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DEVELOPING AN ENVIRONMENTAL KEY PERFORMANCE INDICATORS MONITORING AND CONTROL SYSTEM FOR EDUCATIONAL SMART LABORATORIES

The object of research is a set of processes for monitoring and intelligent control of energy consumption and the state of the SMART laboratory environment, aimed at improving its environmental safety.

The research problem is aimed at implementing integrated automated systems based on: monitoring, forecasting and adaptive control in real time of SMART laboratories. The research used methods for synthesis and analysis of energy consumption monitoring systems, microclimate control, CO_2 concentration forecasting and algorithms for adaptive control of educational environment resources.

Basic and extended key performance indicators (KPIs) have been formed for the SMART laboratory monitoring subsystem, which take into account the state of the microclimate and comfort, energy, environmental and operational indicators, and are the basis of modern eco-maps of the premises. The adaptive control subsystem uses adaptive control logic based on a predictive model. The developed open software and hardware architecture based on Node-RED integrates automation and environmental audit tools into a single analytical platform adapted to different types of educational locations. The adaptive automatic control system for SMART laboratories based on integrated predictive ML models contributes to a controlled reduction in energy consumption by more than 40%, in particular by reducing the average power from 4.1 kW to 2.4 kW. While traditional operating modes of laboratory equipment without adaptation are characterized by a high level of carbon intensity. According to the results of the LCA analysis, the total carbon footprint at the operational stage decreased from 1.85 to 0.47 kg CO_2/hour. The use of the proposed monitoring and control system for SMART laboratories forms a modern technical and software solution that meets the criteria of sustainable development.

Keywords: *SMART laboratory, Eco-KPI, microclimate monitoring, adaptive control, CO_2 forecasting, LCA analysis.*

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1. Introduction

The actualization of environmental threats in the last decade has led to a fundamental revision of environmental control strategies, bringing the concept of sustainable development to the level of a universal methodology. The focus of this paradigm is not only energy conservation, but also the systemic transformation of human activity through increased environmental responsibility.

For the scientific and educational sector, this vector is implemented through digitalization and the deployment of SMART laboratories – heterogeneous environments that integrate software and hardware complexes of different architectures. The functioning of such facilities contributes to the optimization of resource use in conditions of reducing carbon content without losing the quality of research.

Energy conservation in the educational environment is relevant in connection with the periodic repair work of the classroom fund, and recently through modernizations associated with the widespread transition to the principles of sustainable development, but there is often no integration between different conceptual bases and sometimes there is a certain imbalance between environmental and other aspects of sustainability [1]. SMART laboratories consist of various types of digital equipment, automatic systems of varying complexity and purpose, and engineering networks. Their energy consumption is higher than that of traditional laboratory premises. The carbon footprint in SMART classrooms is proportional to energy costs, which in turn directly depend on the amount of equipment and the intensity of its operation.

Environmental indicators are a key tool for monitoring the environment and making control decisions regarding decarbonization and sustainable development in the face of climate change and military challenges [2, 3]. Environmental indicators [4] include quantitative or qualitative variables that reflect the impact of a system or facility on the environment. They are used to assess the consequences of the operation of buildings on the environment and conduct environmental monitoring [5]. An analysis of scientific sources shows that there is a need to clearly distinguish between environmental phenomena and methods for measuring them. If there are even the slightest differences in definitions, it becomes difficult, and sometimes impossible, to exchange data and test scientific theories.

General (universal) environmental indicators are used for different types of objects and systems. These include the amount of energy consumed (kWh) and the share of energy from renewable sources [6]. Important criteria are greenhouse gas (GHG) emissions (CO_2, CH_4, N_2O) per unit of product/territory/housing, total water use (m^3), and water reuse [7, 8]. However, the authors do not consider the life cycle assessment of water consumption in educational SMART laboratories, which does not allow the formation of dynamic environmental KPIs and their use in adaptive control tasks. In addition, the noise level (dB) [9], waste generation and air quality are considered [10]. However, the studies lack a systematic approach to the life cycle assessment of resource consumption (in particular, water, energy and materials) in educational SMART laboratories, which makes it impossible to form dynamic environmental KPIs and use them in adaptive control tasks.

To analyze or describe the environmental performance of SMART buildings, a set of indicators is most often developed. It combines electricity consumption [11, 12] and the impact of carcinogenic toxicity in premises [13], but there are problems in assessing the real environmental impact of the installed smart devices (effective environmental impact of the smart devices installed) within their full life cycle. In [14], the share of energy from renewable sources, noise level [15], thermal efficiency of the building [16] and energy efficiency measures [17] are taken into account. At the same time, these indicators are mostly analyzed in isolation, which complicates a comprehensive assessment of environmental performance and requires integrated approaches.

Systematic studies show that the imbalance between anthropogenic activities, in particular production, urbanization, consumption and the ability of nature to self-renew, creates environmental risks for air, water and climate [18], but existing works lack tools for transferring these global problems to the control of educational SMART laboratories and other educational facilities. This limits the possibility of practical implementation of environmental approaches in educational environment control systems. Scientists identify a complex of environmental risks caused by irrational use of nature [19], environmental pollution [20], man-made accidents [21], imperfection of environmental policy [22], climate change [23], urbanization pressure [24], low environmental awareness of society [25]. It should be noted after analyzing the works [19–25] that the authors do not propose specific environmental key performance indicators (environmental KPIs) for closed spaces with a high concentration of technical equipment, but focus on traditional residential and office spaces. There is also no study of the dynamic relationship between the educational process and instantaneous changes in air quality, heat and electricity consumption, which can be critical for automated control systems. The risks associated with the rapid development of technologies without impact assessment are also considered [26], which leads to the fact that the control system reacts to the current situation and corrects the consequences, rather than preventing the exceeding of limits, for example, CO_2 or energy. Thus, there is no proactive control component based on forecasting. There is a notable mass adoption of IoT in smart homes without assessing their footprint, as energy is monitored without taking into account the full life cycle of the sensors themselves [27], the growth of electronic waste (e-waste) accompanied by the lack of economically viable recycling strategies [28], and electromagnetic radiation from wireless networks [28, 29] using only one tool instead of a set of methods. In this regard, it is necessary to assess the impact of activities on the environment: globally – the ecological footprint, and in detail – life cycle assessment (LCA) [30]. The review [31] noted that life cycle assessment is carried out mainly for building materials and energy efficiency, but without taking into account other factors. In [32], a comparison of the environmental impact of the life cycle of construction of traditional and energy-efficient buildings was made, but the specifics of the working environment were not taken into account. In [33], additional equipment uncertainties are taken into account, but it is not taken into account that for educational SMART laboratories the loading schedule and types of equipment are significantly different from residential premises. Also, eco-maps are used for monitoring, analysis, forecasting and decision-making in the field of ecology, urban planning, industry, etc., but there are no dynamic KPIs that would take into account the real parameters of energy consumption and microclimate [34].

There is a need to use integrated predictive models for SMART buildings that include a set of environmental indicators. For modeling complex nonlinear dependencies and analyzing large data sets when forecasting CO_2 emissions, the most effective is the use of machine learning (ML) methods. Modern studies confirm the advantages of hybrid ML models (without detailing the levels of individual premises [35], and sometimes studies [36] are based mainly on statistical indicators of urban development, ignoring real-time sensor measurements) and neural networks over traditional regression or ARIMA methods [37]. This allows taking into account temporal dynamics, ensuring high accuracy of environmental indicator forecasts. At the same time, the analysis [38] confirms the lack of unified criteria for selecting impact factors for different types of buildings.

A scientific gap is the lack of integrated systems with a combination of monitoring, forecasting and adaptive control based on Eco-KPI in real time. The research is aimed at eliminating these limitations by creating an integrated monitoring and adaptive control system.

The object of research is a set of processes for monitoring and intelligent control of energy consumption and the state of the environment of the SMART laboratory, aimed at increasing its environmental safety.

The aim of research is to develop an automated ecosystem for monitoring and controlling the SMART laboratory. This will allow increasing the energy efficiency of the SMART laboratory in conditions of a stable microclimate and environmental safety of the educational environment.

To achieve the set aim, it is necessary to perform the following objectives:

- to substantiate the structure and functionality of the SMART laboratory monitoring and control systems based on the concept of environmental efficiency;
- to form basic and extended key performance indicators (KPI) for monitoring;
- to develop the concept of an adaptive automatic control system based on a CO_2 emission forecasting model and LCA analysis.

2. Materials and Methods

The research included methods for synthesis and analysis of energy consumption monitoring systems, microclimate control, CO_2 concentration forecasting and adaptive resource control algorithms.

The SMART laboratory monitoring subsystem is based on a typical IoT architecture [27]. Basic information is obtained from digital sensors measuring microclimate characteristics and energy consumption. The discreteness of data collection is every 0.5 min with data transmission via MQTT/HTTP to the Node-RED platform (Great Britain) with further processing and storage in InfluxDB (USA). Technical characteristics of hardware and software tools are given in Table 1.

The functioning of the SMART laboratory is assessed using a system of key performance indicators (KPIs) in accordance with the principles of sustainable development and approaches to "green" technologies [1, 3]. KPIs include energy consumption indicators, microclimate parameters (temperature, humidity, CO_2 concentration), as well as indoor environment comfort indicators [2]. The obtained indicators were determined using a sensor system with subsequent processing and analysis. The adaptive control subsystem is implemented using methods of intelligent data analysis and forecasting. Control is carried out based on the deviation of the obtained current KPI values within the specified regulatory limits using forecast values of environmental parameters. The forecast model of CO_2 concentration is implemented based on a recurrent neural network of the long short-term memory (LSTM) type using historical and current values of the parameters of the experimental environment to predict the CO_2 concentration for a specified time horizon. The set from [39] was used as the initial data for rapid implementation. The model is mathematically described as

$$\hat{y}\left(t+\tau\right)=f\left(\mathbf{x}\left(t-L+1\right),\mathbf{x}\left(t-L+2\right)\ldots,\mathbf{x}\left(t\right)\right),\ \tau=10, \qquad (1)$$

where $x(t) = [T, L, N, PIR, CO_2]$ – respectively, the average values of temperature, illumination, noise from several sensors, the summed value of presence (passive infrared) and the value from the CO_2 concentration sensor in ppm; $\hat{y}\left(t+\tau\right)$ – CO_2 estimate at $\tau = 10$ steps forward (equivalent to 5 minutes); – memory depth. The sample includes values observed during a month in a room with high human activity with a discreteness of 0.5 minutes. The training uses the root mean square error (RMSE) loss function and the Adam optimizer in the Python environment. The evaluation is carried out on the training and test sets using standard regression metrics.

Table 1

Technical characteristics of the system hardware and software

Component	Model/Platform, Manufacturer	Key specifications	Protocol/ Interface
Central controller	Raspberry Pi 4 Model B, Raspberry Pi Foundation (UK)	SoC: Broadcom BCM2711, Quad-core ARM Cortex-A72 64-bit; frequency 1.5–1.8 GHz; RAM: 8 GB LPDDR4; Ethernet 1 Gbit/s; Wi-Fi 802.11ac (2.4/5 GHz); Bluetooth 5.0; GPIO: 40 pin; power supply 5V/3A; operating temperature 0–50°C	Ethernet, Wi-Fi, GPIO, USB 3.0
CO_2, temperature and humidity sensor	Sensirion SCD41, Sensirion (Switzerland)	Principle: photoacoustic NDIR; CO_2: 400–5000 ppm (±40 ppm ± 5%); response time ≈60 s; T: −10...+60°C (±0.8°C); RH: 0–95% (±6% RH); power supply 2.4–5.5 V; consumption ≈15 mA	I^2C
Energy consumption monitor	Shelly Pro 3EM, Shelly Europe (Bulgaria)	3-phase measurement; voltage 110–240 VAC; current up to 120 A (through transformers); Class 1 accuracy (IEC 62053-21); active/reactive power measurement; frequency 50/60 Hz	MQTT, REST API, WebSocket, Ethernet
Light sensor	BH1750, ROHM Semiconductor (Japan)	Range: 1–65535 lx; resolution 1 lx; 16-bit ADC; spectral correction for the human eye; power supply 2.4–3.6 V; consumption <0.2 mA	I^2C
Executive relay	Shelly Plus 1, Shelly Europe (Bulgaria)	Switching up to 16 A (250 VAC); dry contact; Wi-Fi 802.11 b/g/n; built-in MCU ESP32; local scripts (mJS scripting); load state measurement	MQTT, HTTP, Wi-Fi
Software kernel	Node-RED v3.1, OpenJS Foundation (USA/UK)	Flow-based middleware on Node.js; asynchronous event processing; IoT protocol integration; JSON-streaming support	TCP/IP, MQTT, HTTP
Database	InfluxDB 2.x, InfluxData (USA)	Time-series database (TSDB); high-frequency sensor data storage; downsampling; retention policies; Flux query language	HTTP API, Flux

To evaluate the control mechanisms, LCA analysis was used with subsequent calculation of energy and emissions before and after adaptation. Experimental studies were conducted in the SMART laboratory of the educational environment for several weeks under normal operating conditions with continuous collection of information from the sensor system. The experiment included the deployment and calibration of the sensor system, continuous data collection on environmental indicators and energy consumption. In addition, analytical calculations were performed, the CO_2 concentration forecasting model was trained, adaptive control strategies were activated, and energy and environmental indicators were further analyzed.

During the experiment, the analysis of the LCA indicators of the SMART laboratory equipment was carried out under identical operating conditions before and after the implementation of the automated control system. Monitoring was carried out during the same time intervals, with an unchanged configuration of laboratory equipment, a fixed composition of technical means and constant conditions of the educational process. During the experiment, the same mode of equipment use was ensured, there were no changes in the number of active devices, stable environmental characteristics, the use of the same sensors and data collection methods. The only variable in the experiment was the presence or absence of automated control of the operating modes of the experimental SMART laboratory equipment.

3. Results and Discussion

3.1. Justification of the structure and functionality of the SMART laboratory monitoring and control system based on the concept of environmental efficiency

The research proposes an open software and hardware system of the SMART laboratory, which integrates the functionality of monitoring, analytics and automated control of microclimate and energy consumption with a focus on environmental efficiency in the conditions of stable operation of the Ukrainian power system. This system is built using unified hardware and software interfaces that ensure the compatibility of components from different manufacturers and the reproducibility of research. The main functional components include the assessment of microclimate and comfort characteristics, calculation of environmental impact through CO_2 emissions, implementation of adaptive control, comparative assessment of the effectiveness of implemented measures using the LCA methodology (Fig. 1). The structure of the SMART laboratory system is built as a two-level ecosystem that combines physical data collection (Table 1), analytics and automated control. The core of the monitoring and control system is the Node-RED environment, which communicates with external physical devices via industrial and IoT protocols. Node-RED also connects to a database deployed on InfluxDB using standard Node-RED nodes for integration via TCP/IP.

The system is designed for continuous monitoring of measured microclimate and comfort variables, in particular air temperature, relative humidity, lighting level, carbon dioxide concentration, noise load and vibrations. Data collection is carried out using sensors integrated into the Node-RED digital platform [40], after which they are aggregated and processed in real time. Each variable is evaluated in accordance with current hygienic and technical regulations in the microclimate monitoring module.

Data transfer from the sensor network to the Node-RED platform is implemented via MQTT and HTTP API protocols. The monitoring unit's functionalities include identification of deviations of microclimate and comfort characteristics from set values, generation of a dynamic eco-map of the laboratory and other performance indicators.

The process of automated control of energy consumers (lighting, ventilation and air conditioning systems) is assigned to the adaptive control unit, which operates on the basis of a predictive model, and also performs comparative LCA analysis and logging of the number of actuator operations. The system architecture provides for data visualization through interactive graphical interfaces (Dashboards) and long-term storage of structured information in the database. The synergy of predictive analysis methods and continuous monitoring allows minimizing human intervention, ensuring high energy efficiency of the facility while maintaining optimal working conditions.

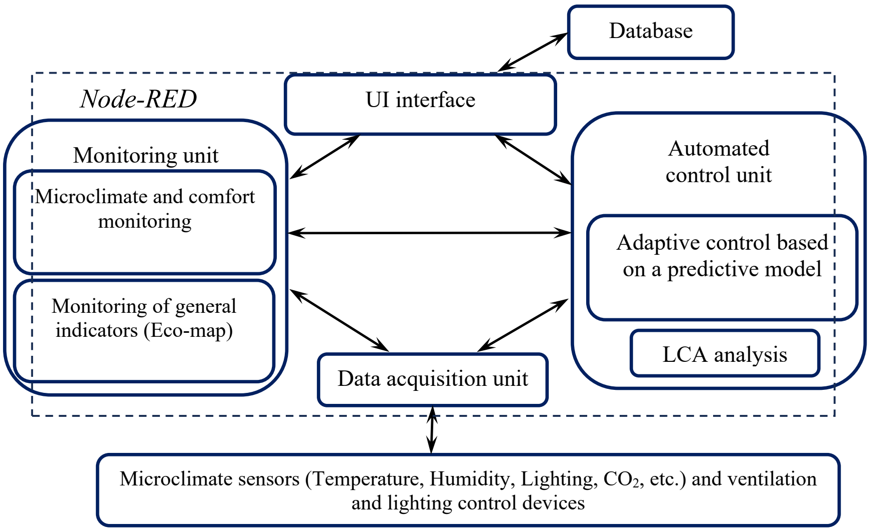


Fig. 1. Structure of the SMART laboratory monitoring and control system

The software component, implemented in Node-RED, provides continuous collection, storage, preliminary and analytical processing of measurements, as well as calculation of indicators. The calculation results are displayed on a set of dashboards in the form of digital values, color indicators and time graphs, which increases the visibility of the assessment of the state of the educational environment and supports control decision-making.

Fig. 2 shows a fragment of the code of the software implementation of the system, developed on the basis of data flow processing and integration of automated analysis, forecasting and control methods. The software architecture, implemented in the Node-RED environment, is based on modular data processing. The execution logic is controlled through the Toggle Flow Flag node, which synchronizes the system operation and cleans the data, and also works with another flow that integrates the CO_2 forecasting model.

3.2. Formation and justification of basic and extended performance indicators (KPI) for monitoring SMART-laboratory

To assess the conditions of the laboratory, a basic KPI was formed. This indicator is an aggregate value of comfort and safety in the laboratory. To take into account environmental efficiency, an extended Eco-KPI indicator was introduced. This indicator is the sum of the basic KPI and the components responsible for energy consumption and carbon dioxide emissions. This approach provides a comprehensive tool for monitoring, optimizing and controlling the environmental footprint of the educational environment. The formulas for calculating the basic and extended KPI are as follows:

$$KPI = w_T \cdot \delta_T + w_H \cdot \delta_H + w_L \cdot \delta_L + w_{\{AQ\}} \cdot \delta_{\{AQ\}} + w_N \cdot \delta_N + w_V \cdot \delta_V, \quad (2)$$

$$\text{Eco-KPI} = \text{KPI} + w_E \cdot \frac{P}{P_{\max}} + w_{CO_2} \cdot \frac{CO_2}{CO_{2,\text{ref}}} \text{ or}$$

$$KPI = \sum_X w_X \cdot \delta_X, \quad (3)$$

where δ_X – the normalized deviation of variable X from the required range or set value, i. e. it is a quantitative reflection of how much the actual value of the variable deviates from ideal conditions; w_X – the weighting factor for each variable X, reflecting its relative importance (Table 1).

The weighting factors (w_X) for each component in (2) and (3) are determined based on expert assessments and priorities established for a comfortable and environmentally efficient educational environment, the values of which are grouped by category and given in Table 2. They reflect the relative importance of each component for the overall assessment.

Since δ_X is the deviation of the current measured value of the variable from the set value, a decrease in the Eco-KPI value leads to an improvement in the environmental efficiency of the laboratory. That is, Eco-KPI is used to monitor the premises, identify problems and develop measures to respond to them.

It is advisable to supplement (2) and (3) with an environmental index (EI), which is the sum of penalty points for deviations of key environmental indicators from their reference values

$$EI = f\left(T, H, AQ, N, V, P_{\text{total}}\right), \quad (4)$$

where P_{total} – the instantaneous power.

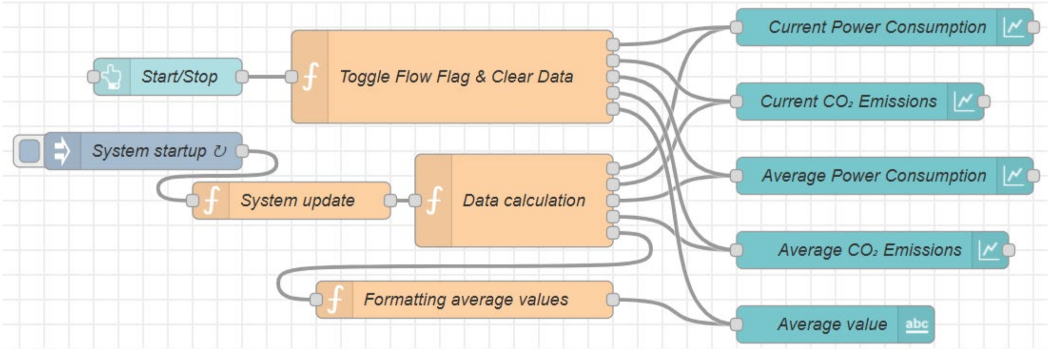


Fig. 2. Fragment of the flow in Node-RED

Table 2

Premises monitoring variables and their weighting factors

Category	Variable X	Designation	Weighting factor (w_X)
Microclimate	Temperature	T	$w_T = 0.2$
	Humidity	H	$w_H = 0.15$
	Air Quality	AQ	$w_{AQ} = 0.15$
Comfortable environment	Lighting	L	$w_L = 0.1$
	Noise	N	$w_N = 0.1$
	Vibration	V	$w_V = 0.05$
Environmental impact	Power	P	$w_E = 0.15$
	Emissions	CO_2	$w_{CO2} = 0.1$

The higher the index value, the worse the environmental condition. For each variable in (4), an individual penalty score is calculated, which reflects the degree of deviation from the specified range and can be changed when configuring the system. These penalties are nonlinear and take into account the specifics of the impact of each variable on comfort and environmental condition.

Effective energy control determines the level of environmental efficiency of a SMART laboratory. The following indicators are used to quantify energy consumption:

– *Instantaneous power – total power* (W) of all electrical devices operating in the laboratory at the current time

$$P_{total} = N_{PC} \cdot P_{PC} + N_{lamp} \cdot P_{lamp} + P_{printer} + P_{AC} + P_{ventilation} + P_{other}, \qquad (5)$$

where N_{PC} – number of personal computers; P_{PC} – power of one PC; N_{lamp} – number of lamps; P_{lamp} – power of one lamp; $P_{printer}$ – printer power; P_{AC} – power of the air conditioning system; $P_{ventilation}$ – power of the ventilation system; P_{other} – total power of other electrical devices (in particular, laboratory equipment, chargers, etc.). The power values of each component are variable depending on the current conditions (presence of people in the room, lighting level and air temperature);

– *Total energy consumption* (kWh) for a certain time interval Δt (sec), which is calculated as the integral of the instantaneous power over this period

$$E = \frac{P_{total} \cdot \Delta t}{3600 \cdot 1000}. \qquad (6)$$

To ensure life cycle monitoring (LCA) of the equipment, it is necessary to integrate carbon dioxide emissions. When using the LCA approach, the calculation of CO_2 emissions is performed using two indicators: instantaneous CO_2 emissions $\left(CO_2^{inst}\right)$, which are directly related to the current energy consumption of the laboratory equipment, and accumulated CO_2 emissions $\left(CO_2^{total}\right)$ for a certain set monitoring time period:

$$CO_2^{inst} = E \cdot K_{CO_2};$$
$$CO_2^{total} = \Sigma CO_2^{inst}, \qquad (7)$$

where K_{CO_2} – CO_2 emission factor (kg/kWh), which takes into account the source of electricity generation and is critically important for LCA.

Indicators (2)–(7) are used to monitor and control the carbon footprint of all types of equipment equipped in the educational laboratory. This is the basis for implementing LCA principles and achieving environmental sustainability.

Table 3 summarizes all developed indicators used for the future system that ensures the environmental efficiency of the SMART laboratory of the educational environment and at the same time allows for the quantitative assessment of their deviations and making informed control decisions.

Table 3

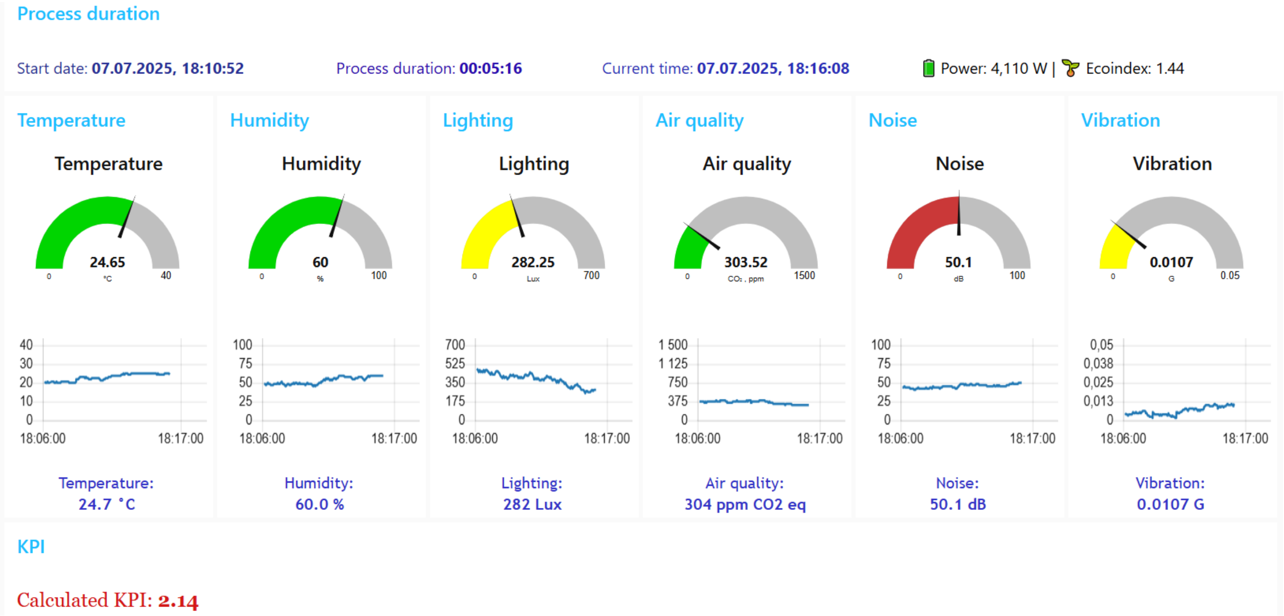
Educational laboratory monitoring indicators

Assessment name	Formula	Designation	Role
Baseline KPI	(2)	KPI	Integral indicator of comfort and conditions of the laboratory's internal environment (temperature, humidity, lighting, air quality, noise, vibration)
Extended eco-KPI	(3)	$Eco\text{-}KPI$	A complex indicator of environmental performance, which contains the sum of the basic KPI, energy consumption and accumulated CO_2 emissions
Environmental index	(4)	EI	The amount of penalties for deviations of environmental characteristics (temperature, humidity, air quality, noise, vibration, power) from reference values
Instantaneous power	(5)	P_{total}	The total electrical power consumed by the laboratory at a given time
Energy consumption	(6)	E	The total amount of electrical energy consumed over a certain time interval
Instantaneous and accumulated CO_2 emissions	(7)	CO_2^{inst} CO_2^{total}	Accordingly, the volume per interval and the total amount of carbon dioxide emissions of the equipment associated with current energy consumption

Fig. 3 shows the SMART laboratory monitoring panel, which displays the current environmental conditions and general efficiency indices. The monitoring time, equipment power consumption and the ecological index value are shown. The interface displays the measured values of six key variables: air temperature, relative humidity, illumination, air quality by CO_2 concentration, noise level and vibration. At the bottom of the panel, the integral indicator $KPI = 2.14$, calculated by (2), is shown. The resulting KPI value indicates a generally acceptable level of comfort and ecological efficiency, while at the same time indicating the presence of individual variables (lighting and noise), the change of which can provide a further increase in the integral efficiency of the educational environment.

Fig. 4 presents the results of an experimental research of the SMART laboratory monitoring system, which reflects overall performance indicators, including environmental indicators (Eco-map).

The laboratory Eco Map reflects aggregated indicators of the state of the environment, in particular: the Ecological Index, the CO_2 emission index, the Energy Consumption Index, the complex Eco-KPI indicator. The obtained index values indicate stable control of the laboratory's environmental assessments with minor short-term fluctuations caused by changes in the operating modes of equipment and life support systems.



Process duration

Start date: **07.07.2025, 18:10:52** Process duration: **00:05:16** Current time: **07.07.2025, 18:16:08** Power: 4,110 W | Ecoindex: 1.44

Temperature: 24.7 °C

Humidity: 60.0 %

Lighting: 282 Lux

Air quality: 304 ppm CO2 eq

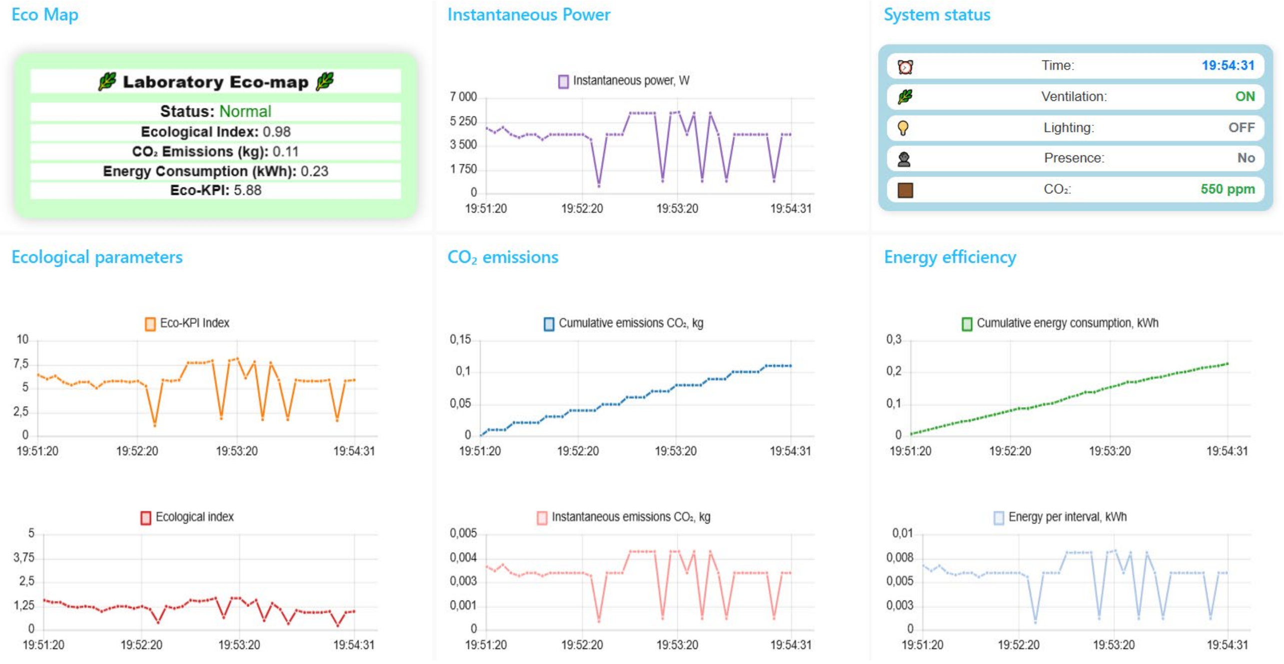
Noise: 50.1 dB

Vibration: 0.0107 G

KPI

Calculated KPI: **2.14**

Fig. 3. Monitoring and assessment of comfortable conditions of the SMART laboratory with calculation of the basic KPI, overall equipment performance and environmental index



Eco Map

Laboratory Eco-map

Status: Normal

Ecological Index: 0.98

CO₂ Emissions (kg): 0.11

Energy Consumption (kWh): 0.23

Eco-KPI: 5.88

System status

Time: 19:54:31

Ventilation: ON

Lighting: OFF

Presence: No

CO₂: 550 ppm

Fig. 4. Monitoring of general indicators (Eco-map)

3.3. Development of the concept of an adaptive automatic control system for a SMART laboratory based on CO_2 forecasting and LCA analysis

To achieve the goals of reducing energy consumption and increasing the environmental efficiency of the SMART laboratory, an adaptive control system based on a machine learning model that predicts carbon dioxide (CO_2) concentrations has been proposed. This allows the system to initiate the necessary adaptive measures in advance, preventing monitoring variables from exceeding reference values. Taking into account the sampling frequency of the measured variables of 0.5 minutes, an additional research was conducted to determine the memory depth of the model and a rational value of $L = 10$ was determined.

When developing the architecture of the LSTM type network, the best number of neurons in the LSTM output space was determined in terms of accuracy according to the metrics used. Thus, it is possible to obtain the following model, which is implemented as a sequential neural network of the LSTM type with the structure:

- one hidden LSTM layer with 50 neurons and ReLU activation;
- Dropout layer with parameter 0.2 to prevent overtraining;
- fully connected output layer for forecasting one scalar value of CO_2.

The results are given in Table 4. High values of the coefficient of determination R^2 and low error values (*RMSE*, *MAE*, *MAPE*) indicate sufficient quality of the model and its suitability for forecasting CO_2 emissions.

Fig. 5 shows graphs comparing actual and predicted CO_2 values for the training (top graph) and test sets (bottom graph). It can be observed that the model reproduces the peak and decreasing areas of CO_2 concentration with high accuracy. In particular, in the training data, the model correctly reproduces both the periods of concentration increase associated with the presence of people and its decrease when ventilation is turned on. In the test data, the forecasting remains accurate even in new scenarios of variable behavior, maintaining deviations within a few ppm. The model allows to reproduce the dynamics of CO_2 ($R^2 = 0.99$), thereby confirming its suitability for proactive ventilation control.

Table 4

Metrics for evaluating the CO_2 forecasting model

Metrics	Training set	Test set
RMSE	9.72	12.99
MAE	5.36	8.43
R^2	1.00	0.99
MAPE (%)	0.84	1.16

Equipment control is implemented through a two-mode operation algorithm: "active" and "economic" modes. All laboratory devices are capable of operating in both modes. The transition to the economic mode occurs under conditions indicating the absence of active activity or optimal environmental characteristics, in particular, the absence of people in the room, maintaining the temperature within the regulatory range and finding air quality within safe limits. This allows significantly reducing energy and resource consumption during periods of reduced demand.

The formula for the effectiveness of such control is defined as

$$\eta_{eco}=\frac{t_{eco}}{t_{total}}, \qquad (8)$$

where η_{eco} – the efficiency of environmental control; t_{eco} – the total operating time in the economic mode; t_{total} – the total operating time of the system. This indicator quantitatively reflects the proportion of time during which the laboratory operated in the energy-saving mode.

Adaptive resource consumption control consists in minimizing energy consumption, while limiting the basic *KPI* (2) to a minimum threshold value (min_threshold), which guarantees the preservation of comfortable conditions. It is based on rules that are built on the basis of measured current values of microclimate variables and the predicted value of CO_2.

Control algorithms for individual subsystems include:

- *ventilation* – the system switches to the "ON" state if the predicted CO_2 concentration exceeds 450 ppm, and switches to the "OFF" state otherwise. This approach ensures effective ventilation only when necessary;
- *lighting* – switches on ("ON") if the presence of people is detected and the lighting level is less than 300 Lux. Otherwise, the lighting is turned off ("OFF"), optimizing the use of natural light and saving electricity in the absence of users.

LCA analysis (Fig. 6, *a*) allowed to assess the environmental impact and compare scenarios before and after the implementation of the system. At the final stage, the effectiveness of sustainable development measures, in particular, energy efficiency and CO_2 emission reduction, is confirmed.

A preliminary LCA analysis was conducted for the following objects of the laboratory's SMART infrastructure: microclimate sensors, actuators, control units, lighting, ventilation and air conditioning systems, software, energy consumption in operation (Fig. 6, *b*).

Thus, based on the previous LCA analysis, it was found that the main source of impact in the operation phase is energy consumption, therefore, the introduction of automatic control significantly reduces the environmental load. For example, the carbon content decreased from 1.85 to 0.47 kg CO_2/h. In addition, adaptive control of lighting and ventilation provides up to 30% energy savings without loss of environmental quality. The SMART system demonstrates high environmental and economic potential. Also, modularity and the ability to update the software have a positive effect on extending the system's life cycle. In turn, it was found that the average power decreased from 4.1 to 2.4 kW (>40%). Therefore, the introduction of an adaptive control system in the operation phase of the equipment is appropriate and leads to increased environmental efficiency, reduced energy consumption and stabilization of the indoor microclimate.

Fig. 7 presents the results of comparative monitoring of energy consumption and CO_2 emissions of the SMART laboratory before and after the implementation of the automated adaptive control system. The graphs of current energy consumption (Current Energy Consumption, kW) demonstrate a significant decrease in the level of power consumption after the application of control algorithms.

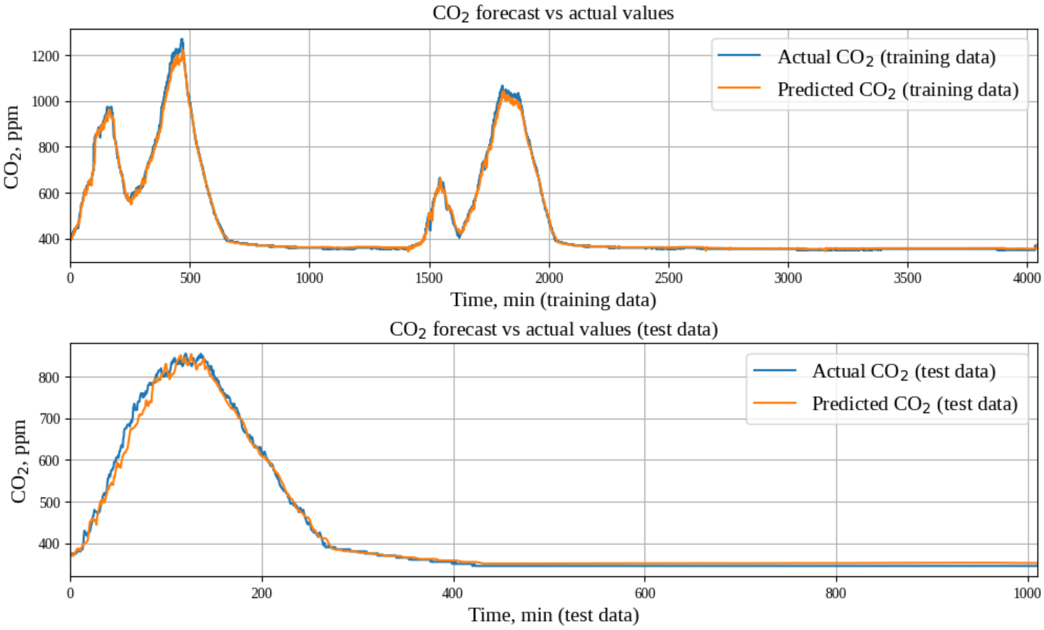
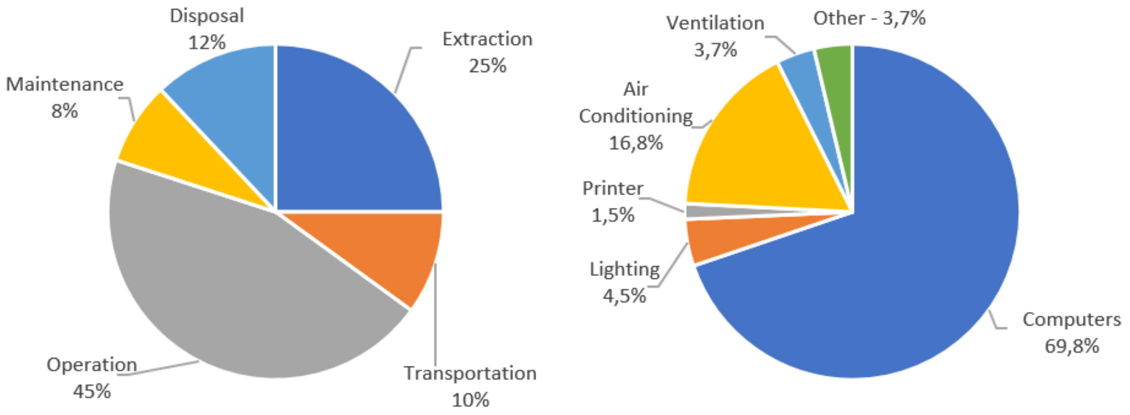
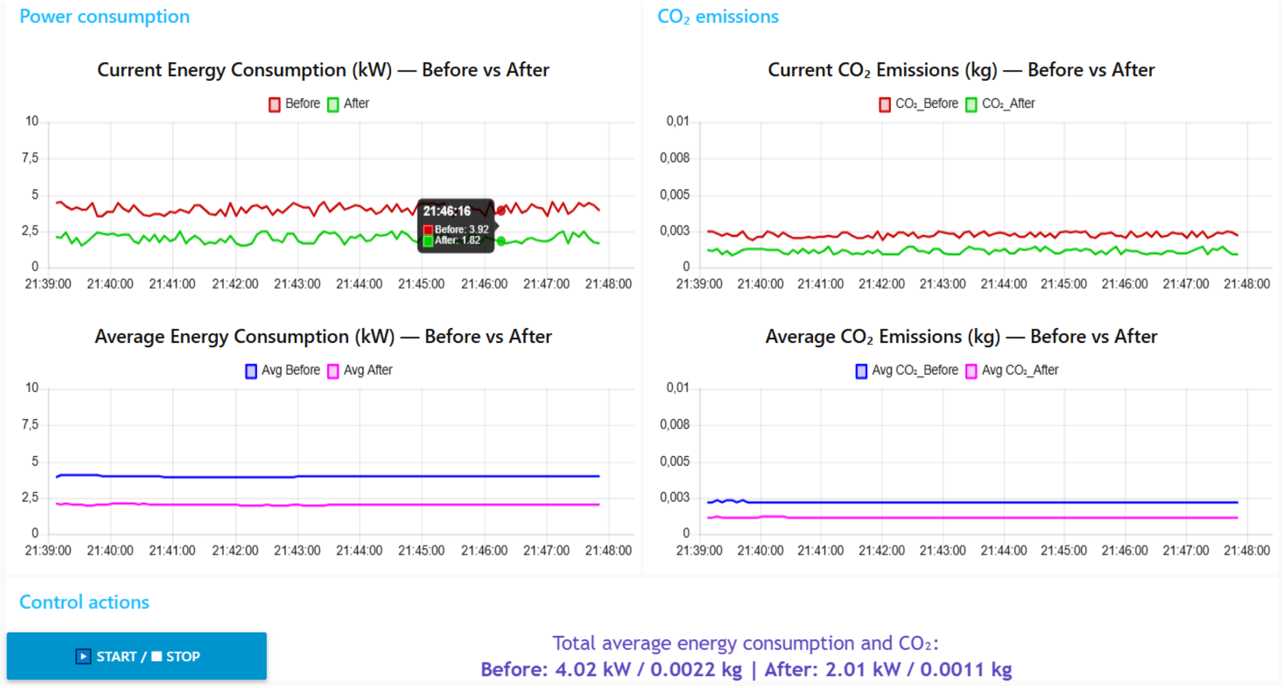


Fig. 5. Comparison of the CO_2 forecasting model with actual values on the training and test datasets



a *b*

Fig. 6. Assessment of the environmental impact and energy consumption of the laboratory SMART infrastructure: *a* – distribution of environmental impact by life cycle phases; *b* – average power distribution by load types



Total average energy consumption and CO₂:
Before: 4.02 kW / 0.0022 kg | After: 2.01 kW / 0.0011 kg

Fig. 7. Equipment monitoring before and after control

Before the implementation of control, stably higher values of energy consumption were recorded (on average 4.1 kW) with minor fluctuations, which indicates the lack of adaptation to the real load. After the implementation of control, the average power level decreases by 41.46% – to 2.4 kW, and the fluctuations become less pronounced, which confirms the adaptation of the equipment operating modes. A similar trend is observed in the graphs of average energy consumption (kW).

The graphs of current CO_2 emissions (kg) reflect a decrease in the intensity of emissions after the implementation of control. The analysis of average CO_2 emissions (kg) confirms the quantitative effectiveness of the approach: the average value decreased from 0.0026 kg to 0.0017 kg (by 34.6%). Considering the principles of LCA, this means a significant reduction in the carbon footprint in the operational phase of the equipment's life cycle.

A comparative analysis of the total LCA CO_2 indicator (t/year) in the operation phase showed a consistently lower average level of emissions after adaptation throughout the entire observation period (Fig. 8). At the same time, the range of CO_2 fluctuations after the implementation of control is smaller, and the total emission indicator decreased from 1.857 to 0.479 kg CO_2/hour. The results of the analysis of the adaptation efficiency showed that the relative reduction in CO_2 emissions after the implementation of automated control varied within 16–35% depending on the operating time intervals and load modes. The results obtained confirm the presence of a stable, albeit uneven, effect of system adaptation in real operating conditions. Analysis of daily consumption profiles showed that the average level of energy consumption stabilized within 1.7–3.1 kWh. The 7-day forecast confirms the stability of the obtained results: the expected average daily consumption is about 15.2 kWh, which corresponds to a stable ecological state of the system ("Eco-state: Norm").

During the verification of the SMART laboratory monitoring and control system in real conditions of the functioning of the educational space, the effectiveness of combining monitoring approaches and analytical calculations with forecasting and adaptive control algorithms was confirmed. The use of Eco-KPI allowed to conduct a quantitative assessment of the current state of the premises and equipment and promptly respond to relevant changes.

Life Cycle Assessment

Laboratory Life Cycle Assessment (LCA)
Time: 16:21:50
Before adaptation:
Energy consumption per hour: 4.56 kWh
CO₂-emissions (operational): 1.82 kg
CO₂ from equipment replacement (hourly): 0.033 kg
General LCA assessmen: 1.857 kg CO₂ / hour
After adaptation:
Energy consumption per hour: 1.16 kWh
CO₂-emissions (operational): 0.46 kg
CO₂ from equipment replacement (hourly): 0.016 kg
General LCA assessmen: 0.479 kg CO₂ / hour

7-day CO₂ emissions forecast

Date	Energy (kWh)	CO₂ (kg)
04.02.2026	16.76	6.71
05.02.2026	15.07	6.03
06.02.2026	16.11	6.44
07.02.2026	15.10	6.04
08.02.2026	14.53	5.81
09.02.2026	14.26	5.70
10.02.2026	14.77	5.91

Eco-state: ● **Norm**

Fig. 8. LCA analysis results

One of the main limitations of research is the problem of setting the weight coefficients in (2) and (3) depending on the purpose of the educational premises and the season of its use. Also, the accuracy of the carbon footprint forecast according to model (8) depends on the stability of external and internal factors, as well as the season. That is, there is a need to introduce regular retraining of the ML model. Due to the nonlinear dependence of comfort and resource saving, there is a need for additional system settings depending on the purpose of the educational audience.

Further research is aimed at developing scalable network architecture of an educational environment that combines premises of different types and purposes, building digital twins and improving predictive algorithms to optimize energy consumption on a building-wide scale.

4. Conclusions

1. It was found that the flexibility of the internal configurations of the developed SMART laboratory monitoring and control system allows it to be adapted to SMART environments of various functional purposes, regardless of the density of the technical park. The developed architecture integrates automation and environmental audit tools into a single analytical platform that can adapt to various types of educational locations. An open software and hardware architecture based on Node-RED was used to implement the system, which provides flexible configuration of the control logic, the ability to expand functionality and implement machine learning methods for analyzing and forecasting environmental indicators. This approach creates conditions for using the developed solution not only as an engineering control system, but also as a training tool in the educational process for training specialists in the field of information technology and automation.

2. It was established that the formed basic and extended key performance indicators (KPIs), as well as microclimate and comfort indicators are the basis for an up-to-date eco-map of the premises, which visualizes energy, environmental and operational indicators in monitoring mode. This allows for a quantitative comparison of different operating modes of the laboratory with subsequent adoption of control decisions taking into account environmental efficiency.

3. The effectiveness of the adaptive automatic control system was experimentally confirmed, where the integration of predictive ML models into the adaptive control circuit made it possible to achieve a stable reduction in energy consumption of more than 40% (in particular, a decrease in average power from 4.1 kW to 2.4 kW was recorded). Such a result, recorded in comparison with traditional operating modes without automatic adaptation, is accompanied by proportional decarbonization of the facility. According to the results of the LCA analysis, the total carbon footprint at the operational stage was reduced from 1.85 to 0.47 kg CO_2/hour.

Conflict of interest

The authors declare that they have no conflict of interest regarding this research, including financial, personal, authorship or other, that could influence the research and its results presented in this article.

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Data availability

The manuscript has no associated data.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies in creating the presented paper.

Authors' contributions

Tetiana Savchenko: Methodology, Software, Writing – reviewing and editing; ***Natalia Lutska***: Conceptualization, Formal analysis, Investigation, Writing – original draft; ***Lidiya Vlasenko***: Validation, Investigation, Writing – original draft; ***Andrii Zahorulko***: Writing – reviewing and editing, Project administration, Supervision.

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