Development of a microcontroller-based climate control system using neural network technologies[*]

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Abstract

The article examines a microcontroller-based climate control system development approaches utilizing neural network technologies. Modern methods of automated climate parameter control are analyzed, including classical algorithms, fuzzy logic, and artificial neural networks. The possibilities of adapting neural network approaches to real-time temperature, humidity, and airflow speed prediction and regulation are explored. The main advantages of intelligent systems over traditional control methods are identified, including improved prediction accuracy, adaptability, and reduced energy consumption. A system's structural model is proposed that incorporates a data collection subsystem, a neural network analysis module, and an adaptive climate control mechanism. A system prototype was implemented and tested in the MATLAB environment. Simulation results confirmed the effectiveness of the developed approach, particularly the ability to accurately determine user comfort levels based on the PMV index and automatically regulate the microclimate. The conducted analysis demonstrates the feasibility of using artificial neural networks for automated climate control in residential, office, and industrial spaces.
Future research will focus on improving machine learning algorithms, integrating with IoT systems, and expanding the functional capabilities of the developed system.

Keywords

intelligent control system, neural networks, microcontroller, microclimate, automated control

1. Introduction

Modern trends in climate control automation are increasingly focused on the use of artificial intelligence and neural network technologies [1, 2]. An optimal indoor microclimate directly affects comfort, employee productivity, and overall business efficiency. A high-quality climate control system enhances work performance and reduces staff fatigue, which is a crucial factor for business success. Additionally, proper climate regulation positively impacts the equipment and materials' condition, which is particularly relevant for enterprises with high technological requirements [3].

Traditional climate control systems are based on mechanical or programmable solutions that regulate temperature and humidity in indoor environments [4]. However, with the advent of new technologies, it is now possible to develop adaptive systems that analyze data in real time and adjust microclimate parameters according to user needs and environmental changes. By leveraging machine learning algorithms, these systems can predict temperature and humidity fluctuations, considering seasonal variations, light levels, and even individual user preferences [5].

The need for intelligent climate control systems arises from increasing demands for energy efficiency, comfort, and automation. The implementation of neural network algorithms enables the development of smart climate control systems capable of autonomously adapting to external conditions and indoor characteristics [6]. These technologies unlock new possibilities for integration with modern IoT devices [7], optimizing energy consumption, and enhancing the overall efficiency of climate solutions [8, 9]. This paves the way for the development of innovative systems that not only improve quality of life but also contribute to sustainable development and lower building maintenance costs. Moreover, such solutions can play a key role in the implementation of the "smart

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city" concept [10], ensuring the interaction of climate control systems with the overall energy infrastructure, thereby reducing carbon emissions and promoting more rational resource utilization.

1.1. Analysis of recent researches and publications

In recent years, the issue of automated climate control has attracted significant attention from the scientific community due to the advancement of microcontroller technologies and artificial intelligence. The implementation of neural network approaches enables the creation of adaptive systems that optimize microclimate parameters based on changes in the external environment and individual user needs [11, 12].

As the conducted analysis has shown, current research in this field can be divided into several directions: the use of classical control algorithms, the application of fuzzy logic, and the integration of neural networks for decision-making and climate parameter prediction.

One of the classical approaches is the use of PID (Proportional-Integral-Derivative) controllers, which stabilize temperature and humidity in controlled environments. In [13], the authors examine the efficiency of PID controllers in HVAC (Heating, Ventilation, and Air Conditioning) systems but highlight their insufficient adaptability to dynamic external conditions.

Another research direction involves the use of fuzzy logic for climate control systems. Studies [14, 15] propose an adaptive temperature regulation method based on fuzzy logic models that consider user behavioral characteristics. This approach improves system efficiency by analyzing multiple factors but requires careful tuning of fuzzy logic rules.

Recently, increased attention has been given to the use of artificial neural networks in climate control systems. In [16], a model utilizing convolutional neural networks is presented, which analyzes historical temperature and humidity data to predict future changes and adjust system parameters accordingly. Studies [17, 18] demonstrate the effectiveness of recurrent neural networks (LSTM) in forecasting climate parameter changes in indoor environments and automatically adjusting air conditioning system operation.

A particularly promising direction is the combination of deep learning with the Internet of Things (IoT) for distributed monitoring of microclimate conditions. In [19, 20], the authors introduce an intelligent control system that uses IoT sensors and neural network algorithms to reduce energy consumption and enhance indoor comfort. This system can autonomously learn from collected data and adapt its algorithms to specific operational conditions.

Thus, an analysis of existing research demonstrates that classical approaches to climate control are gradually being replaced by intelligent methods, particularly those based on neural networks. The implementation of such solutions enhances the efficiency of climate systems, ensures their adaptability, and reduces energy consumption. The further advancements of this field are associated with the improvement of machine learning algorithms and the expansion of neural network model integration into microcontroller platforms.

1.1.2. Analysis of known software/hardware solutions

The analysis of existing software and hardware solutions for climate control management shows that the main approaches are divided into two groups. The first consists of traditional automated control systems based on classical regulation algorithms, while the second includes solutions that utilize machine learning and neural networks.

When considering the first approach [21, 22], traditional automatic climate control systems are typically based on proportional-integral-derivative (PID) controllers. These controllers ensure environmental stability but have limited adaptability to changing conditions. Such systems are most commonly used in industrial and commercial facilities, where maintaining stable operating parameters is crucial.

The second approach involves the use of artificial intelligence methods, particularly neural networks, for forecasting and adaptive regulation of climate parameters [23, 24]. Recent studies demonstrate the effectiveness of such systems, as they can learn from historical data, predict climate parameter changes, and adjust equipment operation modes accordingly.

Among the most well-known solutions in this field, the following can be highlighted:

Nest Learning Thermostat – an intelligent thermostat that uses machine learning algorithms to automatically adjust temperature settings based on user habits [25]. It analyzes resident behavior, creates an optimal heating/cooling schedule, and helps save energy. Strengths: high level of automation and integration with the Google Home ecosystem. Weaknesses: high cost and dependence on an internet connection.

Ecobee SmartThermostat – a climate control system that uses temperature and humidity sensors to optimize energy consumption and enhance comfort [26]. It supports voice control via built-in Amazon Alexa and is compatible with Apple HomeKit. Advantages: flexible settings and integration with other smart devices. Drawbacks: complex initial setup and high price.

Honeywell Home T9 – a solution that utilizes artificial intelligence to manage temperature in different rooms using external sensors [27]. It provides support for various temperature zones, thus increasing heating and cooling efficiency. Key benefits: high climate control accuracy and support for voice commands. Disadvantages: limited compatibility with some smart home ecosystems.

Tado Smart Thermostat – an innovative system that uses user geolocation to control indoor climate [28]. It automatically decreases the temperature when residents leave the house and increases it before they return. Strengths: efficient energy savings and ease of use. Weaknesses: limited compatibility with certain heating systems.

Daikin Intelligent Thermostat – a climate control system from Daikin that utilizes artificial intelligence algorithms to analyze external and internal conditions, predict climate changes, and adapt equipment operation [29]. Benefits: high forecasting accuracy and efficient climate management. Drawbacks: high cost and integration complexity with other systems.

As the analysis shows, modern software and hardware solutions for climate control are incorporating artificial intelligence and neural network technologies at a growing rate. This enhances system efficiency, reduces energy consumption costs, and ensures greater user comfort. However, each solution has its limitations, which should be considered during development.

1.2. The main tasks of the research and their significance

The objective of this study is to develop a microcontroller-based climate control system utilizing neural network technologies. The research aims to create an intelligent system that ensures automated monitoring of climate parameters, their analysis, and adaptive regulation to maintain a comfortable indoor environment. The proposed system should account for dynamic environmental changes and room characteristics to maximize energy efficiency and user convenience.

To achieve this goal, it is necessary to analyze existing climate control approaches, including classical regulators, fuzzy logic, and neural networks, to identify their advantages and limitations. An important stage involves developing the system's structural model. This model includes the architecture of hardware and software components, as well as UML diagrams to illustrate the interaction logic between elements. Based on the obtained results, a data acquisition subsystem must be implemented, working with temperature, humidity, and airflow velocity sensors to provide continuous real-time climate parameter monitoring.

The next task is to create and train an artificial neural network that will utilize the collected data to predict climate changes and make automated decisions for parameter regulation. To evaluate the effectiveness of the proposed approach, system modeling and testing will be conducted in the Matlab environment, allowing an assessment of its adaptability to changes and energy consumption optimization.

The research results address a relevant scientific and practical problem—developing energy-efficient systems that automatically adapt to operational conditions. The proposed approaches and the developed system will contribute to improving climate change prediction accuracy, reducing electricity costs, and ensuring comfortable conditions for users.

2. Major research results

People constantly face the task of maintaining comfortable microclimatic conditions. The human brain analyzes information about temperature, humidity, and airflow speed and makes appropriate decisions for regulation. In modern technological systems, this process is automated using microcontrollers and neural network algorithms. To implement a microcontroller-based climate control system utilizing neural network technologies, several key stages must be implemented:

- First stage – System initialization. This includes configuring the microcontroller, timers, communication interfaces with sensors, and the communication module.
- Second stage – Data collection. The system receives temperature, humidity, and airflow readings from sensors and performs initial processing.
- Third stage – Data transmission. The collected information is sent for processing via communication modules.
- Fourth stage – Data processing using a neural network. Based on the received parameters, the level of thermal comfort is determined.
- Fifth stage – Decision-making. If the parameters exceed acceptable limits, the system automatically adjusts the operation of climate control devices.
- Sixth stage – System adaptation. The neural network analyzes the obtained results, adjusts its parameters, and improves climate control algorithms.

One of the key stages in system development is the application of an object-oriented approach, which allows logically structuring the entire system into a unified model. Utilizing this approach system can be divided into separate classes and objects, each with its own attributes and methods, facilitating complexity management during software design and implementation. Thanks to the object-oriented approach, the development process becomes more understandable, and its outcome is more flexible and scalable [30]. The use of UML diagrams to visualize the system's structure and processes enhances understanding of interactions between its components [31]. The use case diagram shown in Figure 1 illustrates the relationships between actors and use cases.

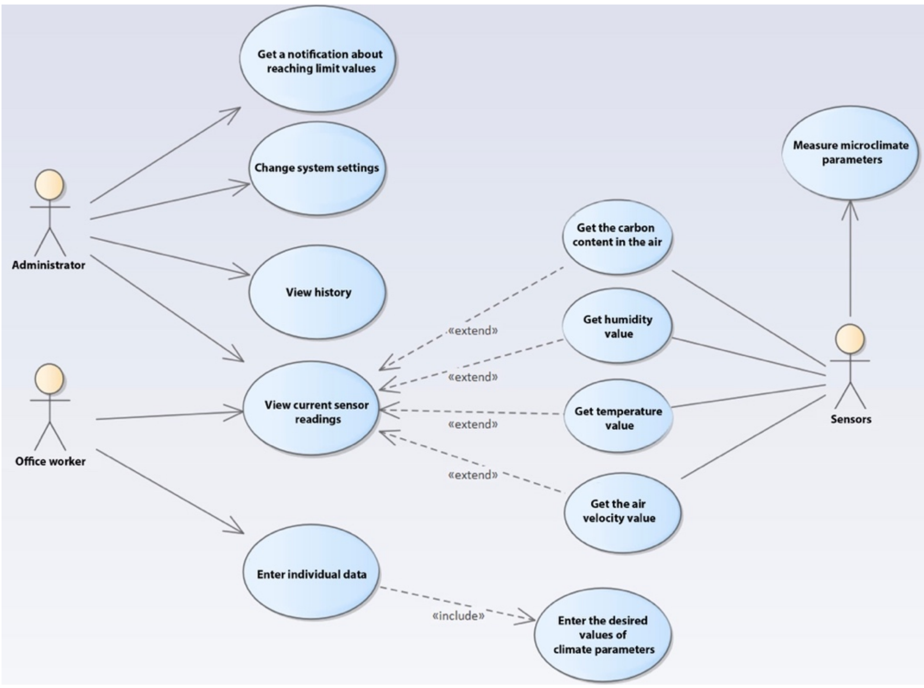


Figure 1: Use-case diagram.

An office worker can input personal climate preferences and monitor the current microclimate status. The administrator has additional capabilities, including configuring the neural network, adjusting system parameters, and remotely monitoring its status. The sensor system is responsible for collecting the data necessary for making management decisions.

This diagram demonstrates how the system interacts with different users and helps identify the main use cases for each, which is crucial for defining further software and hardware requirements.

The class diagram, shown in Figure 2, illustrates the system's structure at the class level, including their attributes, methods, and relationships. It helps clearly define the types of objects that exist within the system, their properties, and how they interact with each other.

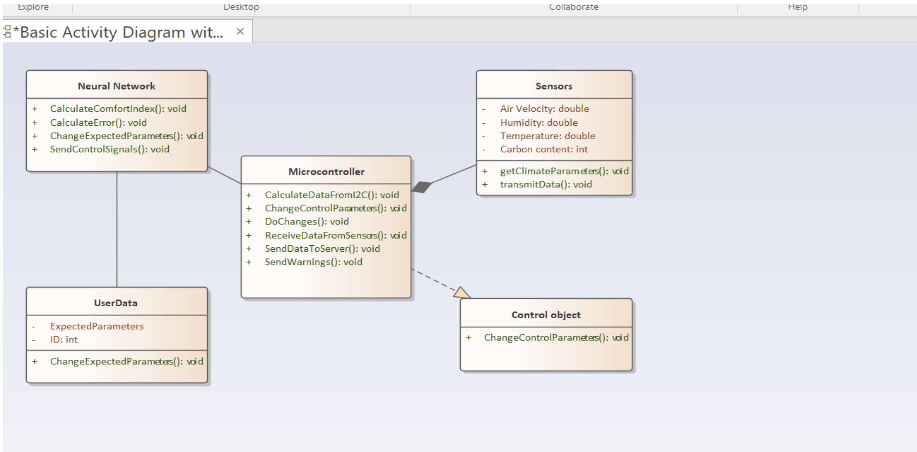


Figure 2: Class diagram.

The class diagram represents the architecture of the climate control system, which consists of several key components.

Neural Network is responsible for calculating the comfort index, computing errors, and adjusting expected parameters. It also sends control signals.

UserData stores the user's expected parameters and their identifier, allowing for parameter modifications.

Microcontroller serves as the central component of the system. It processes data received via the I2C bus, adjusts control parameters, executes necessary changes, collects data from sensors, transmits them to the server, and generates alerts when needed.

Sensors measure environmental parameters such as airspeed, humidity, temperature, and carbon content.

Control Object is responsible for modifying control parameters based on the received data.

The sequence diagram (Figure 3) is a crucial element for visualizing how different objects interact within the system. This diagram illustrates the data lifecycle and the message exchange processes between objects, providing a clear understanding of the interaction order.

In the case of this system, the sequence diagram shows how sensors data is transmitted to the microcontroller, where it is processed by the neural network. The results are compared with the expected values, and based on the comparison outcome, a control signal is generated to adjust the climate control devices. This allows for a precise identification of when and how the system's operation will be corrected.

A key element of the system is the neural network. It is trained using an error backpropagation algorithm. This allows for efficient adjustment of the network's weight coefficients, reducing prediction error and ensuring high accuracy of regulation. The advantage of this approach is the reduction in computational costs compared to deep neural networks, making it suitable for implementation in microcontroller systems [32, 33].

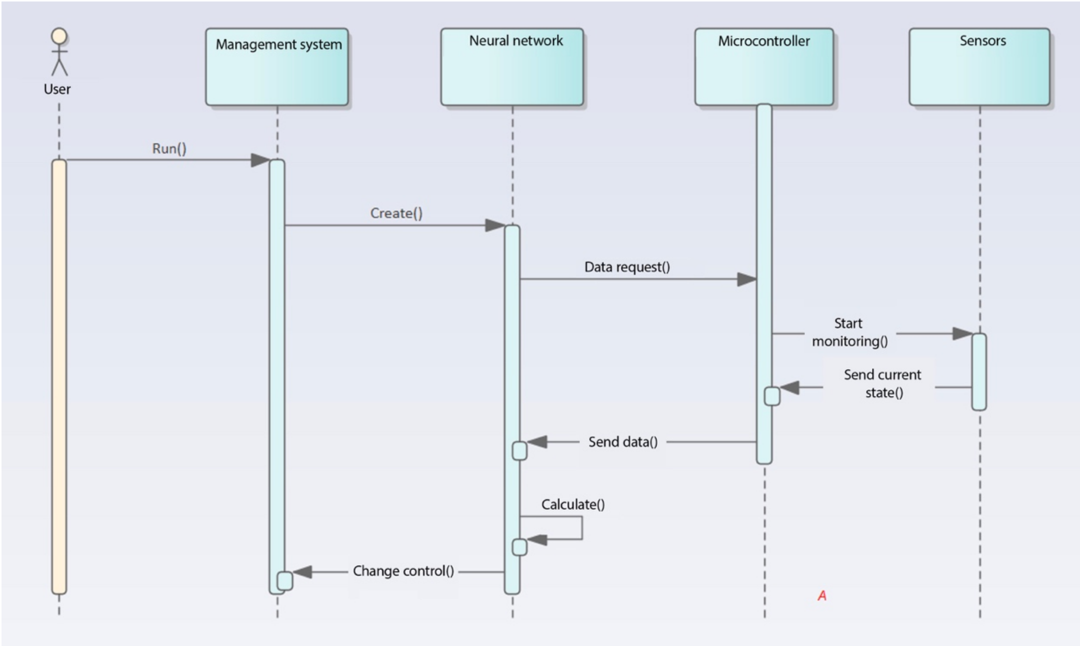


Figure 3: Sequence diagram.

To form the input data, the Predicted Mean Vote (PMV) index is used, which is one of the most effective for determining thermal comfort. The PMV is calculated using Fanger's equation, which allows for the assessment of comfort conditions based on the individual's parameters [34]. The average value of the sample is shown on a seven-point scale of thermal sensation, as shown in Table1.

Table 1
Description of the PMV model

Index	-3	-2	-1	0	+1	+2	+3
Fuzzy characteristic	Very cold	Cold	Slightly cold	Comfortable	Slightly warm	Warm	Very warm

An additional parameter is the use of the Predicted Percentage of Dissatisfied (PPD) index, which reflects the number of people who may experience discomfort under certain conditions, and is described by the following equation [35]:

$$PPD = 100 - 95e^{\left(-\left(0.03353\,PMV^4 + 0.2179\,PMV^2\right)\right)} \quad (1)$$

Next, this data is fed into the neural network, which uses it to adapt the operation of the microclimate control system. According to the relationship presented in Figure 4, the correlation between the PMV and PPD indices allows for the assessment of how comfortable the conditions are for the workers.

If the PMV equals zero, it means that the conditions are thermally neutral. Ideal comfort conditions for most people are defined by PMV values ranging from -0.5 to +0.5. This combination of parameters ensures that the workers satisfaction level will be at least 80%. Thus, the application of a neural network for microclimate control allows for precise control over environmental parameters, taking into account the individual needs of users and ensuring a high level of comfort in the workplace.

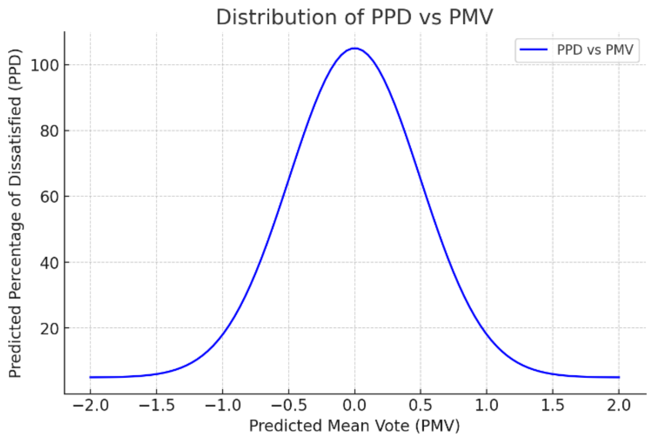


Figure 4: The relationship between the values of the PMV and PPD indices.

One effective approach to implementing predictive control is the use of a Neural Predictive Controller (NPC) [36]. This approach enables the forecasting of the system's state based on empirical, neural network built models. The proposed control strategy takes into account the interrelationships between microclimate parameters, allows adaptive adjustments of the system settings according to operating conditions, and optimizes the control trajectory within allowable states. Figure 5 shows the control configuration diagram.

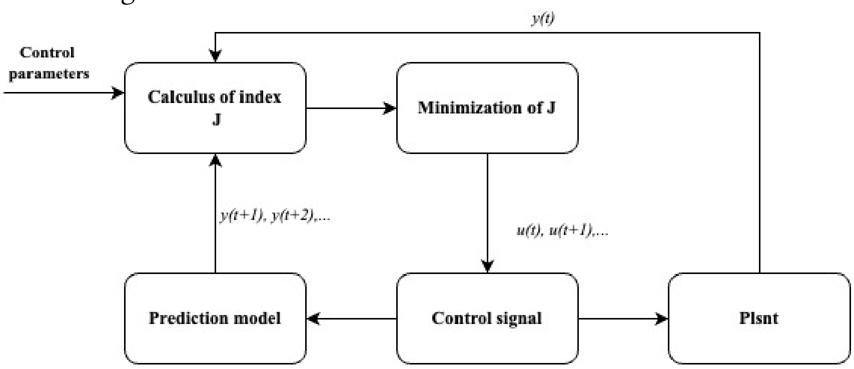


Figure 5: Control configuration diagram using the NPC controller.

The operation of the controller is determined by the empirical model of the controlled process, which is based on previous values of state variables. The control strategy is chosen to account for the relationships between the parameters describing the state of the control object, the limitations of control devices, and the ability to select the best trajectory for state changes within the set of allowable values.

An important element of the system's development is the implementation of the information collection subsystem, which performs the client part function of the microcontroller-based climate control system and is based on the ATMEL ATMEGA series microcontroller [37, 38]. Microcontrollers in this series are single-chip computing devices that allow for signal processing from various sensors, ensuring efficient control of electronic systems. For the implementation of the data collection subsystem in this study, the AVR ATMega32 microcontroller was chosen. It has several advantages, including high performance, low power consumption, and a wide range of built-in functions. The microcontroller in a PDIP package has 40 pins, which are shown in Figure 6.

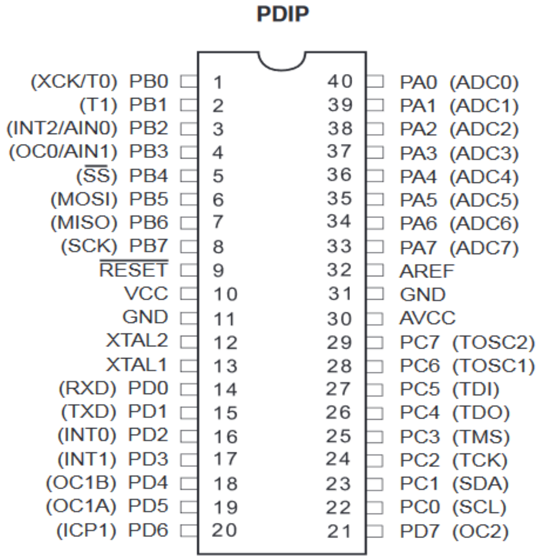


Figure 6: Pinout of the ATMega32 microcontroller in the PDIP package.

In particular, the microcontroller includes 32 KB of flash memory, 2 KB of SRAM, an 8-channel 10-bit ADC, support for serial interfaces (USART, SPI, I2C), as well as power-saving mechanisms. The Harvard architecture ensures high data processing speed, which is crucial for working with real-time climate parameters.

To collect the necessary information about the environmental state, the developed system uses the following sensors:

- Temperature and humidity sensor SHT21 – a high-precision digital sensor that simultaneously measures two parameters. The SHT21 sensor has output signals in I2C, PWM, and SDM formats. Its power consumption is 1.5 μW, making it very energy-efficient. It can measure relative humidity in the range of 0 to 100% and operate in a temperature range of -40 to 125°C. The sensor's response time is 8 seconds, and its measurement accuracy is up to 2%. The sensor's dimensions are a QFN package of 3x3 mm [39].
- Air velocity sensor PAV3005D – a highly sensitive sensor based on MEMS technology, providing air velocity measurements in the range of 0-7 m/s. The use of the I2C digital interface allows for efficient integration of this sensor into the system's overall architecture [40].

To transmit the collected data to the system's server, a module SIM900D [41] (Figure 7) is used.

Figure 7: GSM module board (SIM900D).

This module enables wireless data exchange through mobile networks using the GPRS standard. The interaction between the ATMega32 microcontroller and the SIM900D is carried out via the USART serial interface, allowing for the transmission of collected climate parameters for further processing.

To simulate the operation of the data collection subsystem, the Proteus software platform [42] was used, which allows for testing electrical circuits and verifying the correctness of software operation without the need to create a physical prototype. Proteus VSM Simulation provides a realistic emulation of the interaction between the microcontroller, sensors, and communication tools, enabling optimization of the system's operation at the design stage. Thus, the developed data collection subsystem ensures efficient reception, preliminary processing, and transmission of climate parameters. This is crucial for the subsequent operation of neural network-based data analysis algorithms in the microclimate control system.

The next step was modeling the main stages of system operation using the algebraic algorithms apparatus [43].The first stage of the implementation of the algorithms algebra is the description of unit terms and the synthesis of sequences [43], which is given below.

Formed uniterms: I(s) – uniterm of system initialization; C(d) - is the data collection from sensors uniterm; T(d) - is the unitterm of data transmission via GSM module; N(d) - is the uniterm of data processing by neural network; D - is the uniterm for decision-making and climate regulation; F - is the uniterm of network feedback and adaptation; E – a uniterm of cycle completion and re-reading; u_1 – a uniterm of cycle completion or continuation; u_2 – a uniterm of check if PMV is within limits [-2, +2];. As a result the following sequences and eliminations were synthesized:

S_1 - the sequence of system initialization and completion of the work cycle:

$$S_1 = \overparen{I(s)\ ,\ E}$$

S_2 – the sequence of a full cycle of operation when the condition u_1 is satisfied:

$$S_2 = \overparen{\overparen{\overparen{\overparen{\overparen{I(s)\ ,\ C(d)}\ ,\ T(d)}\ ,\ N(d)}\ ,\ *}\ ,\ F}$$

S_3 – the sequence of a full cycle of operation when the condition u_1 is not satisfied:

$$S_3 = \overparen{\overparen{\overparen{\overparen{\overparen{I(s)\ ,\ C(d)}\ ,\ T(d)}\ ,\ N(d)}\ ,\ D}\ ,\ F}$$

L_1 – the elimination of check if PMV is within limits [-2, +2]:

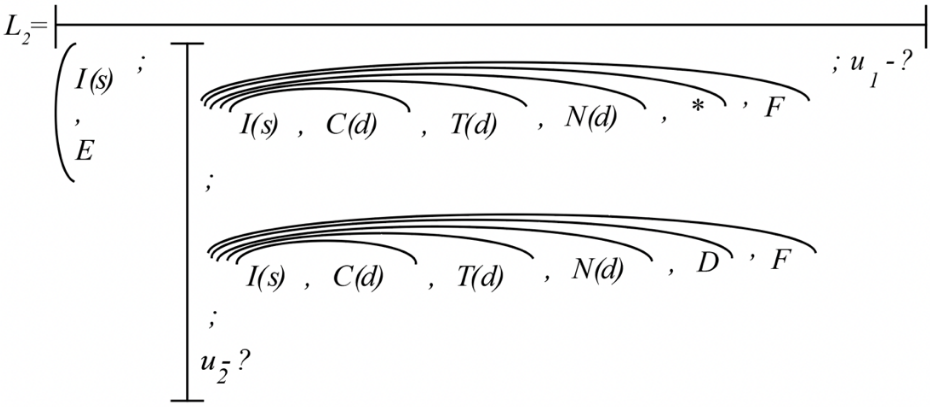
$$L_1 = \vdash\overline{S_2\ ;\ S_3\ ;\ u_2 - ?}\dashv$$

L_2 – the elimination of cycle completion or continuation:

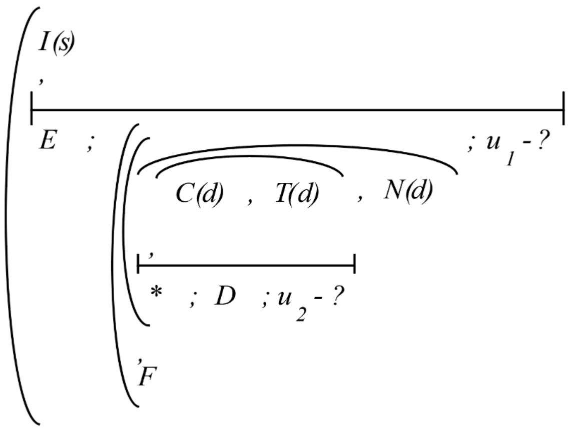
$$L_2 = \vdash\overline{S_1\ ;\ L_1\ ;\ u_1 - ?}\dashv$$

After substituting the corresponding sequences into the elimination, we obtain the following formulas:

$$L_1 = \left[\begin{array}{l} \overparen{\overparen{\overparen{\overparen{\overparen{I(s)\ ,\ C(d)}\ ,\ T(d)}\ ,\ N(d)}\ ,\ *}\ ,\ F} \\ ; \\ \overparen{\overparen{\overparen{\overparen{\overparen{I(s)\ ,\ C(d)}\ ,\ T(d)}\ ,\ N(d)}\ ,\ D}\ ,\ F} \\ ; \\ u_2 - ? \end{array}\right.$$



As a result of using the properties of the algebra of algorithms [43], we subtract the common unit terms by the sign of the elimination operation and obtain the following formula of the algebra of algorithms:



According to the presented model, the first stage is the initialization of the system, which includes setting the clock frequency of the ATMega32 microcontroller to 8 MHz, configuring the timers for processing delays and interrupts, setting up the I2C interface [44] for communication with the sensors, and initializing USART for communication with the GSM module. To do this in the Proteus program, the properties window needs to be opened and the "Timers" section selected. Any AVR microcontroller contains several built-in timers (Figure 8).

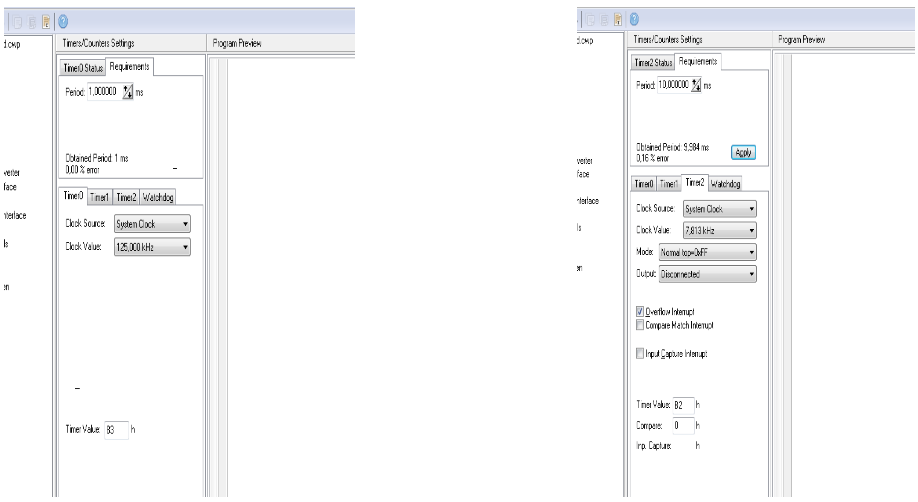


Figure 8: Timer configuration.

Timer 0 will be used to generate delays, while Timer 2 will interrupt every 10 milliseconds and will be used for reading data from the sensor and displaying the results. Unlike Timer 0, Timer 2 will trigger an interrupt.

Configuration of Timers 0 and 2:

```
// Timer/Counter 0 initialization
TCCR0=(0<<CS02) | (1<<CS01) | (1<<CS00);
// Timer/Counter 2 initialization
ASSR=0<<AS2;
TCCR2=(0<<PWM2) | (0<<COM21) | (0<<COM20) | (0<<CTC2) | (1<<CS22) | (1<<CS21) | (1<<CS20); TCNT2=0xB2; OCR2=0x00;
```

In the interrupt mask register of the timer, only the TOIE2 bit is initialized with a value of 1, meaning the interrupt for Timer 2 is enabled.

```
// Timer(s)/Counter(s) Interrupt(s) initialization
TIMSK=(0<<OCIE2) | (1<<TOIE2) | (0<<TICIE1) | (0<<OCIE1A) | (0<<OCIE1B) | (0<<TOIE1) | (0<<TOIE0);
```

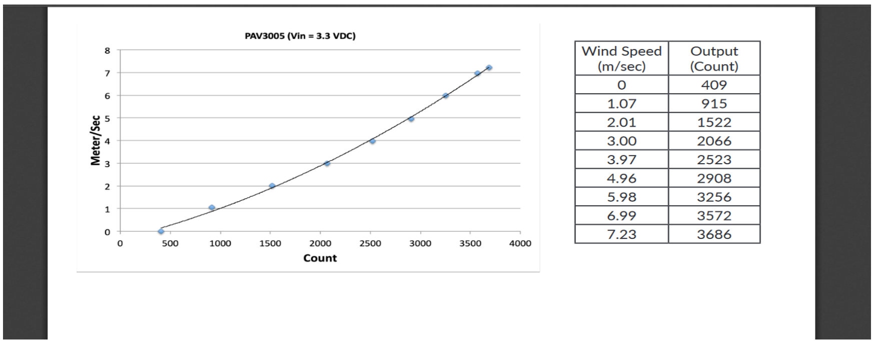
To enable the use of USART, you need to go to the corresponding section and check the "Transmitter" and "Receiver" checkboxes, as well as enable the Rx interrupt. Since the digital signal from the sensor is transmitted via the I2C protocol, it is necessary to configure the controller to work with the sensor in the "Bit-Banged I2C Bus Interface" section. For this, set the 4th pin of port C as the SDA bit and the 5th pin as SCL. Then, the value obtained from the sensor should be converted according to the expression (2) to receive the number in degrees Celsius.

$$T = -46.85 + \frac{175.72 * S_T}{2^{16}} \tag{2}$$

Interrupt handling program listing

```
i2c_start(),
i2c_write(0x80),
i2c_write(0xF3),
timerDelayMs(85);
i2c_start(),
i2c_write(0x81),
tt = i2c_read(1),
tt1 = i2c_read(1),
i2c_read(0),
i2c_stop(),
tmp = tt*256+tt1;
T = (tmp*0.00268127)-46.85;
i2c_write(0xFE);
i2c_start();
i2c_write(0x80);
i2c_write(0xF5);
timerDelayMs(29);
i2c_start();
i2c_write(0x81);
hh = i2c_read(1);
hh1 = i2c_read(1);
i2c_read(0);
i2c_stop();
hum = hh*1024+hh1;
H = hum*0.0019073486-6;
```

In the given listing, T represents the temperature value, and H represents the relative humidity value. Similarly, the air velocity value is calculated, but taking into account the specifics of the output signal from the PAV3005D sensor [40]. The output signal can range from 409 to 3686 units. The approximation graph is shown in Figure 10.



Wind Speed (m/sec)	Output (Count)
0	409
1.07	915
2.01	1522
3.00	2066
3.97	2523
4.96	2908
5.98	3256
6.99	3572
7.23	3686

Figure 9: Output data from the PAV3005D sensor.

Reading control commands via USART is implemented as follow

```
char * pch = strtok(rx_buffer,",");
while (pch != NULL){
  i++;
  if(i==2) {
    NumberSMS = atoi(pch);
    for(z=0;cmd6[z]!='';z++){
      while(!(UCSRA&(1<<UDRE))){};
      UDR = cmd6[z];
    }
    UDR = rx_buffer[i];
    UDR = ('\r');
  }
pch = strtok(NULL, " ");
}
```

Sending the data read from the sensors via the GSM module is described in the following listing:

```
void Send(unsigned char Message[]){
for(n=0;n=2';n++){
  for(z=0; cmd[z]!='';z++){
      while(!(UCSRA&(1<<UDRE))){};
      UDR = cmd [z];
   }
    UDR = ('\r');
 }
for(z=0;Message[z]!='';z++){
  while(!(UCSRA&(1<<UDRE))){};
  UDR = Message[z];
}
while(!(UCSRA&(1<<UDRE))){};
UDR = (26);
}
```

In the Labcenter Electronics Proteus simulation environment, a schematic of the data monitoring subsystem was developed. For this, a transformer-based power supply block with a 5V output was designed. The core of the circuit is the ATMega32 microcontroller, which is connected to the SHT21 sensor and the SIM900D GSM module. An LCD display is used for the digital indication of the measurement results. Monitoring the threshold values of the parameters is carried out with the help of LEDs (green for humidity and red for temperature). The result of the microcontroller system simulation with the temperature and humidity sensor is shown in Figure 10.

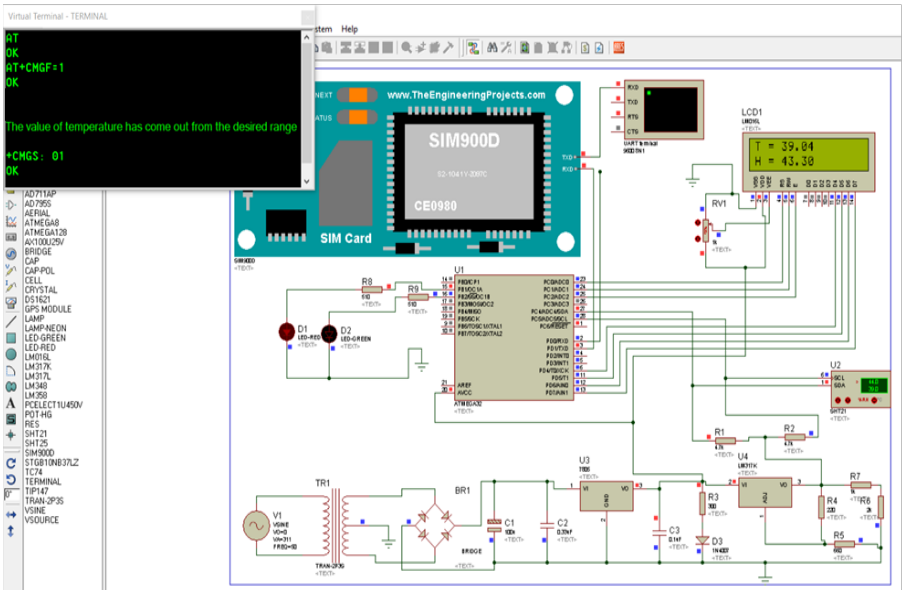


Figure 10: Simulation of the program operation in the Proteus environment.

Using simulation, a dataset for training the neural network was generated. Let's pay attention to the control subsystem for which the data has already been obtained. The constraints of the control system are the use of the PMV index only within the range of -2 to +2. Additionally, the parameters must comply with the ISO 7730 standard [45]: the temperature should be between +10°C and +30°C, humidity between 30% and 70%, and CO_2 concentration should not exceed 1400 ppm. For training the neural network, a test sample from the monitoring system is used, as well as expert assessments from office workers to determine the PMV index.

According to Fanger [46], the thermal comfort equation is as follows (3):

$$\begin{aligned} PMV = & \left(0.303 e^{-0.036M} + 0.028\right)\{M - W - 3.05*10^{-3}*\left[5733 - 6.99(M-W) - P_a\right] \\ & - 0.42\left[(M-W) - 58.15\right] - 1.7*10^{-5} M\left(5867 - P_a\right) - 0.0014 M*\left(34 - t_a\right) \\ & - 3.96*10^{-8} f_{cl}\left[\left(t_{cl}+273\right)^4 - \left(t_r+273\right)^4\right] - f_{cl} h_c\left(t_{cl} - t_a\right)\} \end{aligned} \tag{3}$$

The metabolic rate coefficient M for a relaxed state of a person is 58.15 W/m². The activity coefficient W for office work can be approximated as zero. The clothing insulation coefficient Icl, with a value of 0, represents a person without clothes, while a value of 1 represents comfortable conditions for a person in business attire. The average normalized value of this parameter is 0.078. This value will be used for calculating fcl – the comfort area coefficient (4):

$$f_{cl} = \begin{cases} 1.00 + 1.29 I_{cl}, I_{cl} \le 0{,}078 \\ 1.05 + 0.645 I_{cl}, I_{cl} > 0{,}078 \end{cases} \tag{4}$$

In formula (3), the index Pa represents the partial pressure of water vapor, which is calculated using formula (5):

$$P_a = \frac{RH * P_s}{100}, \tag{5}$$

where:

$$P_s = e^{-16.6536 - \frac{4030.183}{t_a + 235}} \tag{6}$$

The parameter t_{cl} – the surrounding temperature is calculated using formula (7):

$$\begin{aligned} t_{cl} = & 35.7 - 0.0275(M-W) - I_{cl}\{(M-W) - 3.05\left[5.73 - 0.007(M-W) - P_a\right] \\ & - 0.42\left[(M-W) - 58.15\right] - 0.0173 M\left(5.87 - P_a\right) - 0.0014 M\left(34 - t_a\right)\} \end{aligned} \tag{7}$$

The convective heat transfer h_c is determined by formula (8):

$$h_c = \begin{cases} 2.38\left(t_{cl} - t_a\right)^{0.25}, 2.38\left(t_{cl} - t_a\right)^{0.25} > 12.1\sqrt{V_a} \\ 12.1\sqrt{V_a}, 2.38\left(t_{cl} - t_a\right)^{0.25} < 12.1\sqrt{V_a} \end{cases} \quad (8)$$

Since the PMV value is determined by four parameters, the input layer consists of four neurons: the average external temperature, the indoor air temperature, the indoor humidity, and the indoor air flow speed. The output layer has only one value, the PMV, so the number of neurons in the output layer is one. Therefore, the input layer has a 4-dimensional size, and the output layer is one-dimensional.

The PMV index is a complex nonlinear relationship, and the initial weights of the neurons play a crucial role in the training process. They affect the algorithm convergence, the training time, and the likelihood of reaching a local minimum. To avoid the stabilization of the output value at the beginning of the training, the initial weights are randomly generated in the range: [-2 / q, 2 / q].

Analysis of the obtained results.

To create the control system model, the Deep Learning Toolbox package was used, specifically the Neural Network Predictive Controller module. This module consists of a neural network (NN) block and an optimization block. The diagram of the module is shown in Figure 11.

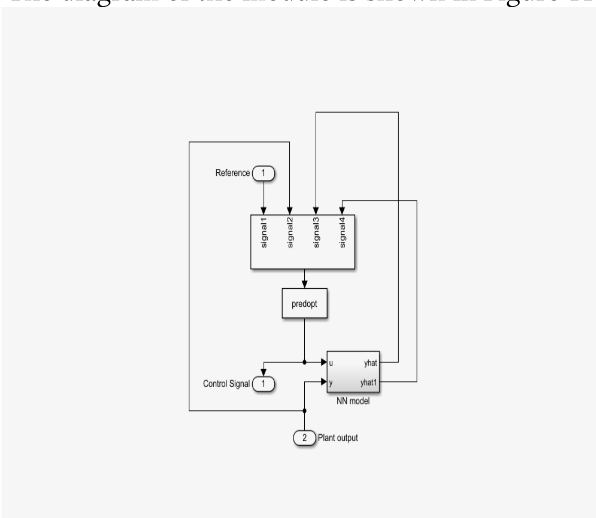


Figure 11: The diagram of the Neural Network Predictive Controller (NNPC) module.

According to the obtained mathematical model, a control scheme was created, which is shown in Figure 12. The mathematical model of the microprocessor subsystem is used as the object of the mathematical model (Plant). First, we input the initial value and the learning efficiency of the weight coefficient for each layer. Then, we define the input vector and the system's output, and compute the error E(k). Next step is calculating the input and output of the neurons in each layer of the neural network, with the output layer being the computed PMV index. Finally, we compute the controller's output and conduct training through the neural networks, performing online adjustment of the weight coefficient to achieve adaptive control of the PMV parameters. We set k = k + 1 and repeat the entire process from the first step.

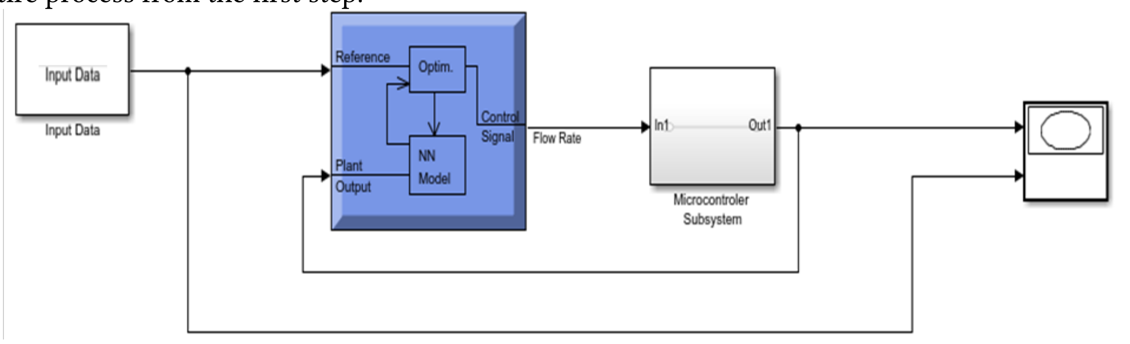


Figure 12: The control system diagram in the MATLAB environment.

The result of the network training is shown in Figure 13. To implement the adaptability of the system, it is necessary to modify the optimal values, which is done through the system performance assessments by office workers.

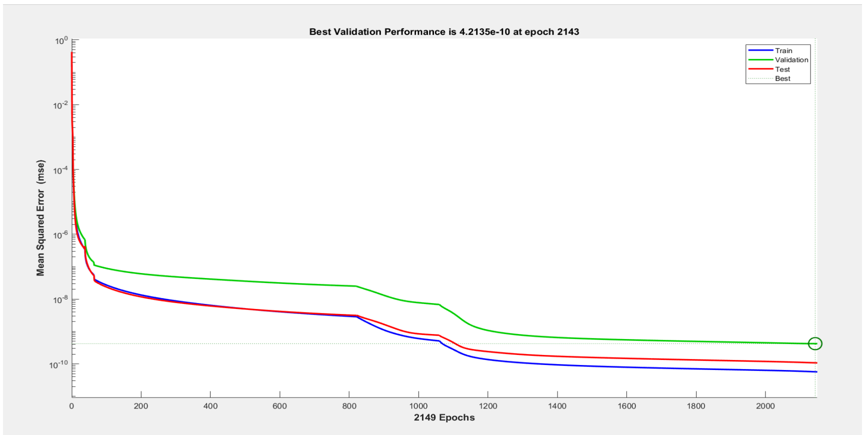


Figure 13: The training result.

As seen from the graphs (Fig. 13), the desired error value of 10^{-4} was achieved after 2149 iterations. The training, testing, and validation graphs are shown in Figure 14.

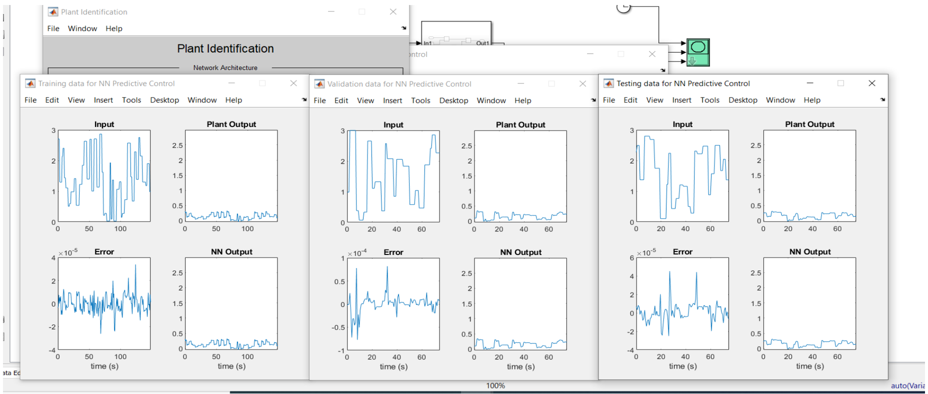


Figure 14: The network training graphs.

To verify the system's functionality, we will run the created model and display the graphs of measured and controlled parameters, as well as the PMV index (Fig. 15).

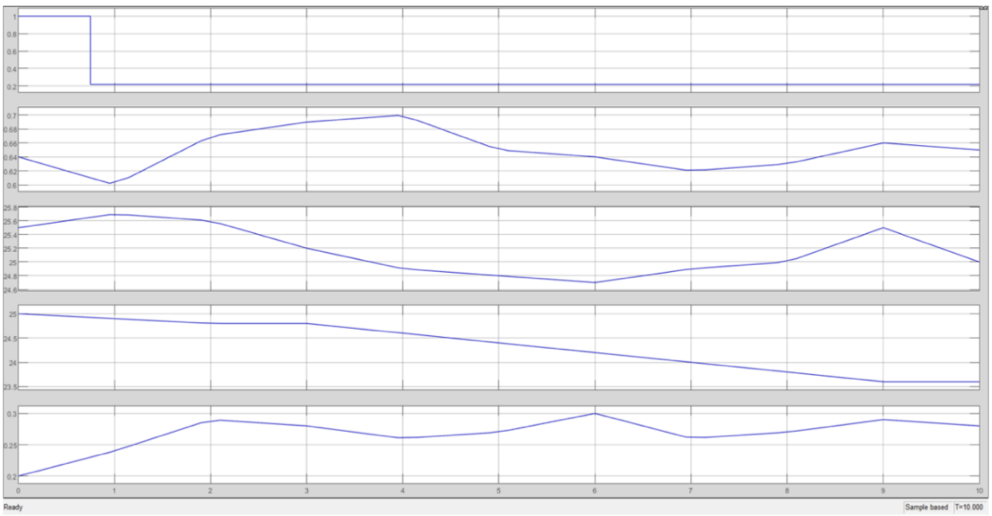


Figure 15: Network operation graphs.

In Figure 14, the graphs of PMV, relative humidity, outdoor and indoor temperatures, and airspeed are shown, respectively. As we can see, the comfort index for employees is maintained at approximately 0.21. Given the above we can conclude that the office climate control neural network, which stabilizes the climatic parameters at the level determined by the mathematical model while considering the PMV index, is ready.

Conclusion

As a result of the conducted research, a microcontroller-based climate control system that uses neural network technologies was developed. Modern methods of regulating climatic parameters were analyzed, including classic control algorithms, fuzzy logic, and neural networks. The study showed that traditional methods, such as PID controllers, have limitations in flexibility when adapting to dynamic environmental changes, while the use of neural network algorithms significantly improves the system's efficiency.

The developed system ensures automated monitoring of microclimate parameters and their adaptive regulation based on data obtained from temperature, humidity, and airspeed sensors. The use of artificial neural networks in decision-making allows the system to predict changes in climatic conditions and adjust the operation of climate devices accordingly. An analysis of the relationship between the PMV index and user comfort levels also enabled the optimization of control algorithms.

The creation of UML diagrams for object-oriented system design allowed for a clear definition of its functional capabilities and interactions between components. The proposed control model was implemented as a prototype, which was tested in the MATLAB environment. The testing results confirmed the effectiveness of the approach: the system ensures the maintenance of microclimate parameters within comfortable limits with minimal energy consumption. It was also confirmed that the application of neural network technologies improves the accuracy of climate control parameters and automates the regulation process without the need for constant user intervention.

Further research will focus on improving machine learning algorithms, expanding the capabilities of adaptive control, and integrating with modern IoT solutions to enhance automation and optimize energy consumption. Methods for improving the accuracy of climate change prediction are planned as well. Those will use deep neural networks and will help refine the system's learning model.

Declaration on Generative AI

During the preparation of this work, X-GPT-4 and Gramby were used for grammar and spelling verification. After utilizing these tools/services, the content was reviewed and edited accordingly. The authors take full responsibility for the content of the publication.

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