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N.M. Tasmurzayev , B.S. Amangeldy* , Sh.Zh. Shynassilov ,
Y.S. Nurakhov , S.D. Bekele

Al-Farabi Kazakh National University, Almaty, Kazakhstan
*e-mail: a.s.bibars@gmail.com

DIGITAL TWIN-BASED HVAC CONTROL FOR SMART BUILDING MANAGEMENT AND SUSTAINABILITY

Abstract. The advent of smart buildings owes much to the emergence of Digital Twins. In contemporary structures, a wealth of data is available, enabling the digital representation of buildings and facilitating improvements in energy management, particularly in heating, ventilation, and air conditioning (HVAC) systems. To effectively implement an energy management strategy within a building, a data-driven approach must accurately assess HVAC system attributes, with a focus on room temperature. Precise temperature forecasts not only enhance thermal comfort but also play a pivotal role in energy conservation. This research aims to explore data-driven methodologies and develop a model for room temperature prediction, employing machine learning algorithms in a case study of an educational building. This article details the methodology, points of interaction, and findings of this study. Relevant model parameters are identified to construct temperature prediction models using real-world data, demonstrating the efficacy of the proposed system, with an average prediction accuracy exceeding 95%. These results underscore its potential to enhance energy efficiency and thermal comfort, highlighting the use of Artificial Neural Networks (ANNs) as a pivotal component in achieving these goals.

Key words: Digital Twin, HVAC systems, Artificial Neural Networks, SCADA, thermal comfort, control box.

1. Introduction

A fatal deficiency for human health is a lack of clean, fresh air. Our well-being can endure on the off chance that we invest a ton of energy inside, working or examining, contingent upon our occupation. In this way, in any occupied structure, having appropriately ventilated spaces is essential. Heating or cooling may be required depending on the season or the building's purpose. It is difficult to keep a reasonable indoor temperature without an appropriately working HVAC framework. Few scientists have expressed that central air systems constitute the most prevalent source of energy consumption within a building, accounting for more than half of the structure's energy usage [1]. As a result, the HVAC system needs to be optimized to ensure occupants' comfort while simultaneously lowering energy consumption.

Building Information Modeling (BIM) can be used in this field to digitally model complex systems with accurate information to make the optimization process more effective and user-friendly. This information can then be used in a variety of applications for performance assessments and decision-making. Users will be able to add new features for automating repetitive tasks, conducting in-depth analysis, and solving complex problems, such as optimizing building thermal properties, through the development of an Application Programming Interface (API) in BIM [2]. Data from the Internet of Things (IoT), such as sensor networks, and feedback from occupants can be connected to BIM as an additional benefit for monitoring the equipment and environment of the building, which is beneficial for the optimization process. This association is important to make what is known as the Digital Twin of the air conditioning framework (HVACDT).

Energy consumption and HVAC system performance must be controlled with the utmost precision as they significantly influence the long-term viability of buildings and the surrounding landscape. Building managers' poor decisions can result in energy waste, high costs, and unsatisfactory heating [3]. The proposed system has demonstrated that it can assist building managers in planning the human resources required to address temperature complaints, thereby improving tenant satisfaction and the building's operational properties [4]. Temperature-related grievances are among the most common types of complaints [5]. Therefore, advanced intelligent digital technologies must be utilized in the context of sustainable facility management business development because these technologies can help improve information flow and make predictions based on sensor data [6]. In this article, the central air Digital Twin framework was created as a constant framework to assist buyers with pursuing more productive choices in the structure's life cycle.

IoT, artificial intelligence, and BIM are utilized in Digital Twin innovation [7]. These technologies have enabled the digitalization of numerous assets, allowing the virtual part of the object to interact with its physical counterpart throughout its entire lifespan [8]. While various definitions of a Digital Twin are available in the literature, for instance, [9] and [10], it is worth noting that Laments initially conceptualized the idea of a Digital Twin in 2012. Several years later, Laments emphasized that he was referring to a dataset that provides a comprehensive representation of an asset, covering its fundamental mathematical characteristics to its most specific capabilities (Laments and Vickers, cited in 2017). The initial step in this article involves developing a module for real-time data collection and feedback from sensors. Then, at that point, all the data from this module will be transmitted to the SCADA platform, a Digital Twin model. The Digital Twin model is incorporated into the smart platform, adjusting parameters according to predefined settings and comparing them with real-time values. As a result, the proposed system maintains thermal comfort in the building while reducing energy consumption.

2. Literature review

When developing control strategies for HVAC systems, indoor temperature prediction is one of the most important methods for determining thermal comfort levels in buildings and identifying potential energy savings. Throughout the past ten years, various investigations have been completed to model HVAC systems and simulate indoor temperature variations.

Physics-based models have conventionally been widely developed to express the intricate physics, energy, heat transfer, and thermodynamics associated with buildings in order to model and optimize HVAC systems. The majority of these models were worked with the objective of system control and enhancing energy efficiency. To optimize the multi-zone HVAC system, [11] developed a supervisory control strategy for a Variable Air Volume (VAV) system based on a simplified physics-based model. As HVAC systems become more perplexing, non-linear, and large-scale, encompassing diverse requirements and factors, the development of physics-based models for building energy management becomes much more challenging [12]. High-order complex models are frequently utilized in order to generate precise physics-based models. However, these latter options are computationally expensive, and reducing model complexity can lead to an increase in prediction errors [13]. Moreover, the implementation of complex models in real-time applications is challenging due to their high computational demands [14]. Consequently, these developed physics-based models typically tend to be deterministic, necessitating numerous assumptions and simplifications of their parameters, rendering them less applicable for addressing and impeding the day-to-day operations of buildings.

In recent years, various data-driven approaches have emerged to address the limitations of traditional physics-based models. Many studies have concentrated on constructing predictive models utilizing data mining techniques. In the realm of artificial intelligence, these data-driven models, often referred to as "black box" models, are constructed directly from data using algorithms that are not easily interpretable or explainable in terms of how they combine variables to make predictions.

As a result, researchers in HVAC system modeling have employed artificial intelligence algorithms to forecast indoor temperatures. Two examples of such models built by these algorithms are deep learning (DL) neural networks and machine learning (ML) tree-based models.

Tree-based machine learning models are constructed by recursively dividing the considered observations based on specific criteria. These splits are determined by evaluating all potential divisions in the data and selecting the one that results in the highest reduction in mean squared error (MSE) for the child nodes. Tree-based ensemble techniques combine multiple decision tree predictors to enhance performance and create more robust predictive models. Several studies [15] have examined the effectiveness of ensemble methods, including Random Forests and Extra Trees, in forecasting time series datasets, particularly within HVAC systems.

The adoption of ensemble techniques like Random Forests and Extra Trees highlights the importance of model robustness in HVAC predictions. These approaches not only enhance accuracy but also provide insights into feature importance, aiding in the understanding of which variables play a pivotal role in temperature forecasting.

On the other hand, ANNs serve as the cornerstone of deep learning strategies. They involve processing data through algorithms to identify relevant features and then combining these features to facilitate rapid learning [16]. These algorithms have the capability to learn from input data and generate outputs based on the patterns and relationships they discover within that data. They can also complete multiple tasks simultaneously without compromising the system's performance. Research indicates that both internal [17] and external [18] disturbances affecting the modeling process can be managed by systems employing the ANN modeling approach.

In addition, robust mathematical foundations have been developed by researchers that enable ANN to handle real-time events by learning from examples and applying that knowledge in similar situations [19]. Several studies [20] developed a variety of straightforward to complex models for a variety of scenarios in order to model indoor temperatures. All of these studies discovered that ANN models provided temperature predictions with an acceptable level of accuracy.

However, it's worth noting that research on ANN modeling for buildings has primarily centered on residential buildings and laboratories. The limited dataset size often used in this field, often focusing on a single building zone, can restrict the generalizability of findings.

Additionally, the preprocessing phase and the selection of input variables are frequently overlooked, leading to a lack of clarity regarding the methodology. In the quest for improving ANN models for HVAC, careful consideration of preprocessing steps and feature selection is imperative. These aspects are often overlooked but can significantly impact model performance and interpretability.

3. Materials and Methods

For precise control of gas, temperature, humidity, and indoor air conditioning (including heating and ventilation), the proposed system involves a complex combination of both software and hardware components. This system comprises two primary modules: one for decision-making and another for the collection, processing, and monitoring of indoor air parameters such as temperature and humidity. The programmable equipment controller plays a central role by receiving temperature data from sensors strategically positioned throughout the room. This data transmission occurs through the information retrieval module, ensuring real-time monitoring and control of the indoor environment.

For this study, we selected a laboratory space at Al-Farabi Kazakh National University as our research environment. To ensure precise data evaluation and the establishment of a dynamic module, we employed various sensors, including temperature, humidity, and voltage sensors, which were strategically installed within the laboratory. Our primary objective was to develop a control system capable of regulating the room's heating and cooling based on the data collected from these sensors. It's worth noting that while we conducted this research in a lab setting, similar results can be achieved in larger rooms by installing sensors at intervals of 10 meters, or in smaller rooms, with sensors placed at intervals of 2-3 meters. Data from the sensors were gathered using a data transmission module equipped with robust redundancy mechanisms (Ethernet/WiFi). We employed the Modbus RTU protocol and an RS-485 controller for efficient data communication. Subsequently, the controller transmitted a MySQL dataset containing the collected data to our dedicated server, conveniently located within the laboratory premises.

The data grouping module is responsible for transmitting temperature data gathered from the sensors positioned throughout the designated space to the programmable equipment controller. Simultaneously, the buffering module plays a crucial role in pre-processing the sensor data, which is subsequently utilized by the decision-making module, aiding in effective and informed decision-making based on the data retrieved from the server.

In this experiment, we only used information about temperature and humidity to prepare the decision-making module, which will then be used to control the room's heating and cooling. The forecasting module comes into play by predicting temperature circulation values for various air conditioning system operation modes. These predictions are generated using a pre-trained neural model. The dynamic module operates by transmitting control signals to the controller, facilitating temperature regulation, and selecting the most suitable temperature mode for the heating and cooling system. This ensures efficient heat transfer within the room and contributes to maintaining the desired indoor climate conditions.

Stochastic Gradient Descent (SGD) played a crucial role in optimizing the model, while the MSE served as the evaluation metric.

The Root Mean Squared Error (RMSE) metric is used in scenarios where it is essential to highlight significant errors and prioritize models that minimize large prediction errors. Conversely, the MSE is employed when the emphasis is on minimizing errors across all data points, without a specific focus on the magnitude of individual errors.

The MSE metric was chosen as the evaluation criterion in this experiment due to its suitability for scenarios where the goal is to comprehensively assess and minimize prediction errors across all data points.

In this context, we analyze the magnitude of neural network connections and the actual values provided by the sensors within a specific time interval. Within this analysis, we compare the true values to the values derived from the assessments. By subtracting the minimum value from the maximum value, we can determine a range that corresponds to a model with minimal prediction errors, typically in the range of 95-100%.

The portion of data extracted from the x-test dataset demonstrates the practical utility of temperature data in our study. In the subsequent section, we delve into the predictions made by the neural network, as illustrated in Figure 2. Following that, in Figure 3, we meticulously examine the disparities between the actual data and the predictions. In this analysis, it becomes evident that the neural network exhibits minimal prediction errors, which is a strong indicator of the model's effective performance.

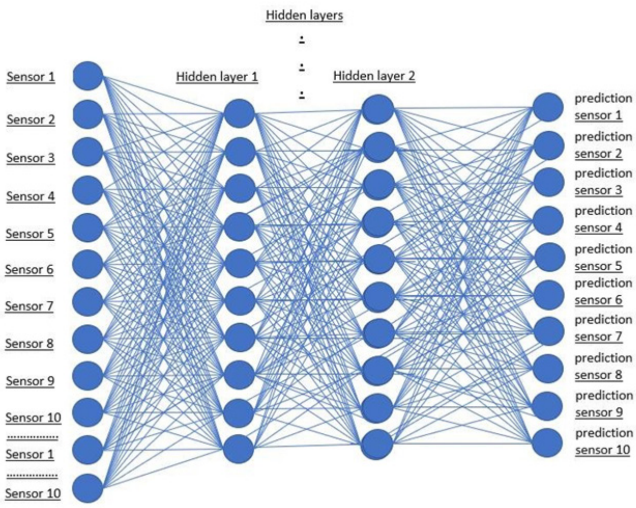

Figure 1 – Neural Network Architecture

22	-	22.050106048583984	->	-0.050106048583984375
21	-	21.204078674316406	->	-0.204078674316640625
23	-	22.827194213867188	->	0.1728057861328125
22	-	22.52977752685547	->	-0.5297775268554688
22	-	23.627410888671875	->	-1.627410888671875
24	-	24.187088012695312	->	-0.18708801269530895
24	-	24.308347702026367	->	-0.30834770202636363
23	-	22.110450744628906	->	0.8895492553710938
22	-	21.939077377319336	->	0.0609226226806406
22	-	22.006561279296875	->	-0.006561279296875
21	-	21.4600830078125	->	-0.4600830078125
25	-	25.44829559326172	->	-0.44829559326171875
22	-	21.890987396240234	->	0.1090126037597656 2
23	-	23.789947509765625	->	-0.789947509765625
22	-	22.50919532775879	->	-0.509195327758789 1
23	-	22.92646026611328	->	0.07353973388671875
25	-	25.003576278686523	->	-0.003576278686523437
22	-	22.510883331298828	->	-0.5108833312988281
24	-	23.160953521728516	->	0.839046478271487 9
24	-	24.11187744140625	->	-0.1118774414062464 5
23	-	23.000776290893555	->	-0.000776290893554687
23	-	22.30359077453613 3	->	0.6964092254638672

Figure 2 – Neural Network Predictions

Prediction errors decrease with each successive iteration of the neural network training and prediction, as shown in figures 2, 3, and 4.

The loss and accuracy visualizations in figure 3 provide an insightful view of the training process. It illustrates how our neural network model's loss and accuracy evolved during training. This visualization helps us gauge the model's learning progress and identify potential areas for improvement.

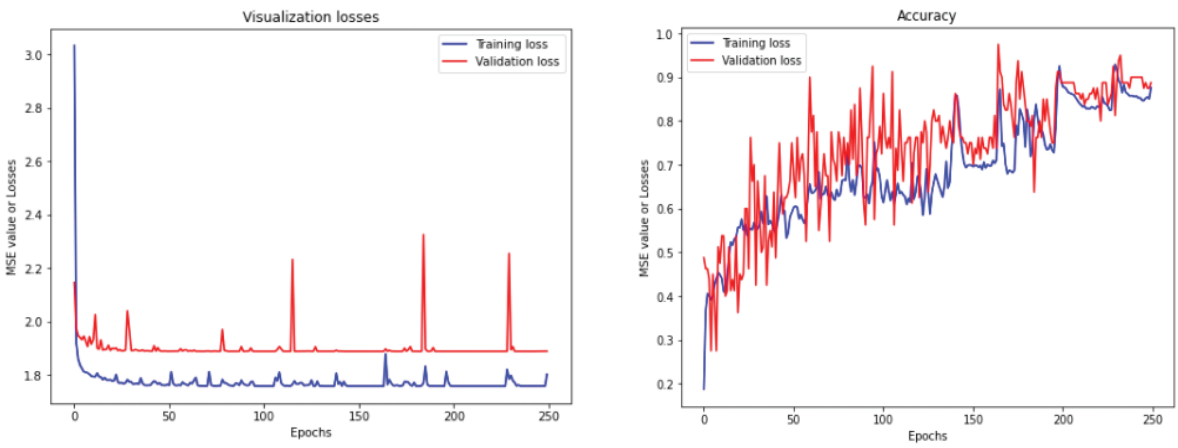

Figure 3 – Loss and Accuracy visualization

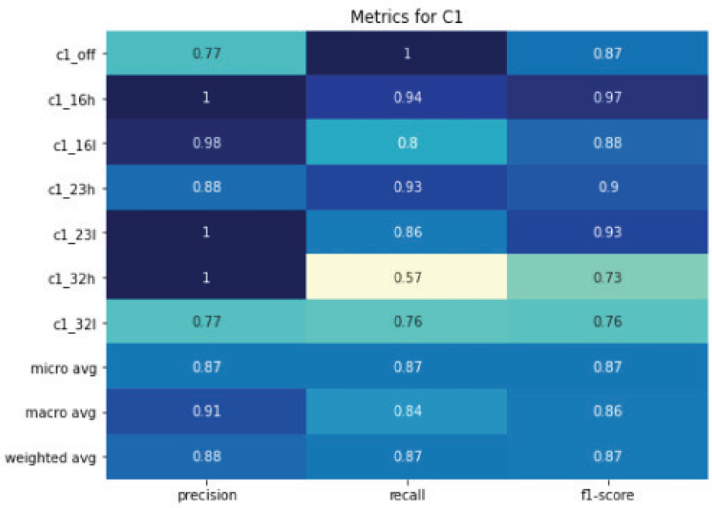

Figure 4 – Performance Metrics for Advisory Mode Control System Evaluation

The performance metrics in figure 4 delves deeper into the evaluation of our advisory mode control system. We calculate precision, recall, and F1 scores for different control modes. These metrics are essential in quantifying the model's ability to make accurate recommendations and provide valuable insights for system optimization.

As a result, we examine the neural network's performance in relation to sensor data. In these visual representations, we compare the actual values to those obtained from the sensors. Within the chart, we calculate the ratio of the highest value to the lowest value, resulting in a range typically between 90-95%. This article presents the development of a neural network, functioning as a recommendation system, for intelligent and optimal control of air conditioners based on temperature parameter forecasting.

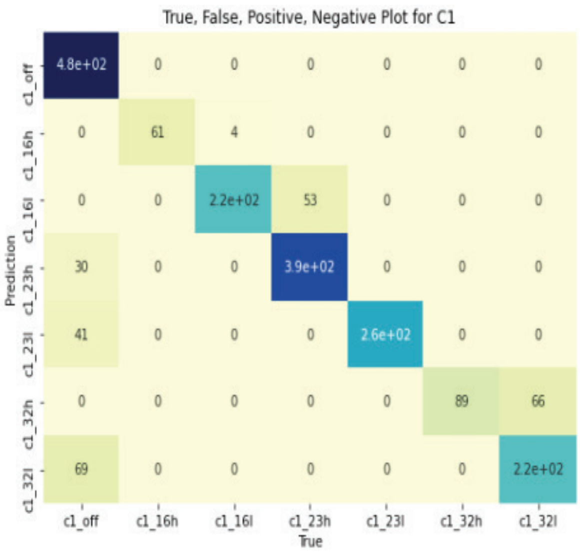

Figure 5 – Comparison of Neural Network Predictions with Real Air Conditioner Control Modes

4. Architecture of the system

A modular structure for a centralized control system should be designed to accommodate future network expansion, which may be necessary based on the building's evolving needs. It should also consider the installation and operational requirements of existing controlled equipment. Figure 6 illustrates a design consisting of three hierarchical levels, as outlined below, from the lowest to the highest level:

Level 1: Drive and data collection equipment (field equipment).

Level 2: Automation controllers with communication interfaces—used in plumbing, electrical supply, air conditioning, and other applications including electrical panels, fireplaces, thermal power plants, ventilation units, etc.

Level 3: Centralized control station for the system: The SCADA system dispatcher.

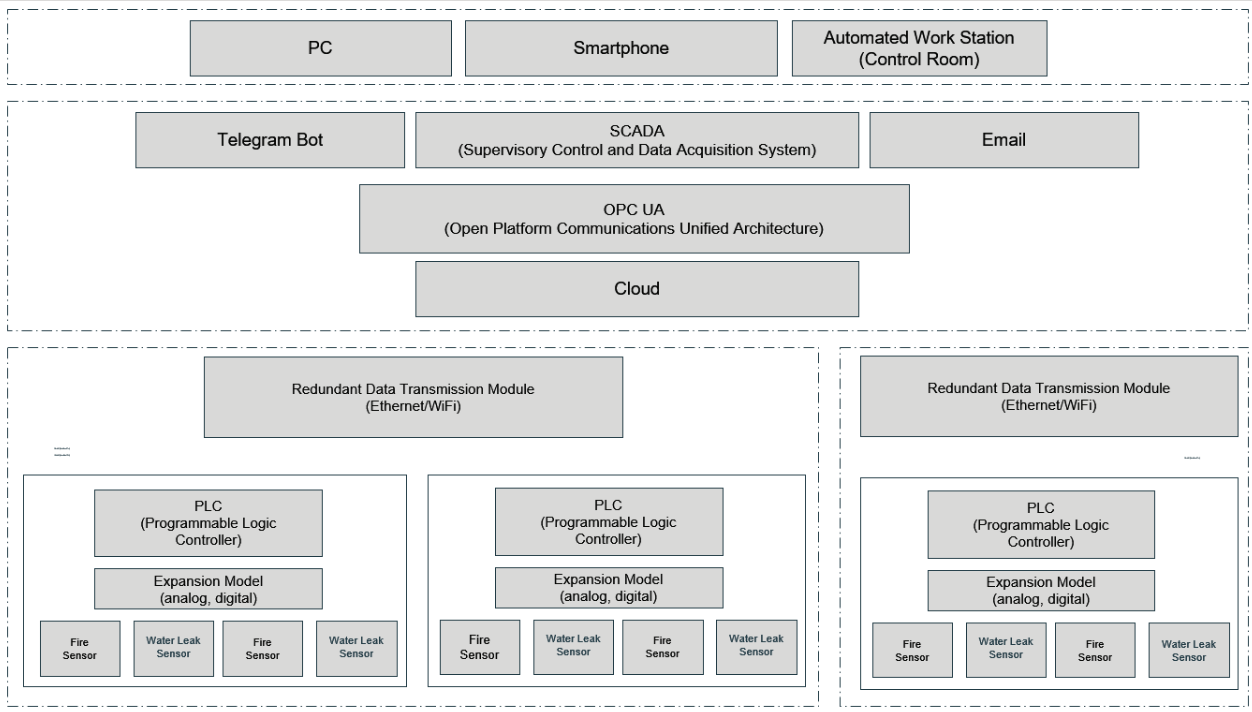

Figure 6 – Architecture of the System

In this architecture, each piece of equipment or automated system can operate independently in its designated local control area (e.g. equipment installation). It is connected to the central dispatcher's communication network for integration into the broader system. To be seamlessly integrated, local automation controllers must be equipped with communication interfaces. The use of specific protocols limits integration capabilities and incurs significant additional costs for subsequent development/integration. On the other hand, the use of standardized communication protocols enables the possibility of further integrating new equipment or systems installed in future stages. This approach enhances flexibility and scalability while minimizing integration complexities and costs.

Communication between local controllers of various systems within the centralized control system (such as HVAC, healthcare, electricity supply, etc.) will be established through multiple networks, each operating in accordance with specific communication protocols (e.g., Modbus). These networks will be meticulously optimized to ensure maximum data transmission speed in the HVAC network, which encompasses components such as air purification units, thermal power stations, central refrigeration units, ventilation convectors, as well as supply and exhaust ventilation systems.

5. Implementation of the system

The illustrated model for building automation using PLC and SCADA is depicted in Figure 7. This system comprises two fundamental components: hardware and software.

Figure 7 – Overview of the Control Box

The Model System's hardware consists of a Siemens programmable logic controller (PLC), heat sensors of the PT 100 type, temperature, and humidity sensors, and a differential pressure sensor. The PLC and SCADA programming, developed for real-time process monitoring and remote system control, enable the operation of the Model System through the PLC in accordance with the developed algorithms. This control is managed by the central computer connected to the system. To program the PLC utilized in the Model System, the Regulator Development System editor was employed, as displayed in Figure 8.

The Model System's PLC software includes automation for HVAC, humidity regulation, alarm systems, and the main software overseeing these subprograms. The system's control structure is depicted in Figure 9, comprising actuators, a control panel with a connection module and controller, sensors, and an information system (system cloud, smartphone, and web-based monitoring and control, notifications via email and Telegram).

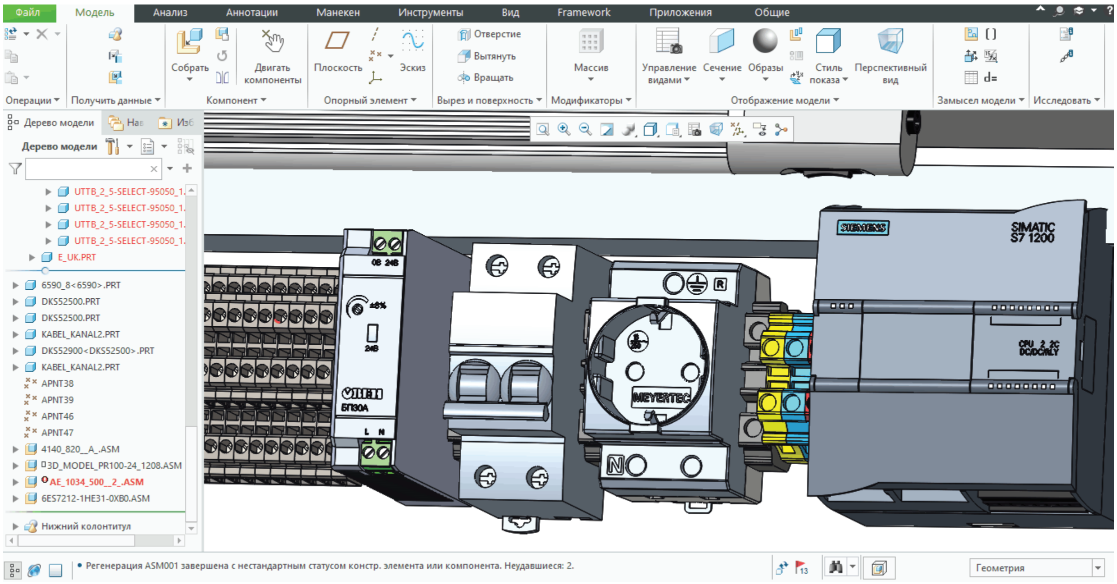

Figure 8 – Overview of the PLC

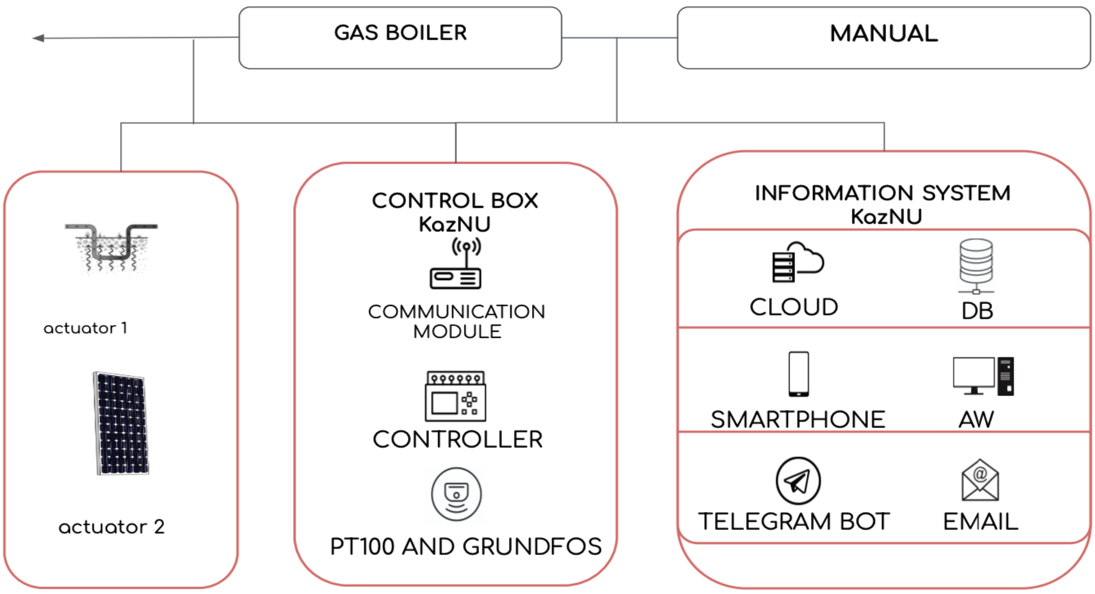

Figure 9 – Control Structure Overview for Model System

SCADA programming was developed to facilitate real-time control of the designed model system, ensuring continuous data collection, assessment, and ongoing management. The SCADA editor was employed for the creation of this software.

Within the software created using the SCADA editor, the points utilized in the model system were initially established using the Modbus protocol. Figure 10 illustrates the HVAC page, which encompasses features for monitoring, control, heating, and cooling operations.

The final stage of system implementation is system testing. Figure 11 displays real-time data obtained from temperature and humidity sensors, which play a crucial role in aiding the intelligent system in decision-making and parameter regulation.

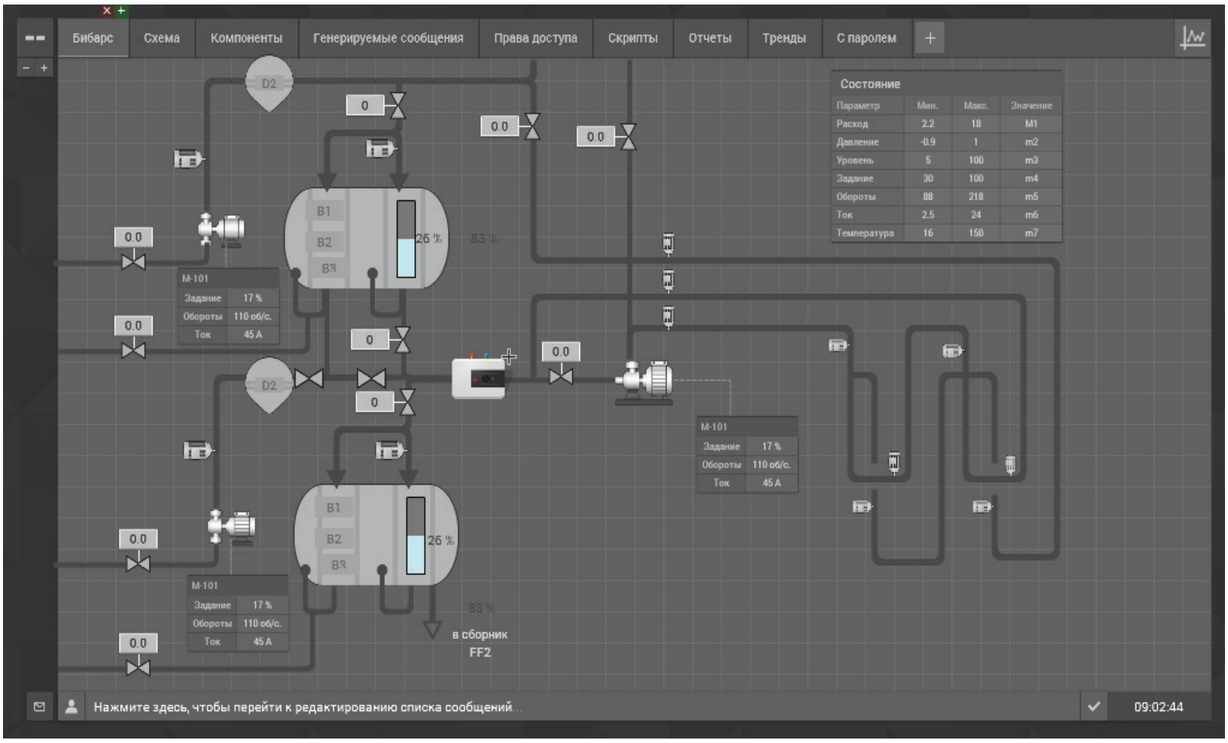

Figure 10 – Visualization in SCADA

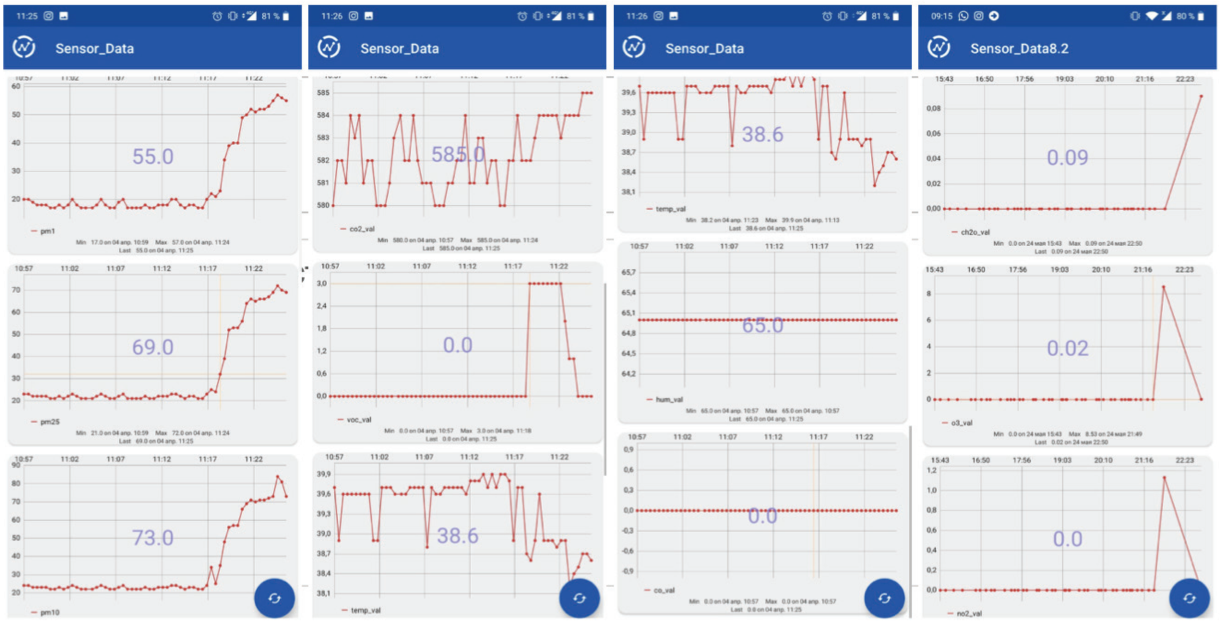

Figure 11 – Monitoring the System from a Smartphone

6. Results and Discussion

In this chapter, we present the outcomes of our study on the development and implementation of an intelligent HVAC system. This system incorporates an intelligent decision-making module for the precise regulation of specific parameters. The system utilizes Siemens controllers, temperature and humidity sensors, air conditioning units, and the SCADA monitoring program. Before delving into the results, let's briefly recap the architecture of our intelligent HVAC system. It comprises several key components:

Siemens Controllers: These programmable logic controllers (PLCs) serve as the brain of the system, responsible for executing control algorithms.

Temperature and Humidity Sensors: PT 100 type heat sensors and DWYER RHP-3W44-LCD heat and humidity sensors provide crucial data inputs to the system.

SCADA Monitoring Program: The SCADA software offers real-time monitoring and control capabilities, enabling continuous data collection and evaluation.

Our system successfully achieved real-time process monitoring, allowing us to gather data and evaluate the performance of the HVAC system under various conditions. The integration of temperature and humidity sensors provided accurate and timely data inputs. The remote control capability of the system allowed us to adjust HVAC parameters remotely. This functionality proved highly valuable for optimizing the indoor environment, particularly in response to shifting external conditions. The intelligent decision-making module demonstrated its effectiveness in regulating specific parameters. It utilized data from the sensors and executed control algorithms to maintain a comfortable and energy-efficient indoor environment.

One of the primary achievements of our study is the improved performance and efficiency of the HVAC system. By utilizing real-time data and the decision-making module, the system effectively balanced heating, cooling, and humidity control, resulting in enhanced comfort and reduced energy consumption. The ability to remotely control and monitor the HVAC system opens up new possibilities for building management and energy optimization. This feature is especially beneficial in scenarios where immediate adjustments are required. Our modular system architecture allows for future expansion and integration with additional components or systems. This scalability ensures the system can adapt to evolving building requirements and technological advancements.

7. Conclusion

In this study, we have endeavored to design, develop, and implement an intelligent HVAC system with a focus on precision, efficiency, and remote accessibility. The system incorporates Siemens controllers, temperature and humidity sensors, air conditioning units, and the SCADA monitoring program. Beyond the immediate scope of HVAC control, our research points to broader possibilities in intelligent building management. The remote accessibility of our system empowers facility managers, engineers, and building owners to exercise precise control over environmental parameters, even from remote locations.

In summary, our study underscores the potential for innovation in building automation. The fusion of advanced hardware, intelligent decision-making, and real-time monitoring has yielded a system that not only optimizes building conditions but also promotes energy conservation and sustainability. As we move forward, we anticipate further refinements and applications of this technology, ultimately shaping a future where buildings are not merely structures but dynamic, adaptable ecosystems that respond intelligently to the needs of their occupants and the environment.

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