only superficially; non-peer-reviewed materials; short abstracts lacking methodological description; duplicate or derivative works; and studies lacking a connection between the model and real physical processes. The combination of these criteria enabled the formation of a representative set of sources relevant to the objectives of the study [51-59].

The search was performed using an extended set of keywords covering several thematic clusters: "microclimate control", "intelligent control", "HVAC predictive model",

ISSN 2071-1077(print)
ISSN 2663-2411(online

"neural networks HVAC", "cyber-physical systems microclimate", "smart manufacturing climate", "NNARX climate model", "temperature humidity $CO_2$ prediction", " microclimate forecasting ". An initial Google Scholar search for "intelligent microclimate control" yielded more than 18,000 sources, approximately 4,200 of which were directly related to models for predicting environmental parameters. A combination of terms such as "cyber-physical systems HVAC" in Scopus and Web of Science produced more than 1,900 unique publications, most of them published after 2016, reflecting the growing interest in integrating microclimate models into CPS [59-72]. Queries related to "NNARX" and "nonlinear autoregressive HVAC models" resulted in more than 850 papers, about 320 of which contained real experimental data or comparative studies with other time-series models.

In total, 112 relevant works were selected for in-depth analysis, including 68 articles in peer-reviewed journals, 27 international conference papers, 9 technical reports, and 8 dissertation studies. All sources were classified by model type [73-80] (PID, Fuzzy, ARX, ML, RNN, NNARX, hybrid architectures), application domain, mathematical complexity, dataset size, and the presence of practical validation. This approach made it possible to form a comprehensive understanding of the development trends in intelligent microclimate control methods, identify their strengths and limitations, and determine the prospects for applying NNARX autoregressive models in industrial cyber-physical systems.

## 2. Approaches to Microclimate Control in Industrial Systems Analysis

The evolution of approaches to microclimate control in industrial environments reflects a transition from simple linear regulators to advanced intelligent systems capable of modelling nonlinearity and forecasting environmental states. In the early stages of automation development, classical PID controllers dominated, providing temperature, humidity, or pressure stabilization through reactive responses to deviations from the setpoint. Their main advantages included ease of implementation, low computational requirements, and proven reliability in standard industrial conditions. However, in systems with high inertia, significant time delays, and multifactor dynamics, classical PID controllers demonstrate limited effectiveness, as their linear structure does not allow for capturing complex nonlinear relationships between microclimate parameters [80-88].

In response to these limitations, a shift toward heuristic methods occurred, with fuzzy-logic-based systems taking a leading place. Fuzzy controllers enable the description of system behavior through a set of rules that approximate expert knowledge and operator experience, providing improved adaptability under uncertainty. As a result, fuzzy systems have been widely used for temperature and humidity regulation, particularly in installations with pronounced nonlinearities. At the same time, their limitations include the complexity of constructing the rule base, high sensitivity to tuning quality, and limited scalability in complex industrial processes where the number of input variables increases substantially.

The further development of Industry 4.0 technologies and the expansion of sensor networks have created conditions for the emergence of machine-learning models capable of analyzing large volumes of data and identifying hidden dependencies between microclimate parameters. Algorithms such as Support Vector Machines, Decision Trees, Random Forest, and multilayer perceptrons (MLP) have shown significant advantages in forecasting temperature, humidity, and gas composition, as well as in solving energy-optimization tasks in HVAC systems. Their

ISSN 2071-1077(print)
ISSN 2663-2411(online

key advantage lies in the ability to model nonlinear functional relationships and improve control accuracy based on data. However, the absence of internal memory and temporal structure limits their applicability in complex dynamic systems where it is essential to account for the history of parameter changes. This became a prerequisite for the transition to recurrent neural networks and NNARX models, which are analyzed in the following section [88-102].

To summarize the differences between the method groups discussed above, Table 1 presents a comparative overview of the key characteristics of classical, heuristic, and machine-learning approaches in the context of their application to industrial microclimate control.

Table 1

Comparison of microclimate control methods

| Criterion / Method | PID | Fuzzy Logic / ANFIS | ML (SVM, DT, MLP) |
|---|---|---|---|
| Nonlinearity modelling | low | medium | high |
| Data requirements | minimal | moderate | high |
| Adaptability | low | medium–high | medium |
| Robustness to disturbances | medium | high | dataset-dependent |
| Predictive capability | none | limited | high |
| Model interpretability | high | medium | low |
| Computational complexity | very low | medium | medium–high |
| Advantages | simplicity, reliability | flexibility, handling uncertainty | modelling complex dependencies |
| Limitations | ineffective for nonlinear systems | complexity of rule design | no temporal memory, data-dependent |
| Applications | simple HVAC | nonlinear systems | $T,\ H,\ CO_2$ forecasting |

### 3. Neural Network Architectures for Microclimate Forecasting

The development of neural network approaches for forecasting microclimate parameters has become one of the key directions in the evolution of intelligent control systems within the context of automation and the integration of production into cyber-physical system architectures. One of the earliest models in this field to gain widespread use were multilayer perceptron (MLP), which, due to their simplicity and ability to approximate nonlinear dependencies, were applied to the forecasting of temperature, humidity, and energy consumption in HVAC systems. However, the absence of an internal memory mechanism significantly limited their effectiveness in tasks requiring consideration of temporal dynamics, system inertia, and external disturbances [103-110]. This stimulated the transition toward models naturally suited for sequential data.

Further progress was associated with the emergence of recurrent neural networks, particularly RNNs, as well as their advanced modifications – LSTM and

 ISSN 2071-1077(print)
ISSN 2663-2411(online

GRU. Unlike MLPs, these networks possess state retention mechanisms that enable them to transfer information across time steps and model dynamic processes with much greater accuracy. LSTM and GRU models have demonstrated high effectiveness in forecasting microclimate parameters, including temperature, humidity, air gas composition, and ventilation characteristics. An analysis of scientific publications from 2010 to 2025 indicates that these architectures dominate microclimate modelling tasks, particularly in industrial environments characterized by high inertia and complex internal process structures [111-122]. Their distinctive features are summarized in Table 2, which presents a comparison of the three most representative architectures: LSTM, GRU, and NNARX.

Table 2

Comparison of neural network architectures (LSTM, GRU, NNARX)

| Criterion / Architecture | LSTM | GRU | NNARX |
|---|---|---|---|
| Nonlinearity modelling ability | high | high | high |
| Time series handling | excellent | excellent | excellent |
| Long-term dependency modelling | strong | strong | depends on lag structure |
| Data requirements | high | high | moderate–high |
| Noise robustness | high | high | high |
| Model interpretability | low | low | medium |
| Computational complexity | high | medium–high | medium |
| Advantages | long memory, stability | faster training than LSTM | autoregression + exogenous inputs, high accuracy |
| Limitations | high computational complexity | less flexible than LSTM | requires correct lag selection |
| Typical applications | long microclimate time series | operational HVAC forecasting | microclimate forecasting in CPS |

Particular attention is drawn to the class of autoregressive models with exogenous inputs, the most widespread of which is NNARX. Unlike classical recurrent networks, NNARX combines an autoregressive structure (accounting for several previous values of the predicted variable, such as indoor temperature) with the ability to incorporate exogenous signals that characterize external and internal influences on the microclimate – outdoor temperature, humidity, $CO_2$ concentration, solar radiation, technological load, and others. As a result, NNARX effectively models both the internal dynamics of the system and its response to external disturbances. A consolidated literature analysis shows that NNARX often provides higher short-term forecasting accuracy compared with traditional ARX/ARMAX models and several neural network approaches, making it one of the most promising tools for integration into industrial CPS solutions.

ISSN 2071-1077(print)
ISSN 2663-2411(online

A separate direction is represented by hybrid models in which neural network approaches are combined with decision-making methods, particularly fuzzy logic (FLC) or model predictive control (MPC). Such systems make it possible to leverage the advantages of predictive models (LSTM, GRU, NNARX) together with mechanisms that generate control actions, ensuring high adaptability, robustness to disturbances, and the ability to operate under varying production loads. Hybrid architectures such as NNARX+FLC or RNN+MPC are considered promising directions for the development of intelligent microclimate control systems within cyber-physical production platforms [123-128].

## 4. Discussion: Models Integration into Cyber-Physical Systems

The integration of intelligent microclimate forecasting models into the architecture of cyber-physical systems (CPS) is a key stage in the transition toward adaptive, data-driven, and predictive control of industrial processes. CPS provides a unified interaction between the physical layer, which includes temperature, humidity, and $CO_2$ sensors, airflow measurement devices, and actuators (fans, valves, heaters), and the cyber layer, where mathematical models, machine-learning algorithms, and neural networks operate. In such an architecture, real-time sensor data are transmitted to the computational core, where models such as NNARX, RNN, or MLP generate forecasts of the future microclimate state. The forecasting results are then passed to the controller, which produces optimal control actions. This creates a closed adaptive control loop in which the system not only reacts to deviations but also anticipates them, thereby improving stability and responsiveness [25-36].

An important feature of modern CPS is that different neural network architectures offer significantly different capabilities in modelling dynamics and interacting with multifactor environments. MLP models demonstrate satisfactory accuracy in static or quasi-static conditions but do not account for the temporal structure of processes. RNNs and their modifications (LSTM, GRU) reproduce dynamic dependencies more accurately but require substantial computational resources and large training datasets. NNARX-type models combine the autoregressive approach with exogenous inputs, enabling effective forecasting of complex, nonlinear, and inertial processes characteristic of industrial ventilation and thermal regulation systems. A comparative analysis of the capabilities of various architectures is presented in Table 3, which summarizes their advantages and suitability for CPS integration.

Table 3

Comparison of neural network models for microclimate tasks

| Criterion | MLP | RNN/LSTM/GRU | NNARX |
|---|---|---|---|
| Forecasting accuracy | medium | high | very high |
| Dynamic modelling | weak | strong | strong + ARX structure |
| External factor consideration | limited | possible | built-in (exogenous inputs) |
| Computational complexity | low | medium/high | medium |
| Suitability for CPS | limited | high | very high |

ISSN 2071-1077(print)
ISSN 2663-2411(online

The dynamics of the development of predictive control methods over the past 10–15 years demonstrate a clear shift from classical PID controllers and fuzzy systems toward recurrent neural networks and hybrid CPS architectures that combine forecasting with optimization of control actions. An analysis of publications in Scopus, Web of Science, and IEEE Xplore shows a steady increase in research focused on RNN/LSTM and NNARX models, reflecting the broader trend toward data-driven control, digital twins, and real-time Edge AI applications. This trend is visualized in Figure 1, which illustrates the evolution of approaches – from PID and Fuzzy Logic to modern NNARX and hybrid CPS-based models.

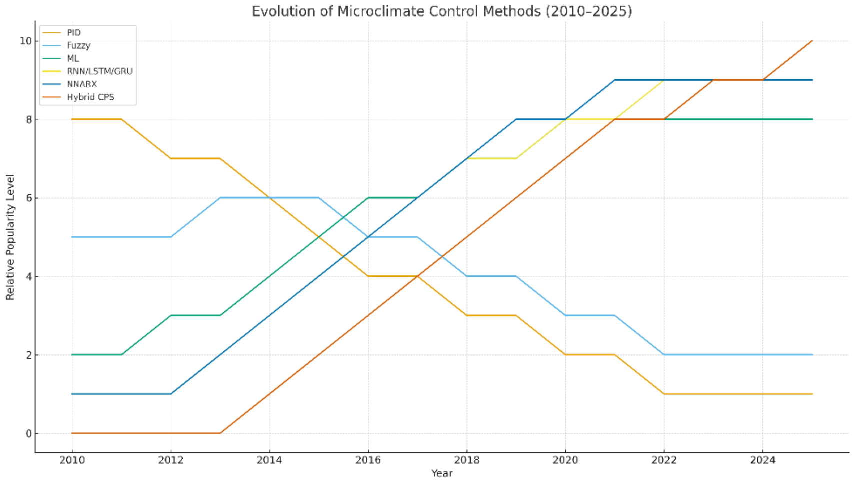


Fig. 1. Evolution of microclimate control methods (2010–2025)

Despite significant progress, the literature review has revealed several research gaps that hinder the scalability and unification of predictive models in industrial environments. Among them there is limited number of models that take into account a complex microclimate (temperature, humidity, $CO_2$ simultaneously), the lack of universal parametric approaches capable of adapting to different temperature ranges, as well as the shortage of real experimental samples from production workshops, where processes have high inertia and significant variability of external disturbances. An additional challenge is the real-time integration of intelligent models within CPS, particularly due to hardware constraints of controllers and the need to ensure system stability in the presence of delays and noise in data transmission channels. The identified research gaps form the basis for future work aimed at developing hybrid approaches, combining forecasting models with optimal control algorithms, and creating digital twins of industrial microclimate systems.

## 5. Conclusions

The systematic review of modern methods for forecasting and controlling microclimate parameters in industrial environments has demonstrated a substantial evolution of approaches – from classical PID controllers and fuzzy systems to intelligent machine-learning and neural-network models integrated into the architecture of cyber-physical systems. The comparative analysis showed that among existing models the NNARX architecture offers the most balanced capabilities for accurately forecasting dynamic microclimate parameters. NNARX combines autoregressive memory with the incorporation of exogenous factors, providing high short-term forecasting accuracy, the ability to reproduce nonlinear behavior of industrial systems, and compatibility with real-time control requirements. These characteristics position NNARX as one of the most promising models for application in intelligent industrial CPS, aligning with the chosen direction of the dissertation research [45-58].

The analysis also confirmed the feasibility of using hybrid control systems in which the predictive capabilities of neural-network models are combined with decision-making algorithms such as fuzzy logic or MPC. In particular, the integration of NNARX with FLC enables the formation of a hierarchical system where the predictive processing of signals is combined with the robustness and interpretability provided by rule-based control. This approach is especially effective in environments with high inertia, numerous disturbances, and the need for real-time adaptation, making it a relevant strategy for developing modern industrial CPS.

At the same time, the literature review revealed several significant research gaps that must be addressed to advance the field. These include the lack of universal parametric models, insufficient consideration of complex microclimate variables ($T + H + CO_2$), the shortage of real industrial datasets, and the challenges of implementing predictive models in real time due to CPS computational limitations. Solving these issues is associated with the development of transfer-learning and federated-learning methods, the optimization of neural networks for edge devices, the application of physically grounded “grey-box” models, and the introduction of standards for semantic data interoperability.

Promising directions for further research include the creation of digital twins of microclimate systems, the development of personalized models in the context of Industry 5.0, the deployment of Edge AI for real-time operation, and the integration of intelligent models with optimal and predictive control systems. It is expected that the combination of the NNARX predictive model, hybrid control strategies, and CPS architecture will form the foundation of a new paradigm of intelligent, adaptive, and human-centric microclimate control in industrial environments.

## References

1. 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

2. 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

3. Goetzler, B., Guernsey, M., & Kassuga, T. (2019). Grid-interactive efficient buildings technical report series: Heating, ventilation, and air conditioning (hvac); water heating; appliances; and refrigeration (No. DOE/GO-102019-5228). Navigant Consulting, Inc., Chicago, IL (United States). https://doi.org/10.2172/1577966

4. Zanetti, E., Blum, D., Fu, H., Weyandt, C., Pritoni, M., & Piette, M. A. (2025). Commercial Building HVAC Demand Flexibility with Model Predictive Control: Field Demonstration and Literature Insights. Energy and Buildings, 116097. https://doi.org/10.1016/j.enbuild.2025.116097

5. Chiao, H. Y. (2025). Enhancing Direct Netload Forecasting through Functional Data Analysis: Evidence from Comparative Evaluation. https://econ.ntu.edu.tw/wp-content/uploads/2025/10/hist_1141120.pdf

6. Merabet, G. H., Essaaidi, M., Ben-Haddou, M., Qolomany, B., Qadir, J.,

ISSN 2071-1077(print)
ISSN 2663-2411(online

Anan, M., ... & Benhaddou, D. Systematic Review of Energy Efficient Thermal Comfort Control Techniques for Sustainable Buildings. https://doi.org/10.1109/ACCESS.2021.3053638

7. Deltetto, D. (2020). Data-driven coordinated building cluster energy management to enhance energy efficiency, comfort and grid stability (Doctoral dissertation, Politecnico di Torino). http://hdl.handle.net/11583/2833316

8. Dou, H., & Zhang, K. (2025). Transfer learning for cross-building forecasting of building energy and indoor air temperature in model predictive control applications. Journal of Building Engineering, 113341. https://doi.org/10.1016/j.jobe.2025.113341

9. Moshari, A., Javanroodi, K., & Nik, V. M. (2026). Real-world deployment of model-free reinforcement learning for energy control in district heating systems: Enhancing flexibility across neighboring buildings. Applied Energy, 402, 126997. https://doi.org/10.1016/j.apenergy.2025.126997

10. Amertet Finecomess, S., Gebresenbet, G., & Alwan, H. M. (2024). Utilizing an internet of things (IoT) device, intelligent control design, and simulation for an agricultural system. IoT, 5(1), 58-78. https://doi.org/10.3390/iot5010004

11. Yadav, S., Samadhiya, A., Kumar, A., Luthra, S., & Pandey, K. K. (2025). Environmental, social, and governance (ESG) reporting and missing (m) scores in the industry 5.0 era: Broadening firms' and investors' decisions to achieve sustainable development goals. Sustainable Development, 33(3), 3455-3477. https://doi.org/10.1002/sd.3306

12. Islam, M., Rashel, M. R., Ahmed, M. T., Islam, A. K., & Tlemçani, M. (2023). Artificial intelligence in photovoltaic fault identification and diagnosis: A systematic review. Energies, 16(21), 7417. https://doi.org/10.3390/en16217417

13. Peffer, T., Fierro, G., Raftery, P., Duarte Roa, C., Pritoni, M., Wetter, M., ... & Paulson, E. (2023). Skewering the silos: using Brick to enable portable analytics, modeling and controls in buildings. https://doi.org/10.1016/j.enbuild.2023.113623

14. Fellah, M., Ouhaibi, S., Belouaggadia, N., Mansouri, K., & Younsi, Z. (2025). Harnessing AI and Sustainable Materials for Greener, Smarter Buildings: A Bibliometric Study. Buildings, 15(20), 3777. https://doi.org/10.3390/buildings15203777

15. Olivieri, G., Volpe, G., Mangini, A. M., & Fanti, M. P. (2024). A User Based HVAC System Management Through Blockchain Technology and Model Predictive Control. IEEE Transactions on Automation Science and Engineering, 22, 3621-3634. https://doi.org/10.1109/TASE.2024.3397561

16. Venkateswarlu, N., & Sathiyamoorthy, M. (2025). Sustainable innovations in digital twin technology: a systematic review about energy efficiency and indoor environment quality in built environment. Frontiers in Built Environment, 11, 1523464. https://doi.org/10.3389/fbuil.2025.1523464

17. Karimi, A., Mohajerani, M., Alinasab, N., & Akhlaghinezhad, F. (2024). Integrating machine learning and genetic algorithms to optimize building energy and thermal efficiency under historical and future climate scenarios. Sustainability, 16(21), 9324. https://doi.org/10.3390/su16219324

18. Agouzoul, A., & Simeu, E. (2024, May). Predictive Control Method for Comfort and Thermal Energy Enhancement in Buildings. In 2024 International Conference on Control, Automation and Diagnosis (ICCAD) (pp. 1-6). IEEE. https://doi.org/10.1109/ICCAD60883.2024.10553948

19. Al Sayed, K., Boodi, A., Broujeny, R. S., & Beddiar, K. (2024).

Reinforcement learning for HVAC control in intelligent buildings: A technical and conceptual review. Journal of Building Engineering, 95, 110085. https://doi.org/10.1016/j.jobe.2024.110085

20. Lim, S. H., Kim, T. G., Yeom, D. J., & Yoon, S. G. (2024). Robust deep reinforcement learning for personalized HVAC system. Energy and Buildings, 319, 114551. https://doi.org/10.1016/j.enbuild.2024.114551

21. Gassar, A. A. A., & Jafar, R. (2025). Artificial Intelligence-Enabled Heating, Ventilation, and Air Conditioning Systems Toward Zero-Emission Buildings: A Systematic Review of Applications, Challenges, and Future Directions. Applied Sciences, 15(19), 10497. https://doi.org/10.3390/app151910497

22. Silvestri, A., Coraci, D., Brandi, S., Capozzoli, A., & Schlueter, A. (2025). Practical deployment of reinforcement learning for building controls using an imitation learning approach. Energy and Buildings, 335, 115511. https://doi.org/10.1016/j.enbuild.2025.115511

23. Zhang, B. (2024). Modelling and Optimization of Multi-Energy System Operation Based on Deep Reinforcement Learning. https://doi.org/10.54337/aau763295893

24. Zhao, S., & Zhang, X. (2025). CGAN-enhanced building HVAC control: A synthetic data-driven approach for grid-responsive air conditioning systems. In 2025 International Conference on Smart Energy and Smart Grid (SESG) (pp. 74–77). IEEE. https://doi.org/10.1109/SESG67016.2025.00020

25. Nakayama, S., Takada, T., Kimura, R., & Ohsumi, M. (2024). Model predictive control of humidity deficit and temperature in winter greenhouses: subspace weather-based modelling and sampling period effects. Machines, 12(1), 56. https://doi.org/10.3390/machines12010056

26. Morcego, B., Yin, W., Boersma, S., Van Henten, E., Puig, V., & Sun, C. (2023). Reinforcement learning versus model predictive control on greenhouse climate control. Computers and Electronics in Agriculture, 215, 108372. https://doi.org/10.1016/j.compag.2023.108372

27. Sorensen, Å. L., Morsund, B. B., Andresen, I., Sartori, I., & Lindberg, K. B. (2024). Energy profiles and electricity flexibility potential in apartment buildings with electric vehicles–A Norwegian case study. Energy and buildings, 305, 113878. https://doi.org/10.1016/j.enbuild.2023.113878

28. Turner, S., Allen, A., Van Geet, O., & Romero, R. (2024). Exploring Grid-Interactive Efficient Building Strategies for Laboratories Through Energy Modeling (No. NREL/TP-7A40-87141). National Renewable Energy Laboratory (NREL), Golden, CO (United States). https://doi.org/10.2172/2349048

29. CaraDonna, C. (2024). End-Use Savings Shapes Measure Documentation: Heat Pump Rooftop Units With Exhaust Air Energy Recovery (No. NREL/TP-5500-89481). National Renewable Energy Laboratory (NREL), Golden, CO (United States). https://doi.org/10.2172/2340766

30. CaraDonna, C., Parker, A., & Meyer, R. (2024). End-Use Savings Shapes Measure Documentation: Heat Pump Rooftop Units (No. NREL/TP-5500-86585). National Renewable Energy Laboratory (NREL), Golden, CO (United States). https://doi.org/10.2172/2439548

31. Yoder, T. A., Pamintuan, B. C., & Salsbury, T. (2024). Building ControlScore: General Service Administration Office Building Deployment (No. PNNL-34418). Pacific Northwest National Laboratory (PNNL), Richland, WA (United States). https://doi.org/10.2172/2481967

32. Yoder, T. A., Pamintuan, B.C., & Salsbury, T. (2023). Building ControlScore: Research Laboratory Building Deployment (No. PNNL-34417). Pacific Northwest National Laboratory (PNNL), Richland, WA (United States). https://doi.org/10.2172/2482017

33. O'Brien, W., Wagner, A., Schweiker, M., Mahdavi, A., Day, J., Kjærgaard, M. B., ... & Berger, C. (2020). Introducing IEA EBC annex 79: Key challenges and opportunities in the field of occupant-centric building design and operation. Building and Environment, 178, 106738. https://doi.org/10.1016/j.buildenv.2020.106738

34. Irdmousa, B. K. (2024). Data Driven and Machine Learning Based Modeling and Predictive Control of Combustion at Reactivity Controlled Compression Ignition Engines (Doctoral dissertation, Michigan Technological University). https://doi.org/10.37099/mtu.dc.etdr/1703

35. Zhang, L., Sun, Y., Lam, H. K., Li, H., Wang, J., & Hou, D. (2021). Guaranteed cost control for interval type-2 fuzzy semi-Markov switching systems within a finite-time interval. IEEE Transactions on Fuzzy Systems, 30(7), 2583-2594. https://doi.org/10.1109/TFUZZ.2021.3089248

36. Chaudhary, G. (2025). Control-Oriented Deep Neural Networks for Building Dynamics Prediction. https://ir.iitr.ac.in/handle/123456789/12345

37. Arroyo, J., Helsen, L., & Spiessens, F. (2022). Synergy between control theory and machine learning for building energy management. https://doi.org/10.34641/clima.2022.378

38. Taiwo, O., & Ezugwu, A. E. (2021). Internet of things-based intelligent smart home control system. Security and Communication Networks, 2021(1), 9928254. https://doi.org/10.1155/2021/9928254

39. Li, M., & Wu, Y. (2022). Intelligent control system of smart home for context awareness. International Journal of Distributed Sensor Networks, 18(3), 15501329221082030. https://doi.org/10.1177/15501329221082030

40. Zielonka, A., Sikora, A., Woźniak, M., Wei, W., Ke, Q., & Bai, Z. (2020). Intelligent internet of things system for smart home optimal convection. IEEE Transactions on Industrial Informatics, 17(6), 4308-4317. https://doi.org/10.1109/TII.2020.3009094

41. Chen, C. W., & Chiu, L. M. (2021). Ordinal time series forecasting of the air quality index. Entropy, 23(9), 1167. https://doi.org/10.3390/e23091167

42. Zhang, W., Wu, Y., & Calautit, J. K. (2022). A review on occupancy prediction through machine learning for enhancing energy efficiency, air quality and thermal comfort in the built environment. Renewable and Sustainable Energy Reviews, 167, 112704.. https://doi.org/10.1016/j.rser.2022.112704

43. Ngarambe, J., Yun, G. Y., & Santamouris, M. (2020). The use of artificial intelligence (AI) methods in the prediction of thermal comfort in buildings: Energy implications of AI-based thermal comfort controls. Energy and Buildings, 211, 109807. https://doi.org/10.1016/j.enbuild.2020.109807

44. Iqbal, F., & Mirzabeigi, S. (2025). Digital Twin-Enabled Building Information Modeling–Internet of Things (BIM-IoT) Framework for Optimizing Indoor Thermal Comfort Using Machine Learning. Buildings, 15(10), 1584.. https://doi.org/10.3390/buildings15101584

45. Pelissero, N., Laso, P. M., & Puentes, J. (2021, September). Model graph generation for naval cyber-physical systems. In OCEANS 2021: San Diego–Porto (pp. 1-5). IEEE. https://doi.org/10.23919/OCEANS44145.2021.9705906

46. Mirshekali, H., Shadi, M. R., Ladani, F. G., & Shaker, H. R. (2025). A

ISSN 2071-1077(print)
ISSN 2663-2411(online

Review of Large Language Models for Energy Systems: Applications, Challenges, and Future Prospects. IEEE Access https://doi.org/10.1109/ACCESS.2025.3610994

47. Li, D., Qi, Z., Zhou, Y., & Elchalakani, M. (2025). Machine Learning Applications in Building Energy Systems: Review and Prospects. Buildings, 15(4), 648 https://doi.org/10.3390/buildings15040648

48. Wei, T., Wang, Y., & Zhu, Q. (2017, June). Deep reinforcement learning for building HVAC control. In Proceedings of the 54th annual design automation conference 2017 (pp. 1-6). https://doi.org/10.1145/3061639.3062224

49. Stieger, A., Stippel, C., Bratukhin, A., Hoch, R., & Sauter, T. (2025). How Many Sensors are Necessary?–Sensor Reduction in HVAC Control Modeling Using Feature Attribution and Rule Extraction. IEEE Sensors Letters. https://doi.org/10.1109/LSENS.2025.3602850

50. Li, G., Hu, Y., Liu, J., Fang, X., & Kang, J. (2020). Review on fault detection and diagnosis feature engineering in building heating, ventilation, air conditioning and refrigeration systems. Ieee Access, 9, 2153-2187. https://doi.org/10.1109/ACCESS.2020.3040980

51. Matetić, I., Štajduhar, I., Wolf, I., & Ljubic, S. (2022). A review of data-driven approaches and techniques for fault detection and diagnosis in HVAC systems. Sensors, 23(1), 1. https://doi.org/10.3390/s23010001

52. Escobar, L. M., Aguilar, J., Garces-Jimenez, A., De Mesa, J. A. G., & Gomez-Pulido, J. M. (2020). Advanced fuzzy-logic-based context-driven control for HVAC management systems in buildings. IEEE access, 8, 16111-16126. https://doi.org/10.1109/ACCESS.2020.2966545

53. de Vries, S. B., Laan, C. M., Bons, P. C., & Heller, R. M. (2024). Model-predictive space heating control for energy flexibility–a case study using a long short-term memory neural network surrogate model and a genetic optimization algorithm. Journal of Building Performance Simulation, 1-20. https://doi.org/10.1080/19401493.2024.2371918

54. Brudermueller, T., Fleisch, E., Vayá, M. G., & Staake, T. (2025, June). HEAPO–An Open Dataset for Heat Pump Optimization with Smart Electricity Meter Data and On-Site Inspection Protocols. In Proceedings of the 16th ACM International Conference on Future and Sustainable Energy Systems (pp. 699-711). https://doi.org/10.1145/3679240.3734637

55. Al-Ismail, F. S. (2024). A Comprehensive and Critical Review on Integrated Electric Power and Gas Networks. IEEE Access. https://doi.org/10.1109/ACCESS.2024.3424890

56. Bergsteinsson, H. G., Sørensen, M. L., Møller, J. K., & Madsen, H. (2023). Heat load forecasting using adaptive spatial hierarchies. Applied Energy, 350, 121676. https://doi.org/10.1016/j.apenergy.2023.121676

57. Huang, Y., Zhao, Y., Wang, Z., Liu, X., Liu, H., & Fu, Y. (2023). Explainable district heat load forecasting with active deep learning. Applied Energy, 350, 121753. https://doi.org/10.1016/j.apenergy.2023.121753

58. Manfren, M., Gonzalez-Carreon, K. M., & James, P. A. (2024). Interpretable data-driven methods for building energy modelling—a review of critical connections and gaps. Energies, 17(4), 881. https://doi.org/10.3390/en17040881

59. Deng, Y., Liu, Y., Liang, R., Xie, D., Zhao, D., Taniguchi, I., ... & Wang, D. (2024, October). Towards machine learning-based model predictive control for hvac control in multi-context buildings at scale via ensemble learning. In Proceedings of the 11th ACM International Conference on Systems for Energy-Efficient Buildings, Cities,

and Transportation (pp. 231-232). https://doi.org/10.1145/3671127.3698705

60. Altayeva, A., Baisholanova, K., Tukenova, L., Abduraimova, B., Nurtas, M., Baishemirov, Z., ... & Omarov, B. (2020, December). Towards smart building: exploring of indoor microclimate comfort level thermal processes. In International Conference on Smart Computing and Communication (pp. 59-67). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-64221-16

61. Almazam, K., Humaidan, O., Shannan, N. M., Bashir, F.M., Gammoudi, T., & Dodo, Y. A. (2025). Innovative Energy Efficiency in HVAC Systems with an Integrated Machine Learning and Model Predictive Control Technique: A Prospective Toward Sustainable Buildings. Sustainability, 17(7), 2916. https://doi.org/10.3390/su17072916

62. Zhu, X., & Li, H. (2025). Heating, Ventilation, and Air Conditioning (HVAC) Temperature and Humidity Control Optimization Based on Large Language Models (LLMs). Energies (19961073), 18(7). https://doi.org/10.3390/en18071813

63. Sun, H., Hu, Y., Luo, J., Guo, Q., & Zhao, J. (2025). Enhancing HVAC Control Systems Using a Steady Soft Actor–Critic Deep Reinforcement Learning Approach. Buildings, 15(4), 644 https://doi.org/10.3390/buildings15040644

64. Khabbazi, A. J., Pergantis, E. N., Premer, L. D. R., Papageorgiou, P., Lee, A. H., Braun, J. E., ... & Kircher, K. J. (2025). Lessons learned from field demonstrations of model predictive control and reinforcement learning for residential and commercial HVAC: A review. arXiv preprint arXiv:2503.05022. https://doi.org/10.48550/arXiv.2503.05022

65. Guo, G., Liu, P., & Zheng, Y. (2024). Early energy performance analysis of smart buildings by consolidated artificial neural network paradigms. Heliyon, 10(4). https://doi.org/10.1038/s41598-024-53995-3

66. Razzano, G., Brandi, S., Piscitelli, M. S., & Capozzoli, A. (2025). Rule extraction from deep reinforcement learning controller and comparative analysis with ASHRAE control sequences for the optimal management of Heating, Ventilation, and Air Conditioning (HVAC) systems in multizone buildings. Applied Energy, 381, 125046. https://doi.org/10.1016/j.apenergy.2024.125046

67. Silvestri, A., Coraci, D., Brandi, S., Capozzoli, A., Borkowski, E., Köhler, J., ... & Schlueter, A. (2024). Real building implementation of a deep reinforcement learning controller to enhance energy efficiency and indoor temperature control. Applied Energy, 368, 123447. https://doi.org/10.1016/j.apenergy.2024.123447

68. Serale, G., Fiorentini, M., Capozzoli, A., Bernardini, D., & Bemporad, A. (2018). Model predictive control (MPC) for enhancing building and HVAC system energy efficiency: Problem formulation, applications and opportunities. Energies, 11(3), 631. https://doi.org/10.3390/en11030631

69. Wald, D., Doronina, O., Johnson, K., King, R., Sinner, M., Griffin, K., ... & Day, M. (2025). A neural-network-enhanced parameter-varying framework for multi-objective model predictive control applied to buildings. Energy and AI, 100566. https://doi.org/10.1016/j.egyai.2025.100566

70. Kougiatsos, N., & Reppa, V. (2024). A distributed cyber-physical framework for sensor fault diagnosis of marine internal combustion engines. IEEE Transactions on Control Systems Technology, 32(5), 1718-1729. https://doi.org/10.1109/TCST.2024.3378992

71. Kim, D., Lee, J., Do, S., Mago, P. J., Lee, K. H., & Cho, H. (2022). Energy modeling and model predictive control for HVAC in buildings: A review of current

ISSN 2071-1077(print)
ISSN 2663-2411(online

research trends. Energies, 15(19), 7231. https://doi.org/10.3390/en15197231

72. Michailidis, P., Michailidis, I., Vamvakas, D., & Kosmatopoulos, E. (2023). Model-free HVAC control in buildings: A review. Energies, 16(20), 7124. https://doi.org/10.3390/en16207124

73. Liu, D., Ling, F., Zhou, X., & Li, Y. (2025). Integrating large language models, reinforcement learning, and machine learning for intelligent indoor thermal comfort regulation. Architectural Science Review, 1-14. https://doi.org/10.1080/00038628.2025.2488522

74. Luan, B., & Feng, X. (2025). Artificial intelligence in Smart Buildings: a bibliometrics-based visualization analysis. Journal of Asian Architecture and Building Engineering, 1-25. https://doi.org/10.1080/13467581.2025.2552448

75. Dounis, A. I., & Caraiscos, C. (2009). Advanced control systems engineering for energy and comfort management in a building environment—A review. Renewable and Sustainable Energy Reviews, 13(6-7), 1246-1261. https://doi.org/10.1016/j.rser.2008.09.015

76. Gharbi, A., Ayari, M., Albalawi, N., Touati, Y. E., & Klai, Z. (2025). Intelligent HVAC Control: Comparative Simulation of Reinforcement Learning and PID Strategies for Energy Efficiency and Comfort Optimization. Mathematics, 13(14), 2311. https://doi.org/10.3390/math13142311

77. Mathews, E. H., Arndt, D. C., Piani, C. B., & Van Heerden, E. (2000). Developing cost efficient control strategies to ensure optimal energy use and sufficient indoor comfort. Applied Energy, 66(2), 135-159. https://doi.org/10.1016/S0306-2619(99)00035-5

78. Heim, D., & Kułakowski, T. (2025). Emerging thermal technologies of building facades–the missing links in energy performance simulation. Journal of Building Performance Simulation, 1-14 https://doi.org/10.1080/19401493.2025.2472304

79. Greer, F., & Horvath, A. (2023). Modular construction's capacity to reduce embodied carbon emissions in California's housing sector. Building and Environment, 240, 110432 https://doi.org/10.1016/j.buildenv.2023.110432

80. Andersson, H., Cehlin, M., & Moshfegh, B. (2024). An investigation concerning optimal design of confluent jets ventilation with variable air volume. International Journal of Ventilation, 23(3), 183-203. https://doi.org/10.1080/14733315.2023.2300231

81. Jin, Q., Sun, Q., & Meng, G. (2024). Outdoor testbeds for studies on performance of building envelopes: review and recommendations. Science and Technology for the Built Environment, 30(8), 877-917. https://doi.org/10.1080/23744731.2024.2378677

82. Vasquez, N. G., Bekö, G., Wargocki, P., Cabovska, B., Teli, D., Dalenbäck, J. O., ... & Langer, S. (2023). Ventilation strategies and children's perception of the indoor environment in Swedish primary school classrooms. Building and Environment, 240, 110450. https://doi.org/10.1016/j.buildenv.2023.110450

83. Verma, A., Gupta, V., Nihar, K., Jana, A., Jain, R. K., & Deb, C. (2023). Tropical climates and the interplay between IEQ and energy consumption in buildings: A review. Building and Environment, 242, 110551. https://doi.org/10.1016/j.buildenv.2023.110551

84. Ding, X., Cerpa, A., & Du, W. (2024). Multi-zone hvac control with model-based deep reinforcement learning. IEEE Transactions on Automation Science and Engineering, 22, 4408-4426. https://doi.org/10.1109/TASE.2024.3410951

85. Tra, V., Amayri, M., & Bouguila, N. (2024). Latent Code Description for Unsupervised AHU Fault Detection Using Adaptive Adversarial Autoencoder. IEEE Transactions on Automation Science and Engineering. https://doi.org/10.1109/TASE.2024.3481211

86. Nesenbergs, K., Blumbergs, E., & Paikens, P. (2025). Cyber-Physical Systems: Securing Latvia's Future. In Cybersecurity in Latvia (pp. 233-263). Routledge. https://doi.org/10.4324/9781003638858-11

87. Zhao, H., Xu, Z., Wu, J., Liu, F., & Guan, X. (2024). A Hierarchical Framework-Based Coordinated Optimization of Building HVAC Systems and EVs. IEEE Transactions on Automation Science and Engineering. https://doi.org/10.1109/TASE.2024.3446908

88. Li, H., Xu, J., & Zhao, Q. (2024). Priority-based energy allocation in buildings through distributed model predictive control. IEEE Transactions on Automation Science and Engineering https://doi.org/10.1109/TASE.2024.3464612

89. Akhtar, T., Khatoon, S., & Mahmood, A. (2024, December). Occupancy Detection for HVAC Systems Using IoT Edge Computing and Vision-Based Image Processing. In 2024 IEEE/ACM 17th International Conference on Utility and Cloud Computing (UCC) (pp. 477-482). IEEE. https://doi.org/10.1109/UCC63386.2024.00074

90. J Khabbazi, A., N Pergantis, E., D Reyes Premer, L., H Lee, A., Ma, J., Liu, H., ... & J Kircher, K. (2024). What have we learned from field demonstrations of advanced commercial HVAC control?. https://docs.lib.purdue.edu/ihpbc/473/

91. Kumkam, S., Trinuruk, P., Chaiwiwatworakul, P., Rakkwamsuk, P., & Bangviwat, A. (2024, October). Study on Adaptation of Model-Agnostic Meta-Learning Integrated Deep Q-Learning for HVAC Control. In 2024 IEEE International Smart Cities Conference (ISC2) (pp. 1-6). IEEE. https://doi.org/10.1109/ISC260477.2024.11004295

92. Mezhuyev, V., Mykhailenko, V., Martynovych, L., Korenkova, H., Leshchenko, V., & Stukalov, S. (2023). Intellectual Improvement of the Control System for Harmful Emissions of a Ship's Utilizing Boiler. In ICST (pp. 153-162). https://ceur-ws.org/Vol-3513/paper13.pdf

93. Sathyanarayanan, K. K., Sauerteig, P., Zometa, P., & Streif, S. (2024, June). Quantized Deep Neural Network Based Optimal Control of Greenhouses on a Microcontroller. In 2024 European Control Conference (ECC) (pp. 400-405). IEEE. https://doi.org/10.23919/ECC64448.2024.10590831

94. Dio, M., Graichen, K., & Völz, A. (2024, October). Time-Optimal Path Parameterization for Cooperative Multi-Arm Robotic Systems with Third-Order Constraints. In 2024 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) (pp. 3043-3048). IEEE. https://doi.org/10.1109/IROS58592.2024.10802342

95. Moore, J., & Sawyer, D. (2024, August). Equipment health monitoring for industrial robotic arms. In 2024 IEEE 20th International Conference on Automation Science and Engineering (CASE) (pp. 1853-1860). IEEE. https://doi.org/10.1109/CASE59546.2024.10711629

96. Chen, Y., Kwak, K. H., Jung, D. D., & Kim, Y. (2024, July). Data-Driven Koopman Model of an Integrated HVAC and Battery Cooling System in Electric Vehicles. In 2024 American Control Conference (ACC) (pp. 2212-2217). IEEE. https://doi.org/10.23919/ACC60939.2024.10644907

97. Trenbath, K., Meyer, R., Woldekidan, K., Maisha, K., & Harris, M.

(2022). Commercial Building Sensors and Controls Systems-Barriers, Drivers, and Costs (No. NREL/TP-6A50-82117). National Renewable Energy Laboratory (NREL), Golden, CO (United States). https://doi.org/10.2172/1880546

98. Zhang, C., Berk Kazanci, O., Attia, S., Levinson, R., Hoon Lee, S., Holzer, P., ... & K Heiselberga, P. (2023). IEA EBC Annex 80-Dynamic simulation guideline for the performance testing of resilient cooling strategies: Version 2. https://orbit.dtu.dk/en/publications/iea-ebc-annex-80-dynamic-simulation-guideline-for-the-performance

99. Vacchi, M., Siligardi, C., Demaria, F., Cedillo-González, E. I., González-Sánchez, R., & Settembre-Blundo, D. (2021). Technological sustainability or sustainable technology? A multidimensional vision of sustainability in manufacturing. Sustainability, 13(17), 9942. https://doi.org/10.3390/su13179942

100. Stornelli, A., Ozcan, S., & Simms, C. (2021). Advanced manufacturing technology adoption and innovation: A systematic literature review on barriers, enablers, and innovation types. Research Policy, 50(6), 104229. https://doi.org/10.1016/j.respol.2021.104229

101. Ashima, R., Haleem, A., Bahl, S., Javaid, M., Mahla, S. K., & Singh, S. (2021). Automation and manufacturing of smart materials in Additive Manufacturing technologies using Internet of Things towards the adoption of Industry 4.0. Materials Today: Proceedings, 45, 5081-5088. https://doi.org/10.1016/j.matpr.2021.01.583

102. Kinkel, S., Baumgartner, M., & Cherubini, E. (2022). Prerequisites for the adoption of AI technologies in manufacturing – Evidence from a worldwide sample of manufacturing companies. Technovation, 110, 102375. https://doi.org/10.1016/j.technovation.2021.102375

103. Peter, O., Pradhan, A., & Mbohwa, C. (2023). Industrial internet of things (IIoT): opportunities, challenges, and requirements in manufacturing businesses in emerging economies. Procedia Computer Science, 217, 856-865. https://doi.org/10.1016/j.procs.2022.12.282

104. Frank, A. G., Dalenogare, L. S., & Ayala, N. F. (2019). Industry 4.0 technologies: Implementation patterns in manufacturing companies. International Journal of Production Economics, 210, 15-26. https://doi.org/10.1016/j.ijpe.2019.01.004

105. Castelo-Branco, I., Cruz-Jesus, F., & Oliveira, T. (2019). Assessing Industry 4.0 readiness in manufacturing: Evidence for the European Union. Computers in Industry, 107, 22-32. https://doi.org/10.1016/j.compind.2019.01.007

106. Schumacher, A., Erol, S., & Sihn, W. (2016). A maturity model for assessing Industry 4.0 readiness and maturity of manufacturing enterprises. Procedia CIRP, 52, 161-166. https://doi.org/10.1016/j.procir.2016.07.040

107. Raj, A., Dwivedi, G., Sharma, A., de Sousa Jabbour, A. B. L., & Rajak, S. (2020). Barriers to the adoption of Industry 4.0 technologies in the manufacturing sector: An inter-country comparative perspective. International Journal of Production Economics, 224, 107546. https://doi.org/10.1016/j.ijpe.2019.107546

108. 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

109. 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

110. Mehrpouya, M., Dehghanghadikolaei, A., Fotovvati, B., Vosooghnia, A.,

 ISSN 2071-1077(print)
ISSN 2663-2411(online

Emamian, S. S., & Gisario, A. (2019). The potential of additive manufacturing in the smart factory industrial 4.0: A review. Applied Sciences, 9(18), 3865. https://doi.org/10.3390/app9183865

111. Xu, X., Lu, Y., Vogel-Heuser, B., & Wang, L. (2021). Industry 4.0 and Industry 5.0 — Inception, conception and perception. Journal of Manufacturing Systems, 61, 530-535. https://doi.org/10.1016/j.jmsy.2021.10.006

112. Leng, J., Sha, W., Wang, B., Zheng, P., Zhuang, C., Liu, Q., ... & Wang, L. (2022). Industry 5.0: Prospect and retrospect. Journal of Manufacturing Systems, 65, 279-295. https://doi.org/10.1016/j.jmsy.2022.09.017

113. Coelho, P., Bessa, C., Landeck, J., & Silva, C. (2023). Industry 5.0: The arising of a concept. Procedia Computer Science, 217, 1137-1144. https://doi.org/10.1016/j.procs.2022.12.312

114. Warke, V., Kumar, S., Bongale, A., & Kotecha, K. (2021). Sustainable development of smart manufacturing driven by the digital twin framework: A statistical analysis. Sustainability, 13(18), 10139. https://doi.org/10.3390/su131810139

115. 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

116. Singh, S. (2025). Neuro-Fuzzy Architectures for Interpretable AI: A Comprehensive Survey and Research Outlook. Journal of Machine Learning Research, 1, 11. https://www.preprints.org/manuscript/202506.1173/v1

117. 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

118. Norouzi, P., Maalej, S., & Mora, R. (2023). Applicability of deep learning algorithms for predicting indoor temperatures: Towards the development of digital twin HVAC systems. Buildings, 13(6), 1542. https://doi.org/10.3390/buildings13061542

119. Fraga-Lamas, P., Lopes, S. I., & Fernández-Caramés, T. M. (2021). Green IoT and edge AI as key technological enablers for a sustainable digital transition towards a smart circular economy: An industry 5.0 use case. Sensors, 21(17), 5745. https://doi.org/10.3390/s21175745

120. Javaid, M., Haleem, A., Singh, R. P., & Suman, R. (2023). An integrated outlook of Cyber–Physical Systems for Industry 4.0: Topical practices, architecture, and applications. Green Technologies and Sustainability, 1(1), 100001. https://doi.org/10.1016/j.grets.2022.100001

121. Park, B. K., & Kim, C. J. (2023). Short-term prediction for indoor temperature control using artificial neural network. Energies, 16(23), 7724. https://doi.org/10.3390/en16237724

122. Kubiak, K., Dec, G., & Stadnicka, D. (2022). Possible applications of edge computing in the manufacturing industry—systematic literature review. Sensors, 22(7), 2445. https://doi.org/10.3390/s22072445

123. Ramachandra, V. (2025). Artificial Intelligence in Climate Science: A State-of-the-Art Review (2020–2025). https://doi.org/10.31223/X5M73J

124. Ojadi, J. O., Odionu, C. S., Onukwulu, E. C., & Owulade, O. A. (2024). AI-Enabled Smart Grid Systems for Energy Efficiency and Carbon Footprint Reduction in Urban Energy Networks. International Journal of Multidisciplinary Research and Growth Evaluation, 5(1), 1549-1566. https://doi.org/10.54660/.IJMRGE.2024.5.1.1549-1566

125. Addas, A. (2023). The concept of smart cities: a sustainability aspect for future urban development based on different cities. Frontiers in Environmental Science, 11, 1241593. https://doi.org/10.3389/fenvs.2023.1241593

126. Abu-Jassar, A. T., Attar, H., Yevsieiev, V., Amer, A., Demska, N., Luhach, A. K., & Lyashenko, V. (2022). Electronic user authentication key for access to HMI/SCADA via unsecured internet networks. Computational intelligence and neuroscience, 2022(1), 5866922. https://doi.org/10.1155/2022/5866922

127. Nevliudov, I., Yevsieiev, V., Maksymova, S., Demska, N., Kolesnyk, K., & Miliutina, O. (2023, September). Mobile Robot Navigation System Based on Ultrasonic Sensors. In 2023 IEEE XXVIII International Seminar/Workshop on Direct and Inverse Problems of Electromagnetic and Acoustic Wave Theory (DIPED) (Vol. 1, pp. 247-251). IEEE. https://doi.org/10.1109/DIPED59408.2023.10269500

128. Pande, A. S., & Burade, P. G. (2025). Integrated ANN-based IPFC for optimal power flow control in power systems. International Journal of Advanced Technology and Engineering Exploration, 12(124), 399. http://dx.doi.org/10.19101/IJATEE.2024.111100683

Надійшла до редакції 01.12.2025, розглянута на редколегії 11.02.2026

# Еволюція підходів до інтелектуального контролю мікроклімату в промислових середовищах: огляд моделей для кіберфізичних систем

У даній статті представлено систематичний огляд сучасних підходів до інтелектуального прогнозування та керування параметрами мікроклімату у виробничих середовищах у контексті розвитку кіберфізичних систем (CPS). Проаналізовано класичні (PID), евристичні (Fuzzy Logic) та машинні методи керування, а також нейромережеві архітектури різної складності, включно з багатошаровими перцептронами (MLP), рекурентними моделями (RNN, LSTM, GRU) та авторегресійними нейромережевими підходами з екзогенними входами (NNARX). Особливу увагу зосереджено на моделі NNARX як одній із найбільш перспективних для задач короткострокового прогнозування параметрів мікроклімату, характерних для інерційних промислових систем вентиляції та теплового регулювання. Розкрито особливості інтеграції прогнозних моделей у структуру CPS, де поєднання датчиків, виконавчих механізмів та обчислювального кібер-рівня формує адаптивний контур керування в реальному часі. Проведено порівняльний аналіз основних нейромережевих архітектур за критеріями точності, здатності до моделювання динаміки, врахування зовнішніх факторів та придатності до впровадження в CPS.

Огляд літератури дозволив виявити низку дослідницьких прогалин: недостатній обсяг робіт, що розглядають комплексний мікроклімат $(T, H, CO_2)$, нестачу універсальних параметричних моделей, обмеженість реальних виробничих датасетів та складність забезпечення роботи прогнозних моделей у режимі реального часу. Сформульовано перспективні напрями подальших досліджень, серед яких розроблення цифрових двійників мікроклімату, використання Edge AI, застосування гібридних стратегій NNARX+FLC та адаптація систем до вимог Industry 5.0.

***Ключові слова:*** інтелектуальне керування мікрокліматом; кіберфізичні

ISSN 2071-1077(print)
ISSN 2663-2411(online

системи; нейронні мережі; RNN; NNARX.

**Відомості про авторів:**

**Євсєєв Владислав В'ячеславович –** професор кафедри КІТАР, вчений секретар спеціалізованої вченої ради, доктор технічних наук, професор, Харківський національний університет радіоелектроніки, Харків, Україна; e-mail: vladyslav.yevsieiev@nure.ua; ORCID: https://orcid.org/0000-0002-2590-7085.

**Голод Ігор Вікторович** – аспірант кафедри комп'ютерно-інтегрованих технологій, автоматизації та робототехніки, Харківський національний університет радіоелектроніки, Харків, Україна. e-mail: ihor.holod@nure.ua; ORCID: https://orcid.org/0009-0005-1056-8614.

**About the authors:**

**Vladyslav YEVSIEIEV –** 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, Kharkiv, Ukraine. e-mail: vladyslav.yevsieiev@nure.ua; ORCID: https://orcid.org/0000-0002-2590-7085.

**Ihor HOLOD** – PhD student, Department of Computer Integrated Technologies, Automation and Robotics, Kharkiv National University of Radio Electronics, Kharkiv, Ukraine. e-mail: ihor.holod@nure.ua; ORCID https://orcid.org/0009-0005-1056-8614.