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DIGITAL TWIN IN THE STRUCTURE OF THE MODERN EDUCATIONAL ENVIRONMENT

In today's world, the advantage of digital twins is the ability to create copies of various physical objects, systems or learning environments, etc. This is especially true in engineering disciplines, where models of digital twins of a given accuracy provide research and experimentation without physical risks and significant financial costs. In the context of the educational environment, this means ensuring the effective functioning of virtual educational laboratories equipped with real equipment. The article develops an educational environment using a digital twin of a SMART laboratory, which functions as a cyber-physical system with end-to-end integration of a sensor network, actuators and a virtual model of the room. The purpose of the work is to theoretically substantiate and experimentally verify the educational environment, that includes a digital twin, focused on improving energy efficiency, comfort and safety of educational spaces. The methodological basis of the study includes system analysis, mathematical modelling of microclimate dynamics, as well as imperative control logic using typical regulators.

Within the framework of the proposed architecture, a microclimate model has been developed that combines the subsystems of monitoring, forecasting and adaptive control. Actualization of the real and virtual state is carried out in real time, which provides the possibility of preliminary testing of control actions and assessment of their impact without risk to the material base. A series of simulations and experiments confirmed the ability of the developed system to reduce resource consumption and stabilize microclimate parameters under the influence of external disturbances. At the same time, the system maintains pedagogical flexibility, supporting various formats of organizing the educational process.

The obtained results testify to the scientific novelty of the proposed approach, which consists in combining models and control systems with educational scenarios in a single software environment. The practical significance of the work is determined by the possibility of scaling the developed solution to other types of laboratories and academic disciplines, as well as the promoting the formation of digital competencies of future specialists in the field of information technology and cyber-physical systems.

K e y w o r d s : *educational environment, SMART laboratory, digital twin, monitoring, KPIs, microclimate.*

AMS 2020 classification: 68M99, 28-04, 93B45, 93C05.

Introduction

Digital twins (DTs) are one of the key technologies of the modern cyber-physical paradigm, enabling the integration of a physical object with its virtual representation in real time. They allow monitoring, forecasting, optimization, and management of objects and processes based on the constant interaction between physical and virtual environments (Thelen et al., 2022). This technology has become widespread in industry, energy, medicine, transport, as well as in Smart environments.

In Smart Home systems, DTs enable the effective solution of tasks related to automatic control of climatic conditions, energy consumption, safety, maintenance of engineering systems and ensuring a comfortable environment for residents. They function as an integration platform that integrates data from different sensors, analytical algorithms, and decision-making systems in real time. The use of digital twins in such systems allows you to optimize resource consumption, increase the level of comfort for users and ensure a prompt response to changes in the environment. At the same time, the use of DTs in the learning environment, including for building Smart labs, has a number of specific requirements. Specifically, there is a need to simulate typical educational processes, ensure the interaction of students with virtual and real equipment, the ability to scale experiments and provide a safe environment for learning. In this context, the digital twin acts not only as a means of automation, but also as a didactic tool for the development of digital, analytical and engineering competencies.

In the current conditions of digitalization of education, there is a need to introduce new forms of organization of laboratory practice, focused on accessibility, personalization and flexibility of the educational process. This problem becomes especially relevant in connection with the development of distance and hybrid learning, when direct access to physical laboratory equipment is limited. DTs enable the educational process to be implemented the educational process in the format of an interactive simulation that reproduces real conditions and provides real-time feedback. In addition, the introduction of DTs in training laboratories contributes to increasing the efficiency of the use of educational, technical and energy resources, which is especially important in the context of sustainable development and rational consumption. In particular, due to the integration with the engineering infrastructure of the premises, it is possible to implement the control of microclimate, energy consumption, security and technical diagnostics systems in an automated mode.

This approach is consistent with strategic documents, including the European Union's Digital Education Action Plan (2021–2027) (European Commission, 2023), which aims to develop high-quality, inclusive and accessible digital education in Europe. It is also in line with the Strategy for Digital Transformation of Education and Science of Ukraine (Ministry of Education and Science of Ukraine, 2025a), which provides for the modernization of educational infrastructure and the introduction of digital technologies into the educational process. In addition, the initiative is in line with the objectives of the Horizon Europe program, which supports research and innovation in the field of digital learning and the development of digital competences (the general objectives of the Horizon Europe program are confirmed in the context of Ukraine's innovation activities, in particular, in the Digital Development Strategy for Innovation until 2030 (Ministry of Education and Science of Ukraine, 2025b; Diia, 2025). These documents emphasize the importance of integrating digital technologies into the field of education to ensure its quality, accessibility and compliance with the modern requirements of the digital society.

The article considers the conceptual foundations of creating a digital twin of the Smart Laboratory, proposes the architecture of the model, and identifies the key technical, software and educational aspects of its implementation in the educational environment of a higher education institution.

The purpose and objectives of the study are the development of an educational environment in the form of a cyber-physical SMART laboratory focused on ensuring the adaptive, safe and resource-efficient functioning of the learning space, as well as the formalization and implementation of DT as a key tool for modeling, monitoring and supporting real-time decision-making.

The object of research is an educational SMART laboratory with laboratory equipment and technical means of automation.

Building a digital twin begins with the choice of architecture (Sai et al., 2024). They are usually multi-level. The literature most often considers the following five levels: Reference Architecture Model for Industry 4.0 (RAMI 4.0) (Junior, 2025) (Tab. 1).

Table 1

Levels of CD architecture

Level	Function	Technologies/Facilities	Literary sources
Physical Layer	Real physical objects that will have a digital twin	Sensors, controllers, actuators, boards	(Herrero, & Dasari, 2025; Hu et al., 2021; Piromalis, & Kantaros, 2022)
Communication Layer	Data transfer between physical devices and the digital layer	Protocols: MQTT, OPC UA, Modbus, Wi-Fi, USB	(Kober et al., 2024; Raza, et al., 2024)
Digital Model Layer	Digitized attributes, metadata, semantics of objects	JSON/XML, Digital Twin Model (DTDL), Device Description Language (DDL), RDF, OWL, SPARQL	(Schlenger et al., 2025; Ramonell, Chacón, & Posada, 2023; Xia et al., 2022)
Cyber Layer	Calculations, algorithms, big data, risk management, optimization and predictive analytics	Cloud/on-premises computing, uses scalable and distributed computing technologies such as AWS, Azure Databricks, Hadoop and Google Analytics, AI models, rule engines, stimulators	(Xie et al., 2025; Gautam et al., 2025; Delgado, & Oyedele, 2021).
Application Layer	User interfaces, analytics, visualization, interaction with the educational environment	LMS, Web UI, Analytics Panels, REST API	(Saif, RazaviAlavi, & Kassem, 2024; Tuhaise, Tah, & Abanda, 2023)

It should be noted that each of the considered layers can have its own implementations in the DT SMART laboratory. The Physical Layer may contain sensors specific to SMART buildings (Peldon et al., 2024; Huang, Zhang, & Zeng, 2022), power supplies, oscilloscopes, mockups of instructional circuits, etc. The Communication Layer provides data transfer to the backend. The server (physical, cloud, or edge – depending on the application) is responsible for the complete DT simulation, including data collection, processing, and analysis, as well as performing calculations that support decision-making processes and providing services to users (Weil et al., 2023). The Digital Model Layer typically focuses on the digital representation of objects and the establishment of semantic relationships. Ontologies are prevalent in scientific literature for working with large arrays of heterogeneous data. Their advantages include: describing complex objects, such as digital twin components, by formalizing their structure (classes, properties) and interrelationships; ensuring integration with AI; and the fact that most ontologies are based on open standards and languages (OWL, RDF), which significantly facilitates their integration into cross-platform systems (Vlasenko et al., 2022; Lutska, et al., 2022). The digital layer provides a virtual representation of physical objects by formalizing their geometric and other properties in a digital format that can be stored and managed on a variety of electronic media. In contrast to the Digital Model Layer, the Cyber Layer utilizes scalable and distributed computing technologies. The SMART lab's DT Application Layer can be responsible for the user interface, graph viewing, tasks, progress analytics, and more (Van der Valk et al., 2024).

Depending on the tasks set at different stages of construction and levels of DT, different models are used to describe approaches to its creation, structure and functioning. Among the most used models are the following:

- mathematical models that are built on the basis of physical laws, material, energy balances, etc. (Jia et al., 2024; Nezzi et al., 2025);
- data-driven model based on statistical data, ML algorithms that learn on historical/real data (these include regressions, neural networks, decision trees) (Beke et al., 2021);
- hybrid models that combine mathematical models and machine learning, which improves adaptability and increases accuracy (Lu et al., 2024; Yu, Liu, & Li, 2020; Luo et al., 2020);

- agent-based models, which consist of a set of autonomous agents with certain behaviors, rules, and interactions (Pretel et al., 2024);
- ontological models to describe the semantics of objects (Ropero, 2022);
- Knowledge graph-based models for representing DT as nodes and edges (Meyers et al., 2022).

The ISO 23247 series of standards forms a common glossary, conceptual model and multi-layer digital twin architecture for production systems, describing domains, entities and data flows throughout the full lifecycle of assets, thereby ensuring unified data exchange between physical and virtual components of production. According to a systematic review (Semeraro et al., 2021), such standardization enhances interoperability, simplifies the integration of IoT devices and enables real-time predictive maintenance and process optimization, and generalized analysis (Sharma et al., 2022) demonstrates additional benefits, including improved simulation accuracy, reduced design time, and support for physics-data-analytics feedback-based decision-making. In addition, the review (Javaid, Haleem, & Suman, 2023) confirms that the application of ISO 23247 minimizes the risks of testing new process scenarios and contributes to the safe transfer of the developed models to production lines. At the same time, the authors of these works and practitioners note a number of shortcomings: the focus of ISO 23247 mainly on the discrete manufacturing sphere, incomplete coverage of cybersecurity and semantic interoperability issues, as well as significant implementation costs and high staffing requirements, which limits the scaling of the standard to cross-industry ecosystems and small and medium-sized businesses (Wallner et al., 2023).

Building digital twins for educational laboratories has its own characteristics related to the educational context of their use. In such laboratories, it is important not only to ensure technical integration with physical devices and engineering infrastructure, but also to create conditions for simulating various experiments, accumulating and analyzing data, and interactive interaction of students with the laboratory environment. The DT of the training laboratory acts as a platform for the development of competencies in the field of the Internet of Things (IoT), automation, analytics and cyber-physical systems, contributing to the approximation of the educational process to the real conditions of modern engineering activities.

In the investigated educational lab, which is integrated with IoT technology, it is intended to monitor and maintain a wide range of variables to ensure effective, safe and adaptive educational interaction. These variables can be collected in real time, simulated with the digital environment, compared with DT model data, output to the digital interface of the system, providing visualization, fault forecasting, process adaptation and remote access to the laboratory. The laboratory model as part of the digital twin also has a simulation interface to study its features. To provide feedback from the model, elements of recommendations and forecasting are used, which are aimed at improving the key performance indicators (KPIs) of the laboratory.

1. General system architecture

To build a conceptual model (Fig. 1) of the educational digital environment, it is necessary to consider and analyze the physical and virtual components. The Physical World includes the object of study: an educational SMART laboratory equipped with sensors (measuring parameters affecting room comfort and safety), along with equipment and actuators that influence the efficiency of its functioning. External factors affecting the facility's operation include equipment usage, the presence of students and teachers in the lab, and the weather. The components of the Physical World interact with the virtual component.

The Virtual World comprises External Systems that ensure enhanced functionality and interaction between the DT and the Physical World. These External Systems include network exchange protocols between sensors and the digital environment, such as MQTT (running on TCP/IP) and Modbus, as well as databases. The DT itself consists of three main components: a Data Manager (which receives heterogeneous data from sensors or the Monitoring system), a Models Manager (which includes a mathematical model of the object), and a Services Manager (responsible for managing DT functions). Within the DT structure, in addition to the virtualization module, a component responsible for coordinating the physical and digital environments is implemented.

The collection and transmission of data from real sensors to the processing system is provided through the Monitoring Manager. Based on the collected information, the Decision-Making Manager generates appropriate actions that are transmitted to the level of executive devices. The Simulation Manager, in turn, is responsible for creating and maintaining simulation scenarios in a virtual environment. In this work, the implementation of the monitoring and DT subsystems is performed by the Node-RED tool for visual programming of data streams (Savchenko et al., 2025).

In terms of the RAMI 4.0 reference model presented in Tab. 1, the Physical World corresponds to the Physical Layer, including sensors, actuators, and laboratory equipment. The communication between physical devices and the DT infrastructure is implemented at the Communication Layer. The Models Manager represents the Digital Model Layer, while the computational services for simulation, forecasting, and KPI evaluation correspond to the Cyber Layer. Finally, visualization dashboards, user interaction tools, and learning interfaces belong to the Application Layer.

Thus, the developed architecture reflects the bidirectional integration of Physical World (laboratory equipment, sensors, actuators) and Virtual World (Data, Models, Services Manager), complemented by external factors and components of the educational digital platform (Fig. 1).

2. External data sources

The paper examines environmental and safety variables in the educational Smart Laboratory, which affect both the comfort and safety of staying in the room, and the efficiency of laboratory equipment. Data is collected by sensors and transmitted to a single digital environment in real time for visualization, analysis and adaptation of working conditions. Safety indicators are critical for protection of users and equipment. They allow you to quickly respond to emergencies, prevent accidents and keep an event log for audit. For each variable, the terms of reference are given: task, devices, control influences and operating range (Tab. 2, 3).

3. Methodology for Environment Assessment Based on KPI Criteria

To ensure the safe, comfortable, and energy-efficient operation of the digital environment, a multi-criteria system for assessing the condition by key performance indicators (KPIs) is proposed. A reasonable choice of criteria is based on modern regulatory documents [DSanPiN, ISO, WHO] and practical requirements for the microclimate and operational safety of technical equipment.

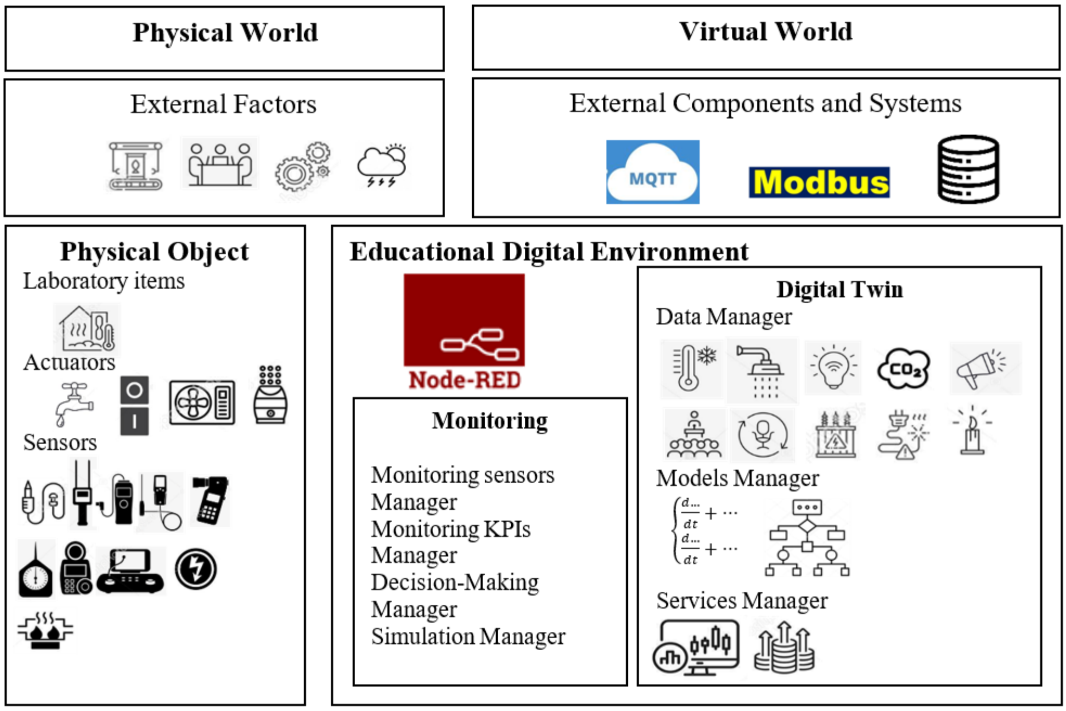

Fig. 1. A library's DT architecture

Table 2

The main variables affecting the comfort and safety of staying in the room

Variable	Problem statement	Sensor type	Control actions	Regulatory limits
Air temperature	Ensuring a comfortable microclimate and preventing overheating of equipment	Temperature sensors	Ventilation, air conditioning, notification control	+20...+24 °C (winter), +23...+26 °C (summer)
Air humidity	Humidity control for electronics accuracy and comfort	Humidity sensors	Switching on the humidifier / ventilation, logging	Optimal: 40-60%, acceptable: 30-70%
Illumination	Providing the appropriate level of lighting for visual work	Light sensors	Lighting adjustment, automatic on/off	300–500 lux (general works), > 500 lux (precision works)
Air quality	Monitoring CO_2, dust, and volatile organic compounds (VOCs) to provide fresh air	Air quality sensors	Ventilation control, alarms, logging	CO_2: < 1000 ppm; TVOC: < 500 ppb; PM2.5: < 25 μg/m³
Noise (sound pressure)	Noise control for a comfortable learning environment	Acoustic sensors	Noise fixation, alarm, logging	Up to 50 dB (normal for classrooms)
Vibration	Detection of vibrations of equipment or structures	Vibration sensors	Emergency shutdown, alarm, logging	<0.005–0.012 m/s² (depending on equipment sensitivity)

Table 3

Main variables affecting the efficiency of equipment

Variable	Problem statement	Sensor Type (Examples)	Control actions	Regulatory limits
User presence	Tracking the entrance to the laboratory within the allowed time. Ensuring the safety of equipment operation	Motion sensors	Presence logging, signaling in case of violation of access mode	User access only at allowed times
Overheating of equipment	Overheating detection to prevent equipment failure	Temperature sensors	Notifications, Auto Shutdown, Logging	The temperature should not exceed 70–80 °C (depending on the equipment)
Short circuit (overload)	Monitoring of the power grid to avoid emergencies	Current/Voltage Sensors	Emergency shutdown, alarm, logging	The current and voltage should not exceed the permissible values for the equipment (usually 10–16 A and 180–250 V)
Smoke and flame control	Prompt detection of fire hazards	Smoke and flame detectors	Emergency Power Off, Alert, Alarm	The presence of smoke or flames is a critical situation

The following KPIs were identified in the work:

✓ The comfort index ($Comfort\ Index$) determines how the environmental parameters correspond to those recommended for normal human activity. The set of controlled variables includes:

- air temperature (T, °C): recommended range of 20–26 °C;
- relative humidity (H, %): recommended range of 30–60 %;
- light level (L, lx): at least 300 lux;
- air quality (CO_2 level, ppm): CO_2: <1000 ppm;
- noise level (N, dB): up to 50 dB;
- vibration level (V, m/s²): up to 0.005 m/s².

Assessment is carried out according to the formula:

$$Comfort\ Index = \frac{1}{6}\sum_{i=1}^{6} \delta_i \cdot 100,$$

where

$$\delta_i = \begin{cases} 1, if\ the\ variable\ i\ is\ within\ the\ standard \\ 0, in\ other\ cases. \end{cases}$$

Thus, the maximum value $Comfort\ Index$ is 100 (perfect comfort), and the minimum is 0 (complete non-compliance of the conditions with the norms).

✓ The safety index ($Safety\ Index$) reflects the compliance of the technical condition of the environment with the criteria of electrical safety and fire safety. Contains controlled variables:

- temperature of equipment surfaces (T_dev, °C): up to 70 °C;
- consumption current (I, A): up to 16 A;
- voltage (U, V): in the range of 180–250 V;
- flame detection sign (F): Boolean signal.

The safety index is defined as:

$$Safety\ Index = \frac{1}{4}\sum_{j=1}^{4} \sigma_i \cdot 100,$$

where

$$\sigma_i = \begin{cases} 1, & if\ the\ variable\ j\ is\ in\ safe\ range \\ 0, & in\ other\ cases. \end{cases}$$

This index is also normalized in the range from 0 to 100, where 100 means full compliance with all safety requirements.

✓ The Energy Efficiency Index ($Efficiency\ Score$) reflects the ability of the system to consume electricity economically, in particular, during non-working periods. It takes into account:

- presence of personnel in the room (*presence*, Boolean signal);
- current energy consumption by lighting, temperature and equipment load.

The efficiency index is calculated as:

$$Efficiency\ Score = (1 - \frac{E_{waste}}{P + \varepsilon}) \cdot 100,$$

where is a small number to avoid division by zero. $\varepsilon = 0.001$.

Power consumption *P* is estimated as:

$$P = \frac{U \cdot I}{1000},$$

where *U* is the voltage (V), *I* is the current (A) and *P* is the power in kW.

Energy losses are defined as the weighted sum of consumption components when staff are absent:

$$E_{waste} = \sum_k \omega_k \cdot (1 - presence),$$

where $\omega_k \in [0,1]$ are the weighting factors for temperature, lighting, and consumption.

The Digital Twin dynamically adjusts the importance of specific criteria by modifying the weighting factors ωk. For the practical implementation within the platform, three fundamental distribution profiles are defined:

- a profile with safety priority ($\omega_{temp} = 0.6$, $\omega_{light} = 0.2$, $\omega_{cons} = 0.2$);
- a profile with resource-saving priority ($\omega_{temp} = 0.2$, $\omega_{light} = 0.2$, $\omega_{cons} = 0.6$);
- 0.33, $\omega_{light} = 0.33$, $\omega_{cons} = 0.34$).

These values ensure the adaptability of the assessment model to different operational modes of the SMART laboratory.

The weighting coefficients satisfy the normalization condition $\sum_k \omega_k = 1$ and can be modified to reflect alternative pedagogical or operational strategies.

The general condition of the laboratory is determined by the number of critical deviations:

$$Overall\ Status = \begin{cases} stable, & if\ criticalCount = 0 \\ warning, & if\ 1 \leq criticalCount \leq 3 \\ critical, & if\ criticalCount > 3, \end{cases}$$

where $criticalCount$ is the number of indicators that have gone beyond the standard.

The proposed methodology for evaluating KPIs is distinguished by its versatility and scalability, which allows it to be applied in different types of environments. It combines technical and human comfort indicators, providing a comprehensive assessment. In addition, the approach is open to integration with modern monitoring and optimization systems, in particular based on IoT, artificial intelligence and energy audits.

4. DT Model

For the DT model, a discrete dynamic structure in the space of state variables with constant coefficients is chosen. Such a model provides flexibility in analysis, simplifies calculations and increases system stability, allowing for its effective adaptation the model to different scenarios. This approach also improves forecasting accuracy and process optimization due to its clear mathematical framework, making it a convenient tool for exploring and managing complex dynamical systems.

The model of the microclimate of the laboratory is presented in discrete time in the form of a system of difference equations of the type:

$$x[k+1] = Ax[k] + Bu[k] + Ed[k], \quad (1)$$

$$y[k] = Cx[k],$$

where:

$x[k]$ is the vector of states at the time k ($x_0[k]$ is the air temperature in the room, °C; $x_1[k]$ – relative humidity, %; $x_2[k]$ – illumination, lx; $x_3[k]$ – CO_2 level, ppm; $x_4[k]$ – noise level, dB; $x_5[k]$ – vibration, 10^{-3} m/s²;

$u[k]$ – vector of control actions ($u_0[k]$– air conditioning (cooling) (0 – 10), $u_1[k]$ – ventilation (0 – 10), $u_2[k]$– humidifier (0 – 10), $u_3[k]$ – lighting (0 – 10);

$d[k]$ – perturbation vector (external conditions): $d_0[k]$ – external temperature, °C; $d_1[k]$ – external humidity, %; $d_2[k]$ – natural light (sun), Lux; $d_3[k]$ – number of people in the room; $d_4[k]$ – street noise, dB;

$y[k]$ – system output (measurement);

A, B, E, C – coefficient matrices: A – internal dynamics; B – influence of control actions; E – the influence of external factors; C – matrix of outputs/measurements.

The following values are used as initial values for these matrices (I – unit matrix):

$$A = \begin{bmatrix} 0.92 & 0.03 & 0 & 0.01 & 0 & 0 \\ 0.02 & 0.90 & 0 & 0.01 & 0 & 0 \\ 0 & 0 & 0.95 & 0 & 0 & 0 \\ 0.01 & 0.02 & 0 & 0.91 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.96 & 0 \\ 0 & 0 & 0 & 0 & 0.01 & 0.90 \end{bmatrix}, \quad B = \begin{bmatrix} -0.4 & -0.2 & 0 & 0 \\ 0 & -0.1 & 0.3 & 0 \\ 0 & 0 & 0 & 0.5 \\ 0 & -0.5 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix},$$

$$E = \begin{bmatrix} 0.25 & 0 & 0 & 0.3 & 0 \\ 0 & 0.2 & 0 & 0.2 & 0 \\ 0 & 0 & 0.3 & 0 & 0 \\ 0.15 & 0.1 & 0 & 0.5 & 0 \\ 0 & 0 & 0 & 0 & 0.3 \\ 0 & 0 & 0 & 0 & 0.2 \end{bmatrix}, \quad C = I_{6x6}.$$

Initial state:

$$x[0] = \begin{bmatrix} 22.0\,^0C \\ 45.0\,\% \\ 400\ lux \\ 800\ ppm \\ 45.0\ dB \\ 0.006\ m/sec^2 \end{bmatrix}.$$

The structure of the model was determined on the basis of a preliminary analysis of the physical relationships between parameters (the effect of temperature on humidity, or the number of people on CO_2). The coefficients of the dynamics model matrices (A, B, E, C) were taken from the scientific literature and a priori assumptions based on the typical behavior of similar systems. Their values are consistent with theoretical principles and can be adapted to specific conditions (Yao et al., 2013). The initial conditions of the model were set on the basis of typical values characteristic of the laboratory environment, which allows obtaining plausible results already at the initial stages of the simulation. However, given the theoretical nature of the parameters, they can be clarified in the process of calibrating the model for specific experimental data collected in the process of work. Thus, such a DT model is a rapid implementation model that will be further identified/calibrated through operation or student training.

5. Algorithm for optimizing resources and comfort

The algorithm for improving resource efficiency and safety in the SMART laboratory is based on the integrated application of a digital twin (DT), which acts as a virtual model of the environment with the ability to predict, simulate scenarios and assess the impact of control actions before their implementation in physical space.

The main stages of the algorithm (Fig. 2):

1. Synchronized monitoring of the state of a physical object. All sensors send data to *Monitoring Manager sensors,* where pre-processing (filtering, normalization, time alignment) is performed. Data is duplicated in DT *Data Manager*, maintaining its up-to-date virtual state in real time.

2. Evaluation of quality indicators (KPIs). DT analyzes current variables and calculates three main indicators: Comfort Index – a generalized characteristic of microclimate favorability; Safety Index – an indicator of approaching dangerous modes (exceeding temperature, overloading power lines, etc.); Efficiency Score is the ratio between energy consumption and the achieved levels of comfort and safety.

3. Forecasting based on the DT model. DT simulates the development of events for the next few steps, taking into account the current state space $(x_1[k],\ldots,x_5[k])$ and perturbations $(d_1[k],\ldots,d_4[k])$ and current control actions $(u_1[k+1],\ldots,u_3[k+1])$, behavioral patterns of laboratory use (presence of people, equipment activity). This forecast allows you to assess whether KPIs are expected to fall below critical thresholds and take action in advance.

4. Formation of recommended control actions. In case of detecting trends towards deterioration of conditions, the system generates recommendations through the DT model to optimize operation: changing the intensity of ventilation, heating or lighting; activation/deactivation of certain areas of the laboratory; switching the system to energy-saving mode in the absence of people. These actions are pre-simulated in DT, and only those that show an improvement in KPIs without deteriorating other indicators are suggested to the operator or applied automatically.

5. Implementation and monitoring of results. After implementing the recommended actions, DT conducts a performance analysis (before/after), updates the scenario database and forms new templates for successful configurations, this allows for improving the quality of recommendations over time based on accumulated experience.

It should be noted that the DT model takes into account which work scenario is activated (real, simulated, mixed) and automatically changes the weight of KPIs in the priority system. In particular, for a real scenario, safety is prioritized; for a simulated scenario, energy efficiency is prioritized; and for a mixed scenario, a balance among all indicators is maintained. Thus, there is an adaptation to the educational scenario.

Therefore, DT acts not only as a visualizer or a virtual copy of the laboratory, but as an active element of the decision support system. It provides behavior prediction, virtual testing of actions, assessment of efficiency without risk to the physical object, which significantly increases the safety, reliability and energy efficiency of the educational environment of the laboratory.

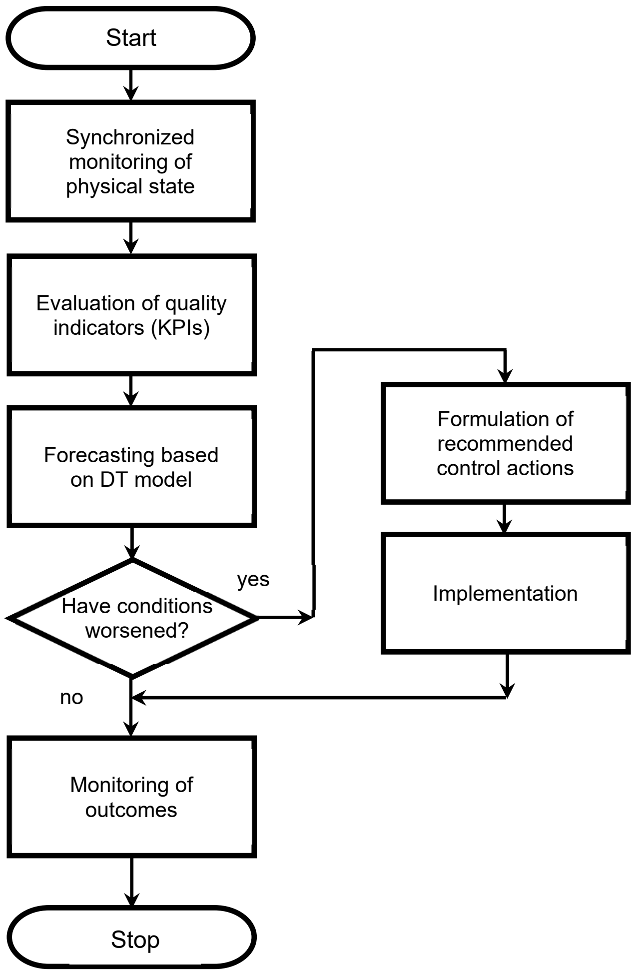

Fig. 2. The main stages of the control algorithm

6. Research results

Within the framework of this work, the educational environment is considered as a cyber-physical system. This system integrates the integration of physical objects (equipment, laboratory installations, sensors) and digital components (models, interfaces, analytical services) aimed at supporting the educational process. Such an environment not only reproduces the real conditions for the functioning of the laboratory space, but also serves as a tool for the development of digital competencies in students, in particular, in the field of information technology, IoT, data analytics, systems management and engineering thinking. The proposed architecture of the digital twin architecture for the laboratory covers all the key components of the educational environment: physical infrastructure, communication channels, virtual models, analytical algorithms, and user interfaces. In this paradigm, the educational environment becomes adaptive, context-sensitive, and focused on optimizing the learning process, thereby providing flexibility, accessibility, and personalization of educational interaction.

The developed DT SMART laboratory system was tested in simulation conditions with the involvement of real microclimate and safety parameters, as well as in the context of the implementation of the educational process. The results of the study showed the effectiveness of the selected architecture, control algorithms and approaches to resource monitoring.

Figure 3 demonstrates an online visualization of raw measurements with time graphs, deviation indicators, and color-coded risk levels, which facilitates the quick identification critical trends.

The panel in Fig. 4 combines the calculated Comfort, Safety and Efficiency indices, warning messages. The drill-down tools enable users to detail the contribution of individual parameters to the reduction of the generalized indicator.

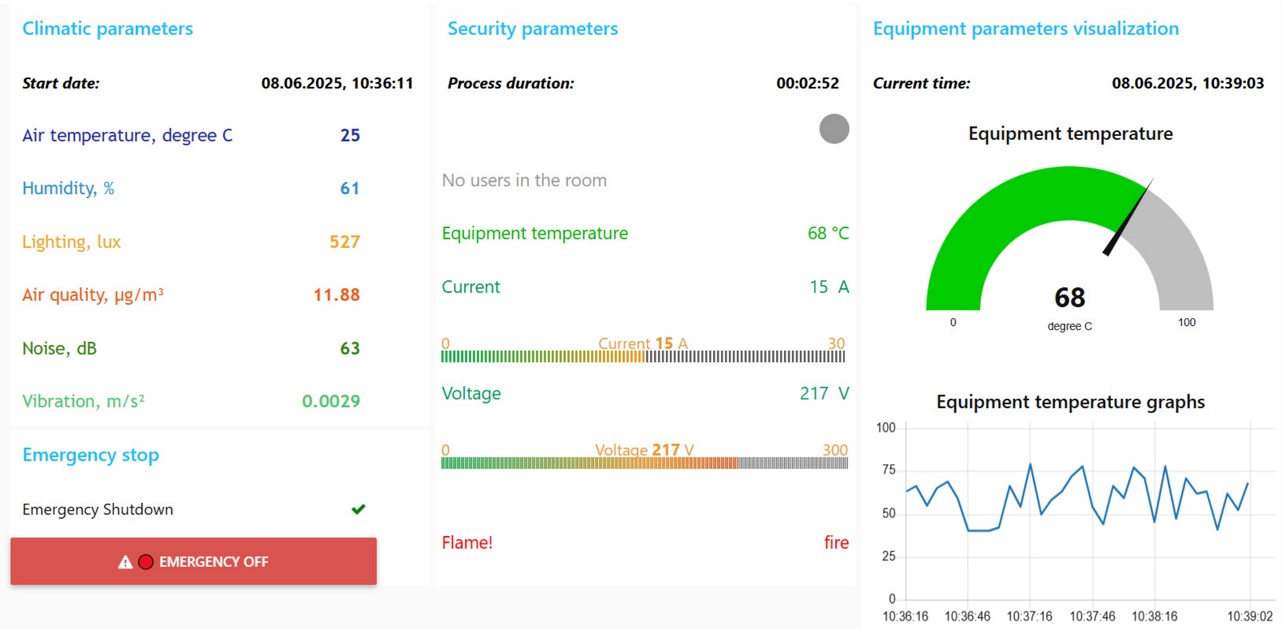

Fig. 3. Visualization Monitoring sensors Manager

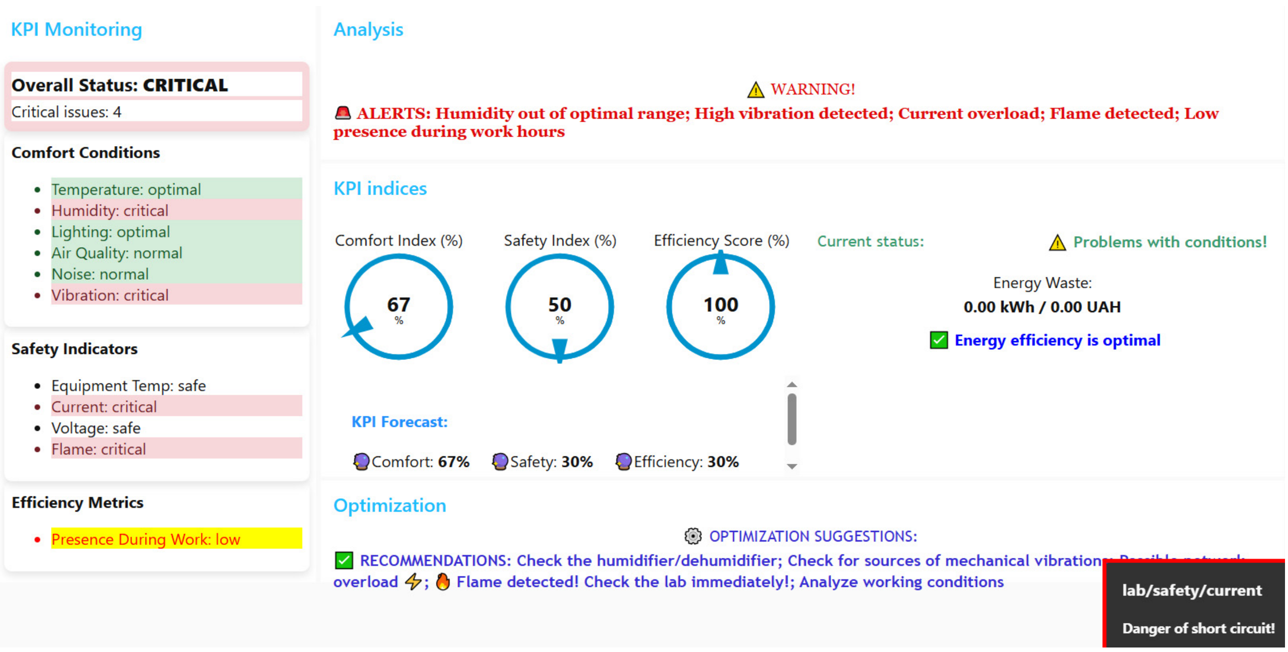

Fig. 4. Visualization Monitoring KPIs Manager

Figure 5 presents a fragment of the functional implementation of the DT SMART laboratory, developed in the Node-RED environment. The model integrates three main logical components: the microclimate model, perturbation actions and control actions, which are combined into a single computational flow with automatic regulation of environmental variables. Specifically, the matrix calculations for internal dynamics (A), control actions (B), and external disturbances (E) defined in (1) are handled by the 'Model: x = Ax + Bu + Ed' function node. This node performs discrete-time state-space integration at a 5-second frequency, serving as the core computational engine that links the theoretical mathematical model with the practical Node-RED data flow. This fragment simulates the dynamic changes in key microclimate variables such as temperature, humidity, lighting, CO_2 concentration, noise and vibration levels based on the input variables, with subsequent transmission of results to visualization and control nodes.

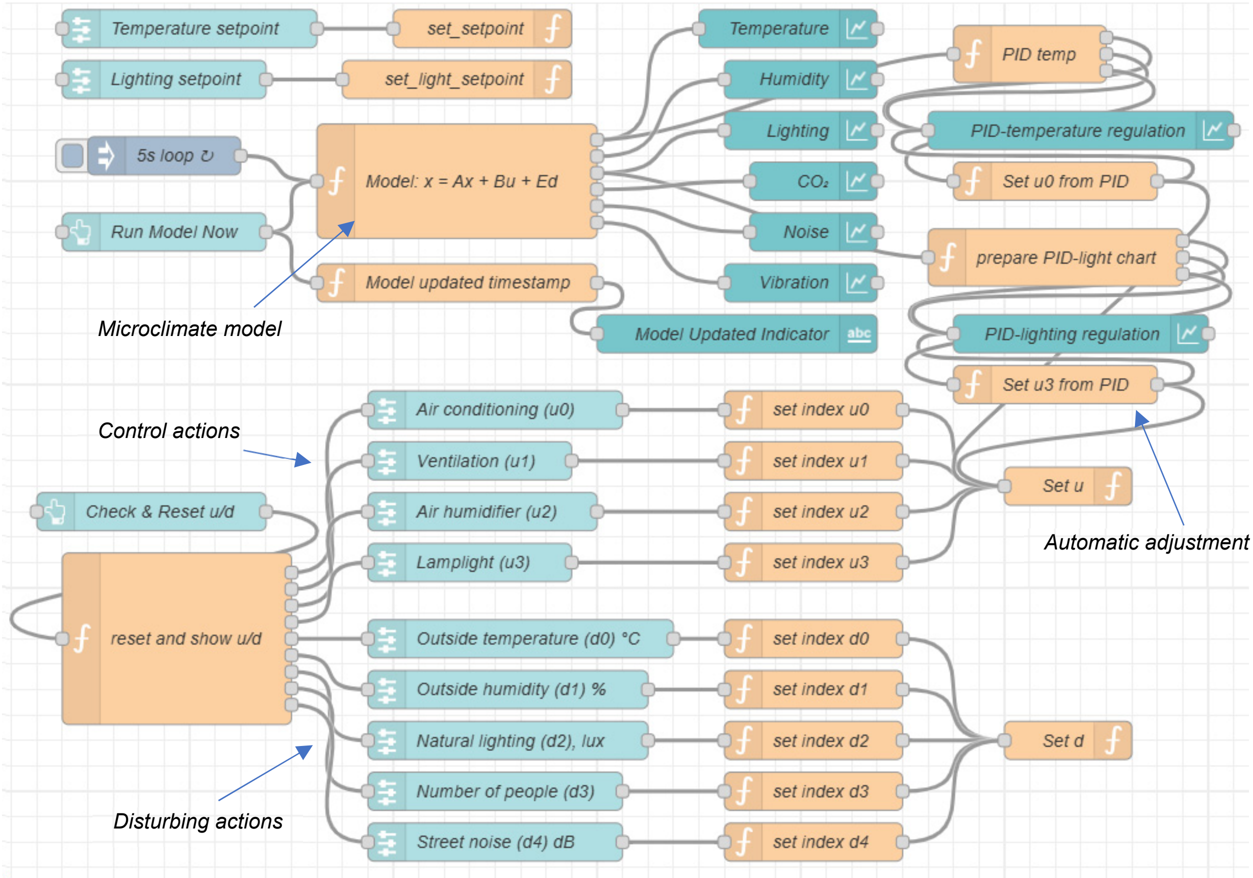

Fig. 5. Digital Twin Implementation

Disturbance inputs $(d_1, \ldots, d_4)$ are represented by signals which include outdoor temperature, humidity, natural light, the number of people in the room, and the level of street noise. These parameters can be entered manually or come from sensors, acting as external disturbances. Control actions $(u_1, \ldots, u_3)$ are responsible for operating actuators, specifically for air conditioning, ventilation, humidification, and lighting. Control can be carried out manually through the "set index" functions or automatically using PID controllers ("PID temperature controllers", "PID lighting controllers"), which analyze the simulated variables and generate appropriate control signals. The interconnection between the components demonstrates how DT integrates simulation, data collection, control, and regulation into a single, interactive, real-time environment.

Figure 6 displays a visualization of the DT model's simulation screen. In particular, users can set external perturbations and controls, then observe the predicted dynamics of state variables $x_1[k+1], \ldots, x_5[k+1]$ calculated according to equations (1).

Figure 7 demonstrates how automatic temperature and lighting controls compensate for perturbations and return variables to standards, comparing system operation to a "no control" scenario.

Thus, DT integration with the laboratory's physical environment enables experiments, simulations, and real-time automatic control.

Discussion and conclusions

In the context of implementing a DT for an educational laboratory, three primary scenarios for conducting lab work are proposed:

1. Scenario of a real physics experiment with digital duplication: students work directly with physical equipment, with DT carrying out parallel monitoring and analysis of indicators. This allows you to compare real and virtual data, get an advanced view of the system's operation, detect obsolescence of DT model parameters, and automatically visualize and evaluate KPIs in real time.

2. Simulated experiment scenario without physical access: Under distance or hybrid learning conditions, DT fully simulates the behavior of the laboratory environment, allowing virtual experiments to be conducted, input variables can be modified, simulation results can be observed, and analyzed according to training tasks.

Fig. 6. Room climate simulation mode on the Digital Twin model

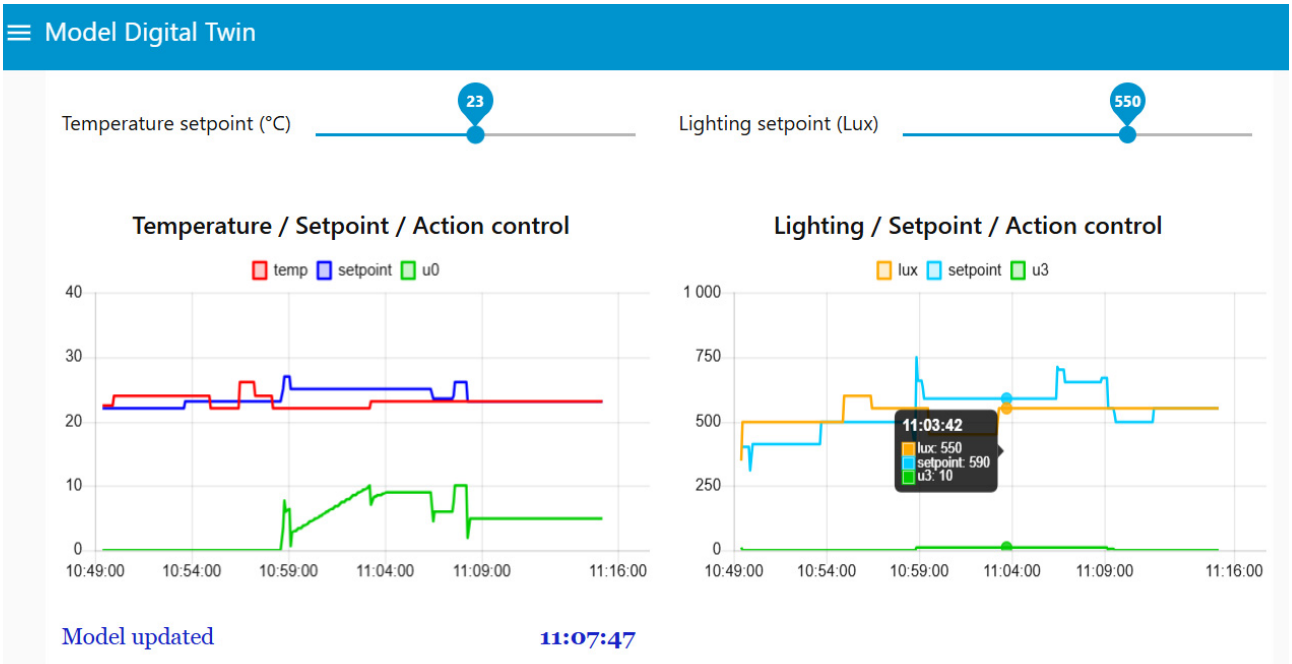

Fig. 7. Simulation mode of the automatic adjustment system on the Digital Twin model

3. Mixed-type scenario with adaptive environmental control: combines elements of real interaction and virtual model with the ability to control the microclimate, energy consumption and safety. Thanks to the use of DT, dynamic adjustment of the working conditions is implemented in accordance with the context (presence of students, type of experiment, resource constraints, etc.).

The proposed scenarios ensure the adaptability of the laboratory course to different learning formats, increase the efficiency of resource use, and create a safe and stimulating educational environment. In addition, each scenario is accompanied by an analytical block, which allows for continuous improvement of the methodology of conducting classes based on the analysis of the collected data.

The developed system of the educational environment of the SMART laboratory was tested in simulation conditions with the involvement of real microclimate and safety parameters, as well as in the context of the implementation of the educational process. The pedagogical evaluation of the proposed digital twin-based laboratory environment was conducted during regular laboratory classes in control systems and automation courses. The study involved 24 undergraduate students divided into small working groups. The experimental tasks included microclimate parameter analysis, PID controller tuning for temperature and lighting regulation (Fig. 7), and comparative analysis of system behavior under different disturbance scenarios. Data collection was carried out over a two-week period, covering six laboratory sessions with repeated task execution in real, simulated, and mixed scenarios.

The results of the study showed the effectiveness of the chosen architecture, management algorithms and approaches to resource monitoring. In this case, it is necessary to note:

1. Simulations using a discrete dynamic microclimate model and an automatic regulator showed that a system with a DT is capable of:

– stabilize the temperature and humidity within the standard values within 2–4 minutes after a disturbance;

– react to anomalies in the safety system (exceeding the current or temperature of the equipment) within 1-2 minutes;

– to reduce the total electricity consumption by approximately 5.4–11.2 % with the same quality of control compared to manual mode.

2. Average values of KPIs for the entire simulation period (7 days of continuous simulation):

– Comfort Index: 91 %

– Safety Index: 96 %

– Efficiency Score: 87 %

These values demonstrate the high quality of adaptive control and the consistency of all subsystem operations.

3. Within the framework of conducting classes according to three scenarios (real, simulated, mixed), the effectiveness assessment was carried out according to the following criteria:

– Number, variability, and speed of task completion: In the virtual scenario, an average of 23 % less time was spent on each task due to adjustable simulation time and the ability to work with saved data.

– Accuracy of measurements and repeatability of experiments. The use of DT reduced the variation of measurement results to 5.2 %, which is half that of traditional approaches.

– Interactivity and adaptability. A mixed scenario that combines physical access to equipment with remote simulation is the most effective for building analysis competencies and optimizing processes.

Thus, the DT integration into the educational space not only improves teaching quality but also ensures the flexibility of the educational process, which is critically important in today's environment. Virtualization allows you to scale the laboratory into different academic disciplines while maintaining the conceptual integrity of the environment. At the same time, further DT improvement requires model expansion and the development of an ontological knowledge base to ensure semantic interoperability between different types of laboratories.

Therefore, the study confirmed the feasibility and effectiveness of the developed system as both a technical and pedagogical tool for higher education. The developed educational environment in the form of a SMART laboratory with integrated DT is an example of the practical implementation of modern approaches to the digitalization of education. It combines physical measurements, mathematical modeling, automatic regulation and visualization in a single software environment. Such integration allows not only to effectively manage microclimate and safety indicators, but also creates conditions for the active involvement of students in the educational process.

The DT acts as a key element of adaptive management, providing not only the current display of the environment's state but also its forecasting, assessing the quality of the learning space using key indicators, forming recommendations for improvement, and storing successful configurations for future use.

In contrast to industrial standards like ISO 23247, which often entail high implementation costs and require specialized staffing, the proposed Node-RED-based environment offers a significantly more accessible alternative. Due to its open-source nature and low entry threshold provided by visual programming, Node-RED allows students to interact with complex digital twin structures without extensive coding knowledge. This cost-effective approach facilitates the scaling of SMART laboratories in academic settings where budget and time for specialized technical training are limited.

The system's implementation in the open Node-RED environment has demonstrated the platform's technical accessibility and flexibility, enabling the approach to be scaled to other educational laboratories. The implementation of DT also supports flexible forms of learning, in particular, distance and mixed formats, which is extremely important in the context of modern educational transformation. Overall, the proposed approach demonstrates a new level of interaction among the student, the digital model, and the physical object, not only enhancing learning quality but also fostering the digital competencies necessary for future specialists.

The results obtained prove the effectiveness of the concept and create the basis for scaling the approach to other types of classrooms and for further research towards the ontological integration of DTs from different laboratories into a unified educational ecosystem.

Authors' contribution: Natalia Lutska – conceptualization; methodology; Tetiana Savchenko – software; Tetiana Savchenko, Natalia Lutska – collection and verification of empirical data; Tetiana Savchenko, Natalia Lutska, Lidiya Vlasenko, Ivan Parkhomenko – empirical research; Lydia Vlasenko, Ivan Parkhomenko – analysis of sources, preparation of a literature review or theoretical foundations of research.

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References

Beke, Á. K., Gyürkés, M., Nagy, Z. K., Marosi, G., & Farkas, A. (2021). Digital twin of low dosage continuous powder blending–Artificial neural networks and residence time distribution models. *European journal of pharmaceutics and biopharmaceutics*, 169, 64–77. https://doi.org/10.1016/j.ejpb.2021.09.006

Delgado, J. M. D., & Oyedele, L. (2021). Digital Twins for the built environment: learning from conceptual and process models in manufacturing. *Advanced Engineering Informatics*, 49, 101332. https://doi.org/10.1016/j.aei.2021.101332

Diia. (2025). *The Government approved the Strategy for Digital Development of Innovations until 2030.* https://tinyurl.com/3y4zy6kz

European Commission. (2023). *Digital Education Action Plan (2021-2027).* European Education Area. https://education.ec.europa.eu/focus-topics/digital-education/action-plan

Gautam, A., Aryal, M. R., Deshpande, S., Padalkar, S., Nikolaenko, M., Tang, M., & Anand, S. (2025). IIoT-enabled digital twin for legacy and smart factory machines with LLM integration. *Journal of Manufacturing Systems*, 80, 511–523. https://doi.org/10.1016/j.jmsy.2025.03.022

Herrero, R., & Dasari, M. (2025). Edge-based physical asset and digital twin virtualization framework to support cognitive digital twins. *Internet of Things*, 31, 101601. https://doi.org/10.1016/j.iot.2025.101601
Hu, C., Fan, W., Zeng, E., Hang, Z., Wang, F., Qi, L., & Bhuiyan, M. Z. A. (2021). Digital twin-assisted real-time traffic data prediction method for 5G-enabled internet of vehicles. *IEEE Transactions on Industrial Informatics*, 18(4), 2811–2819. https://doi.org/10.1109/TII.2021.3083596
Huang, W., Zhang, Y., & Zeng, W. (2022). Development and application of digital twin technology for integrated regional energy systems in smart cities. *Sustainable Computing: Informatics and Systems*, 36, 100781. https://doi.org/10.1016/j.suscom.2022.100781
Javaid, M., Haleem, A., & Suman, R. (2023). Digital twin applications toward industry 4.0: A review. *Cognitive Robotics*, 3, 71–92. https://doi.org/10.1016/j.cogr.2023.04.003
Jia, K., Wang, H., Ren, D., Liu, B., Zhao, Q., & Hong, J. (2024). A general mathematic model framework for assembly process driven digital twin of assembly precision. *Journal of Manufacturing Systems*, 77, 196–211. https://doi.org/10.1016/j.jmsy.2024.09.007
Junior, O. C. (2025). Digital Twin in Industry 4.0: Systematic review and content analysis and an architectural reference model. *Procedia Computer Science*, 253, 2919–2928. https://doi.org/10.1016/j.procs.2025.02.016
Kober, C., Medina, F. G., Benfer, M., Wulfsberg, J. P., Martinez, V., & Lanza, G. (2024). Digital twin stakeholder communication: characteristics, challenges, and best practices. *Computers in Industry*, 161, 104135. https://doi.org/10.1016/j.compind.2024.104135
Lu, Y., Li, Y., Fu, G., Jiang, Y., Huang, Y., Zhu, J., & Sheng, B. (2024). The physical information LSTM surrogate model for establishing a digital twin model of reciprocating air compressors. *Applied Soft Computing*, 167, 112309. https://doi.org/10.1016/j.asoc.2024.112309
Lutska, N., Vlasenko, L., Ladanyuk, A., Zaiets, N., & Korobiichuk, I. (2022). Ontological support system of managerial decision-making of production tasks for a food enterprise. *Machinery & Energetics*, 13(3), 53–61. https://doi.org/10.31548/machenergy.13(3).2022.53-61
Luo, W., Hu, T., Ye, Y., Zhang, C., & Wei, Y. (2020). A hybrid predictive maintenance approach for CNC machine tool driven by Digital Twin. *Robotics and Computer-Integrated Manufacturing*, 65, 101974. https://doi.org/10.1016/j.rcim.2020.101974
Meyers, B., Van Noten, J., Lietaert, P., Tielemans, B., Hristov, H., Maes, D., & Gadeyne, K. (2022). Knowledge graphs in digital twins for manufacturing-lessons learned from an industrial case at Atlas Copco Airpower. *IFAC-PapersOnLine*, 55(10), 13–18. https://doi.org/10.1016/j.ifacol.2022.09.361
Ministry of Education and Science of Ukraine. (2025a). *Digital transformation of education and science.* https://tinyurl.com/2bx5he74
Ministry of Education and Science of Ukraine. (2025b). *WINWIN: Ukraine approved the Strategy for Digital Development of Innovations until 2030.* https://tinyurl.com/2vjz8ztd
Nezzi, C., Gufler, V., Vidoni, R., & Rauch, E. (2025). Kinematic and dynamic modeling of mechanical systems towards Digital Twins. *Results in Engineering*, 104874. https://doi.org/10.1016/j.rineng.2025.104874
Peldon, D., Banihashemi, S., LeNguyen, K., & Derrible, S. (2024). Navigating urban complexity: The transformative role of digital twins in smart city development. *Sustainable Cities and Society*, 111, 105583. https://doi.org/10.1016/j.scs.2024.105583
Pretel, E., Moya, A., Navarro, E., López-Jaquero, V., & González, P. (2024). Analysing the synergies between Multi-agent Systems and Digital Twins: A systematic literature review. *Information and Software Technology*, 174, 107503. https://doi.org/10.1016/j.infsof.2024.107503
Piromalis, D., & Kantaros, A. (2022). Digital twins in the automotive industry: The road toward physical-digital convergence. *Applied System Innovation*, 5(4), 65. https://doi.org/10.3390/asi5040065
Ramonell, C., Chacón, R., & Posada, H. (2023). Knowledge graph-based data integration system for digital twins of built assets. *Automation in Construction*, 156, 105109. https://doi.org/10.1016/j.autcon.2023.105109
Raza, M., Sartori, A., Bilberg, A., & Schlette, C. (2024). Communication between two distinct digital counterparts of a robotic cell digital twin via MQTT. *Procedia CIRP*, 130, 959–963. https://doi.org/10.1016/j.procir.2024.10.191
Ropero, J. (2022). Peer review of "Toward human digital twins for cybersecurity simulations on the metaverse: Ontological and network science approach". *JMIRx Med*, 3(2), e38583. https://doi.org/10.2196/38583
Sai, A. M. V. V., Wang, C., Cai, Z., & Li, Y. (2024). Navigating the digital twin network landscape: A survey on architecture, applications, privacy and security. *High-Confidence Computing*, 4(4), 100269. https://doi.org/10.1016/j.hcc.2024.100269
Saif, W., RazaviAlavi, S., & Kassem, M. (2024). Construction digital twin: a taxonomy and analysis of the application-technology-data triad. *Automation in Construction*, 167, 105715. https://doi.org/10.1016/j.autcon.2024.105715
Savchenko, T., Lutska, N., Vlasenko, L., Sashnova, M., Zahorulko, A., Minenko, S., Ibaiev, E. & Tytarenko, N. (2025). Risk analysis and cybersecurity enhancement of Digital Twins in dairy production. *Technology audit and production reserves*, 2(2(82)), 37–49. https://doi.org/10.15587/2706-5448.2025.325422
Semeraro, C., Lezoche, M., Panetto, H., & Dassisti, M. (2021). Digital twin paradigm: A systematic literature review. *Computers in Industry*, 130, 103469. https://doi.org/10.1016/j.compind.2021.103469
Schlenger, J., Pluta, K., Mathew, A., Yeung, T., Sacks, R., & Borrmann, A. (2025). Reference architecture and ontology framework for digital twin construction. *Automation in Construction*, 174, 106111. https://doi.org/10.1016/j.autcon.2025.106111
Sharma, A., Kosasih, E., Zhang, J., Brintrup, A., & Calinescu, A. (2022). Digital Twins: State of the art theory and practice, challenges, and open research questions. *Journal of Industrial Information Integration*, 30, 100383. https://doi.org/10.1016/j.jii.2022.100383
Thelen, A., Zhang, X., Fink, O., Lu, Y., Ghosh, S., Youn, B. D., Todd, M. D., Mahadevan, S., Hu, Ch., & Hu, Z. (2022). A comprehensive review of digital twin–part 1: modeling and twinning enabling technologies. *Structural and Multidisciplinary Optimization*, 65(12), 354. http://dx.doi.org/10.48550/arXiv.2208.14197
Tuhaise, V. V., Tah, J. H. M., & Abanda, F. H. (2023). Technologies for digital twin applications in construction. *Automation in Construction*, 152, 104931. https://doi.org/10.1016/j.autcon.2023.104931
Van der Valk, H., Schmelzer, R., Rose, D., & Dinter, B. (2024). Towards a Process Model for Digital Twin Implementation: The Implementation Canvas. *Procedia CIRP*, 122, 903–908. https://doi.org/10.1016/j.procir.2024.01.123
Vlasenko, L., Lutska, N., Zaiets, N., Korobiichuk, I., & Hrybkov, S. (2022). Core ontology for describing production equipment according to intelligent production. *Applied System Innovation*, 5(5), 98. https://doi.org/10.3390/asi5050098
Wallner, B., Zwölfer, B., Trautner, T., & Bleicher, F. (2023). Digital twin development and operation of a flexible manufacturing cell using iso 23247. *Procedia CIRP*, 120, 1149–1154. https://doi.org/10.1016/j.procir.2023.09.140
Weil, C., Bibri, S. E., Longchamp, R., Golay, F., & Alahi, A. (2023). Urban digital twin challenges: A systematic review and perspectives for sustainable smart cities. *Sustainable Cities and Society*, 99, 104862. https://doi.org/10.1016/j.scs.2023.104862
Xia, H., Liu, Z., Efremochkina, M., Liu, X., & Lin, C. (2022). Study on city digital twin technologies for sustainable smart city design: A review and bibliometric analysis of geographic information system and building information modeling integration. *Sustainable Cities and Society*, 84, 104009. https://doi.org/10.1016/j.scs.2022.104009
Xie, W., Zeng, Y., Zhang, X., Wong, H. Y., Zhang, T., Wang, Z., Wu, X., Shi, J., Huang, X., Xiao, F., & Usmani, A. (2025). AIoT-powered building digital twin for smart firefighting and super real-time fire forecast. *Advanced Engineering Informatics*, 65, 103117. https://doi.org/10.1016/j.aei.2025.103117

Yao, Y., Yang, K., Huang, M., & Wang, L. (2013). A state-space model for dynamic response of indoor air temperature and humidity. *Building and environment*, 64, 26–37. https://doi.org/10.1016/j.buildenv.2013.03.009

Yu, J., Liu, P., & Li, Z. (2020). Hybrid modelling and digital twin development of a steam turbine control stage for online performance monitoring. *Renewable and Sustainable Energy Reviews*, 133, 110077. https://doi.org/10.1016/j.rser.2020.110077

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ЦИФРОВИЙ ДВІЙНИК У СТРУКТУРІ СУЧАСНОГО ОСВІТНЬОГО СЕРЕДОВИЩА

У сучасному світі перевагою цифрових двійників є можливість створення копій різних фізичних об'єктів, систем або навчальних середовищ тощо. Це особливо актуально для інженерних дисциплін, де моделі цифрових двійників заданої точності забезпечують проведення досліджень та експериментів без фізичних ризиків і суттєвих фінансових витрат. У контексті освітнього середовища це означає забезпечення ефективного функціонування віртуальних навчальних лабораторій, оснащених реальним обладнанням.

У представленій статті розроблено освітнє середовище з використанням цифрового двійника SMART-лабораторії, що функціонує як кіберфізична система з наскрізною інтеграцією сенсорної мережі, виконавчих механізмів і віртуальної моделі приміщення. Мета роботи – теоретичне обґрунтування й експериментальна верифікація освітнього середовища, що містить цифровий двійник, орієнтований на підвищення енергоефективності, комфортності й безпеки навчальних просторів. Методологічною основою дослідження є системний аналіз, математичне моделювання динаміки мікроклімату, а також імперативна логіка регулювання з використанням типових регуляторів.

У межах запропонованої архітектури розроблено модель мікроклімату, що поєднує підсистеми моніторингу, прогнозування й адаптивного керування. Актуалізація реального та віртуального стану здійснюється в реальному часі, що забезпечує можливість попереднього тестування керуючих дій та оцінювання їхнього впливу без ризику для матеріальної бази. Проведена серія симуляцій та експериментів підтвердила здатність розробленої системи зменшувати споживання ресурсів і стабілізувати параметри мікроклімату за умов дії зовнішніх збурень. Водночас система зберігає педагогічну гнучкість, підтримуючи різні формати організації навчального процесу.

Одержані результати засвідчують наукову новизну запропонованого підходу, що полягає в поєднанні моделей і систем керування з освітніми сценаріями в єдиному програмному середовищі. Практичне значення роботи визначається можливістю масштабування розробленого рішення на інші типи лабораторій і навчальні дисципліни, а також сприянням формуванню цифрових компетентностей майбутніх фахівців у галузі інформаційних технологій і кіберфізичних систем.

Ключові слова: ***освітнє середовище, SMART-лабораторія, цифровий двійник, моніторинг, KPI, мікроклімат.***

Автори заявляють про відсутність конфлікту інтересів. Спонсори не брали участі в розробленні дослідження; у зборі, аналізі чи інтерпретації даних; у написанні рукопису; у рішенні про публікацію результатів.

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