https://doi.org/10.31891/csit-2025-1-2
UDC 004.5

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HEATING OPTIMIZATION SYSTEM IN A SMART HOME BASED ON FUZZY LOGIC AND INTEGRATION WITH CLOUD SERVICES

Smart home technologies are increasingly being used to automate various aspects of everyday life, and one of the main problems these systems solve is energy optimization. Heating is one of the largest energy consumers in a home, so its efficient management plays a key role in reducing energy costs and increasing the comfort level of residents. A fuzzy logic-based system for optimizing the use of heating in a smart home is an important step towards energy efficiency and comfort in modern residential buildings.

The relevance of this work lies in the fact that existing heating systems in Smart Homes are often not fully optimized, especially in terms of fuel management and reducing the frequency of temperature fluctuations. Many current systems do not fully take into account variable conditions such as outdoor temperature, time of day, humidity levels, or individual user needs. This results in inefficient operation: fuel consumption can be excessive and room temperatures fluctuate frequently, creating discomfort for occupants. Frequent changes in temperature can also negatively affect human health, and excessive fuel consumption leads to economic losses and increased environmental impact. Optimization of these processes through the use of fuzzy logic can achieve a more stable and energy-efficient heating system, which is essential for improving comfort and reducing costs.

This paper proposes a fuzzy logic-based system for optimizing the use of heating in a Smart home. According to the results obtained, the use of fuzzy logic significantly improves the stability of the temperature in the house, which is important for the comfort of the residents. For the experiments, two models were compared: a basic heating model and a model based on fuzzy logic. The basic system, which does not take into account variable factors with this level of flexibility, leads to large and sharp temperature fluctuations, which can create discomfort and increase energy consumption. Instead, the fuzzy logic model demonstrates smoother and more stable temperature control, which can significantly reduce energy costs.

Keywords: heating system optimization, fuzzy logic, control system

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СИСТЕМА ОПТИМІЗАЦІЇ ВИКОРИСТАННЯ ОПАЛЕННЯ В РОЗУМНОМУ БУДИНКУ НА ОСНОВІ НЕЧІТКОЇ ЛОГІКИ ТА ІНТЕГРАЦІЇ ІЗ ХМАРНИМИ СЕРВІСАМИ

Технології «розумного дому» все частіше використовуються для автоматизації різних аспектів побуту, і одна з основних проблем, яку вирішують ці системи – це оптимізація енергоспоживання. Опалення є одним з найбільших споживачів енергії в будинку, тому його ефективне управління відіграє ключову роль у зменшенні витрат на енергоресурси та підвищенні рівня комфорту мешканців. Система оптимізації використання опалення в Розумному будинку на основі нечіткої логіки є важливим кроком у напрямку енергетичної ефективності та комфорту в сучасних житлових приміщеннях.

Актуальність даної роботи полягає в тому, що існуючі системи опалення в Розумних будинках часто не є повністю оптимізованими, особливо в аспектах управління витратами палива та зменшення частоти коливань температури. Багато сучасних систем не враховують в повній мірі змінні умови, такі як зовнішня температура, час доби, рівень вологості або індивідуальні потреби користувачів. Це призводить до того, що система працює неефективно: витрати палива можуть бути надмірними, а температура в кімнатах часто коливається, що створює дискомфорт для мешканців. Часті зміни температури можуть також негативно впливати на здоров'я людей, а надмірні витрати палива призводять до економічних збитків і підвищеного навантаження на навколишнє середовище. Оптимізація цих процесів через використання нечіткої логіки дозволяє досягти більш стабільної та енергоефективної роботи системи опалення, що має важливе значення для підвищення комфорту та зниження витрат.

У даній роботі пропонується система пропонується оптимізації використання опалення в Розумному будинку на основі нечіткої логіки. Згідно із отриманими результатами, використання нечіткої логіки значно покращує стабільність температури в будинку, що є важливим для комфорту мешканців. Для проведення експериментів порівнювались дві моделі – базова модель опалення та модель на основі нечіткої логіки. Базова система, яка не враховує змінні фактори з таким рівнем гнучкості, призводить до великих і різких коливань температури, що може створювати дискомфорт та збільшувати споживання енергії. Натомість модель з нечіткою логікою демонструє більш плавне та стабільне регулювання температури, що дозволяє значно знизити витрати на енергоресурси.

Ключові слова: оптимізація системи опалення, нечітка логіка, система керування

Introduction

Smart home technologies are increasingly being utilized to automate various aspects of household management, with energy consumption optimization being one of the primary challenges addressed by these systems. Heating is one of the largest energy consumers in a home, making its efficient management crucial for reducing energy costs and enhancing residents' comfort [1, 2].

The relevance of this work lies in the fact that existing heating systems in smart homes are often not fully optimized, particularly in terms of fuel cost management and minimizing temperature fluctuations. As a result, these systems may operate inefficiently: fuel consumption can be excessive, and room temperatures may frequently vary, causing discomfort for residents. Frequent temperature changes can also negatively impact people's health, while excessive fuel consumption leads to economic losses.

The structure of this article is organized as follows: first, the basic heating model in a Smart Home is researched and formalized. Next, optimization criteria are proposed, along with a heating optimization system for Smart Homes based on fuzzy logic. Finally, a study is conducted to evaluate the efficiency of heating systems according to the defined criteria, comparing the basic operational model with control systems based on fuzzy logic.

Related works

Various methods have been proposed to date, demonstrating significant potential for improving heating systems. One notable advancement is the use of hydraulic heating systems combined with a nighttime shutdown strategy. Due to high thermal inertia and quality insulation, this approach reduces fuel consumption by 10% without significant comfort losses [3]. Other approaches include developing mathematical models for heat supply systems to optimize energy consumption with minimal deviations.

In [4], a mathematical model of centralized heating supply was developed, divided into flow, thermal, and pressure stages, enabling efficient system parameter calculations and optimization with deviations of only 1% after calibration. The methodology in [5] proposes expanding heating networks using mixed-integer programming, accounting for spatial aspects and adapting to various building connection scenarios. Similarly, the work in [6] introduces numerical optimization for large-scale heating networks, employing constraint aggregation for consumers and an approximation strategy for discrete parameters. This approach reduced pipe costs by 23% and pumping costs by a factor of 14 within an hour of computation.

Moreover, [7] introduced an intelligent controller for a "smart" energy grid that minimizes energy imports, optimizes costs, and enhances microgrid reliability. An integrated control strategy featuring load forecasting and real-time temperature correction was also studied, reducing the temperature imbalance coefficient in rooms from 0.0310 to 0.0196 [8].

The reviewed studies propose various approaches for analyzing, optimizing, and managing heating systems, including strategies for reducing energy consumption, enhancing thermal comfort, and improving the accuracy of heat load forecasts. The advantages of these methods include improved energy efficiency, reduced fuel consumption, increased hydraulic network stability, and scalability for large centralized heating systems. However, limitations include the models' inability to fully account for dynamic changes in heat demand, dependency on precise tuning of control parameters, and the complexity of integrating diverse management strategies to balance comfort and efficiency.

To further enhance the efficiency of heating systems in Smart Homes, the use of fuzzy logic is proposed, offering resource optimization within Smart Home heating systems.

Abstract model of system functioning

To describe complex systems, such as a heating optimization system, it is convenient to use an abstract model that generalizes its functionality in the form of a tuple. At the highest level of abstraction, the model can be represented as:

$$AbstractModel = (\{Inputs\}, \{FunctionalBlocks\}, \{Outputs\}) \quad (1)$$

where $Inputs$ – set of inputs; $FunctionalBlocks$ – set of functional blocks; $Outputs$ – set of outputs.

This approach allows any system to be described as an interaction of three main components: the set of inputs, the set of functional blocks, and the set of outputs.

($Inputs$) represent all external signals or parameters that influence the operation of the system. They serve as the source of information upon which the system performs its functions.

$FunctionalBlocks$ are the key elements of the model responsible for processing, transforming, and analyzing input data. These blocks model the internal processes of the system, enabling computations, data transmission between subsystems, and decision-making. They may include mathematical models, algorithms, physical characteristics of components, or even software modules.

$Outputs$ get the results of the system's operation. They reflect how the system responds to input signals after processing through functional blocks. Output parameters allow the evaluation of system performance, provide feedback, or enable monitoring of task execution.

This approach to system modeling ensures modularity and hierarchy. The abstract level not only helps understand the general logic of operation but also provides the ability to detail each component at lower levels of the model. Thus, as the abstraction level decreases, each element of the model can be described in more detail, considering the specifics of individual processes or system components.

Basic heating model in a Smart Home

To model the process of heating optimization system in a smart home based on fuzzy logic, we will first formalize the process for the model presented in [9]. The purpose of this approach is to identify the key components of the model (inputs, functional blocks, outputs) and present them in a standardized form, which facilitates analysis, adaptation, comparison and ways to improve the system.

We will present the basic model of the entire heating system in a Smart Home $M_{HeatingModel}$ in the form of:

$$M_{HeatingModel} = (\{T_{exp}, T_{avg}\}, \{M_{Control}, M_{Heater}, M_{HouseTermal\ Network}, ABlocks\}, \{T_{avg}\}) \quad (2)$$

where T_{exp} – set (expected) room temperature; T_{avg} – current average room temperature; $M_{Control}$ – model of control system; M_{Heater} – model of heater; $M_{HouseTermal\ Network}$ – model of house thermal network; $ABlocks$ – additional blocks for model operation.

The proposed model represents the heating system of a Smart Home and its management. This model contains blocks for temperature control, heating equipment (heater), modeling of heat losses in the house and external factors.

All processes of functioning in this heating system are simulated as a combination of thermal convection, thermal conductivity and thermal mass. A generalized basic model of the heating system in a Smart Home is presented in Fig. 1.

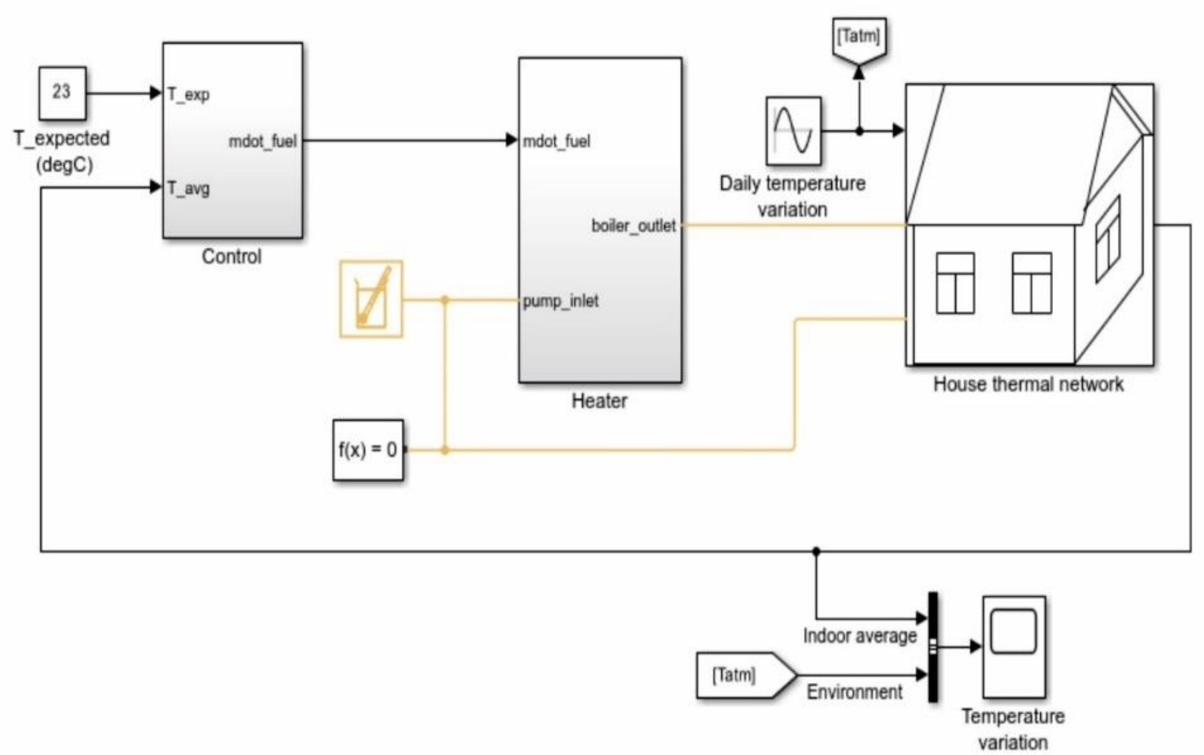


Fig. 1. Generalized basic model of the heating system in a Smart Home

The presented model consists of the following components: model of control system ($M_{Control}$), model of heater (M_{Heater}) and the model of house thermal network ($M_{HouseTermal\ Network}$).

Additional blocks for the functioning of the model include a block for modeling daily temperature variation and a graphical display for tracking the system's performance (Temperature variation).

In this model, the controller compares the expected temperature (T_{exp}) with the average current temperature (T_{avg}). Based on the difference between them (error), the controller calculates the value of the mass fuel consumption ($mdot\_fuel$) for the heater.

The heater accepts the mass fuel consumption ($mdot\_fuel$) as an input signal. Generates heat for heating water or air in the heating system. The outputs of the heater block are $boiler\_outlet$ – thermal output (heat supplied to the system) and $pump\_inlet$ – a signal showing the current state of the heater.

One of the components of the basic heating system model is the model of house thermal network. This is a model of the thermal dynamics of the house, which takes into account such aspects as heat loss through walls, windows, roof; heat received from the heater, as well as the influence of external conditions (ambient temperature).

The inputs of the house thermal network are $boiler\_outlet$ – thermal energy supplied by the heater and Daily temperature variation [Tatm] – daily fluctuations in the external temperature. The output is the value T_{avg} – the average temperature inside the house.

Let us present the model of the house thermal network $M_{HouseTermal\ Network}$ in the form of the following tuple:

$$\mathrm{M}_{\text{HouseTermal Network}} = (\{\mathrm{T}_{atm}, \mathrm{T}_{\text{avg}}\}, \{\mathrm{M}_{Rooms}, \mathrm{M}_{Radiators}, IAT, HC\}, \{\mathrm{T}_{\text{avg}}\}) \quad (3)$$

where T_{atm} is the outdoor temperature that affects the heat loss of each room through walls and ventilation, T_{avg} is the current average temperature in the room, M_{Rooms} is the model of the room heating network $M_{Rooms} = \{M_{Room}\}_{i=1}^{4}$,, $M_{Radiators}$ is the model of heating sources (radiators) $M_{Radiators} = \{M_{RoomRadiator}\}_{i=1}^{4}$, IAT is the block for calculating the average temperature in the house, HC (Heat Control) is the block for regulating the heat flow between the input flow and radiators.

The model of the model of house thermal network is shown in Fig. 2. The system receives the outdoor temperature T_{atm} and the average room temperature T_{avg} at the input.

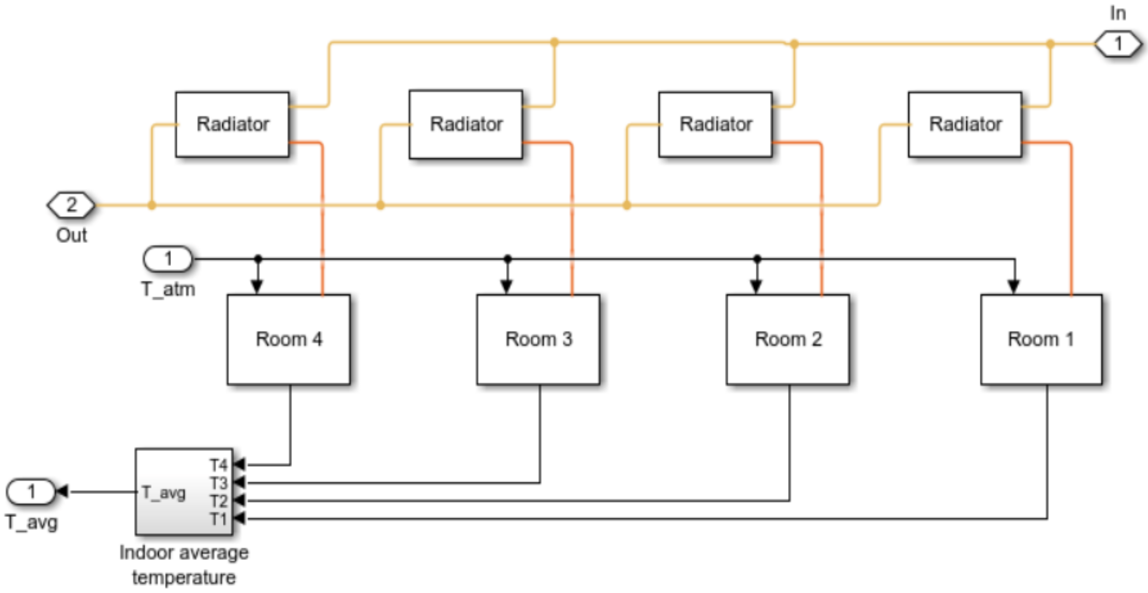


Fig. 2. The model of the model of house thermal network

In the proposed system, the model of house thermal network consists of four rooms. Each room has a radiator, which is the only source of heat transfer in the room. Each room is affected by the external temperature, which changes over time. In this system, the external temperature is modeled according to the following law:

$$T_{outside} = 6 \cdot \sin\left(\frac{2\pi}{12 \cdot 360} \cdot t\right) + 5 \quad (4)$$

$M_{Radiators}$ generate heat for rooms based on HC heat control signals, which take into account heat loss and the desired (set) temperature. The average temperature (obtained in the IAT block) is defined as a control parameter that allows maintaining the desired heat balance in the rooms.

One of the main components of the heating system model in the Smart Home (equation 2) is the model of room heat network $M_{Rooms} = \{M_{Room}\}_{i=1}^{4}$ (Fig. 3). This model is a set of four elements, each of which describes the processes of modeling heat exchange between the internal air of the room, its structural elements (roof, walls, windows), the external environment, and the heat source (heater).

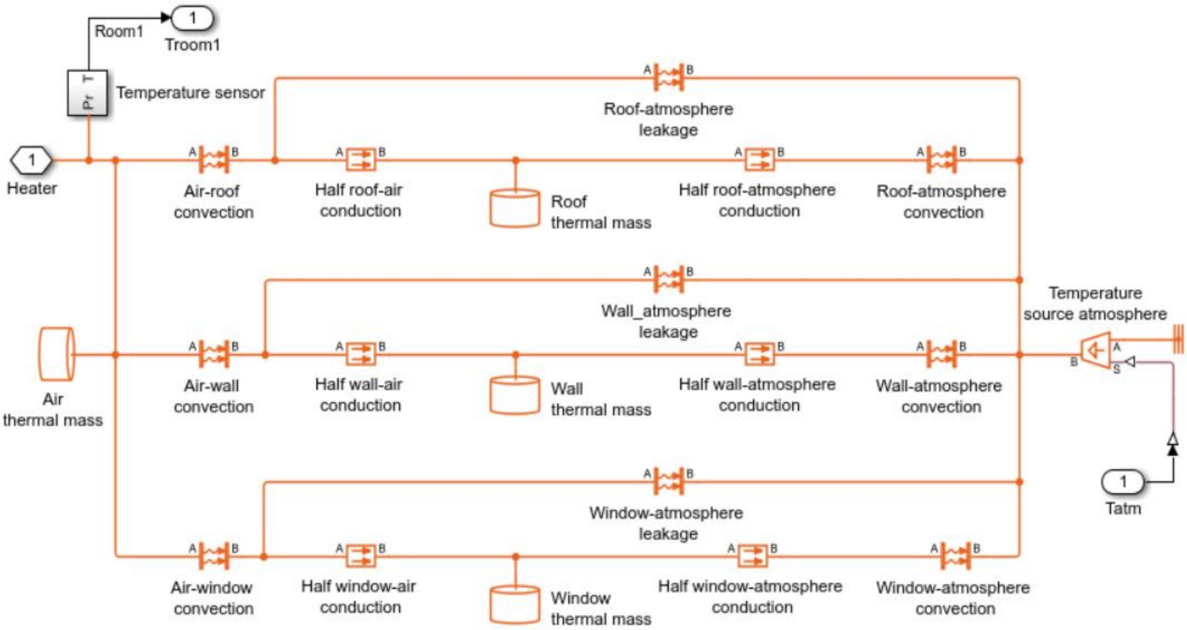


Fig. 3. The model of room heat network

Let us represent the model of the room heating network M_{Room} in the form of the following tuple:

$$\mathrm{M}_{Room} = (\{\mathrm{T}_{\mathrm{atm}}, H\}, \{TM, Conv, Cond, TS\}, \{\mathrm{T}_{\mathrm{room}}\}) \tag{5}$$

where T_{atm} is the outdoor temperature, H is the heat source, TM is the thermal mass set, $Conv$ is the convection set; $Cond$ is the conduction set; T_{room} is the room temperature, TS is the temperature sensor;

In the M_{Room} model, the thermal mass set TM describes the physical objects that store heat and transfer it both indoors and outdoors. This set consists of four elements.

$$TM = \{TM_{Air}, TM_{Roof}, TM_{Wall}, TM_{Window}\} \tag{6}$$

where TM_{Air} is the thermal mass for modeling the indoor air of the room, TM_{Roof} is the thermal mass for modeling the roof as a volume that accumulates and transfers heat, TM_{Wall} is the thermal mass for modeling the wall as a volume that accumulates and transfers heat, 〖TM_{Window} is the thermal mass for modeling the window as a volume that accumulates and transfers heat.

In this set, TM_{Air} represents the air in the room, as it has a low heat capacity, therefore it responds quickly to changes in heat sources (heater, heat loss through structures). TM_{Roof} represents the roof, which usually has a significant heat capacity and affects heat loss, especially due to contact with the external environment. TM_{Window} models the window as a thermal mass, although its heat capacity is much lower than that of the roof or walls, nevertheless windows are the main source of heat loss due to their low thermal insulation coefficient.

The main components of the M_{Room} model are thermal mass blocks, convection blocks and thermal conduction blocks. The air inside the room interacts with the roof, walls and windows through heat transfer (convection and thermal conduction), which is modeled by separate blocks. Each structural element (roof, walls, windows) is represented as a separate thermal mass, which models the accumulation and transfer of heat. The roof, walls and windows are connected to the atmosphere through heat loss blocks, which take into account both thermal conduction and convection. For a more accurate modeling of heat transfer, the thermal conduction between the air and the structural elements (roof, walls, windows) is divided into two halves: Half roof-air conduction, Half wall-air conduction and Half window-air conduction. They provide a sequence of heat transfer between the air in the room, the thermal mass of the elements and the external environment.

The heat source is a heater H, which transfers heat to the air in the room. The air in the room is also modeled as a thermal mass (Air thermal mass), which takes into account its ability to accumulate and transfer heat. The external temperature T_{atm} is modeled as a temperature source, which is connected to the thermal masses through heat transfer blocks. These blocks take into account heat losses through the roof, walls and windows to the atmosphere.

The presented model implements the interaction of the air inside the room with the roof, walls and windows through heat transfer, which constitute three heat chains. In this model, these chains are typical, in particular, for the roof, the heat chain is modeled as follows:

1. Heat transfer from the room air to the inner surface of the roof. This stage is modeled by the Convection Air Roof block (convection between the room air and the inner surface of the roof). As a result, heat is transferred from the room air to the inner surface of the roof.

2. Heat transfer through the first half of the roof material (Half Roof Air Conduction). At this stage, heat spreads through the inner half of the roof thickness. This is modeled by the Half Roof Air Conduction block. As a result, some of the heat reaches the middle of the roof thickness.

3. Heat transfer through the second half of the roof material (Half Roof Atmosphere Conduction). Heat spreads through the second half of the roof thickness to the outer surface. This is modeled by the Half Roof Atmosphere Conduction block. As a result, the heat reaches the outer surface of the roof.

4. Heat loss through leaks between the roof and the atmosphere (Roof Atmosphere Leakage). At this stage, heat leakage through possible cracks or leaks in the roof is taken into account. This is modeled by the Roof Atmosphere Leakage block. As a result, this leads to a loss of some heat through leaks in the roof.

5. Heat transfer from the outer surface of the roof to the atmosphere (Convection Roof Atmosphere). The outer surface of the roof transfers heat to the atmosphere through convection. This is modeled by the Convection Roof Atmosphere block. As a result, some of the heat is transferred to the external environment through convection.

Thus, it is worth noting that each heat exchange circuit is divided into two conditional zones to account for heat flows in two directions from the room to the external environment and from the external environment to the room. This allows for a more accurate simulation of the heat transfer process and provides for a dynamic change in heat flows depending on the conditions.

Another important component of the basic model of the heating optimization system is the heater model $\mathrm{M_{Heater}}$. Let's represent the heater model as a tuple:

$$\mathrm{M_{Heater}} = (\{\mathrm{mdot\_fuel}\ inlet\}, \{SS, Pump, Boiler, CC\}, \{outlet\}) \tag{7}$$

where mdot_fuel is the mass flow of fuel; inlet is the flow of liquid that goes to the boiler for heating; outlet is the flow of liquid that goes from the boiler after heating; SS is the source of speed – used to control the flow rate of liquid through the pump; $Pump$ is responsible for creating the flow of liquid; M_{Boiler} is the boiler model – used to heat the liquid; CC is the circulation system and heat exchangers – redirect and transfer heat between components.

The M_{Boiler} defines the main component that performs liquid heating. It has one inlet input, representing the liquid entering the system, and an $outlet$ – the heated liquid leaves the boiler and is directed to the heat exchangers. The boiler receives thermal energy from the fuel supplied through the mdot_fuel stream. The liquid is heated to the required temperature.

The CC system consists of a heat exchanger block and a circulation block. A heat exchanger transfers heat energy between a heated fluid and a working medium. In this subsystem, input A defines the heated fluid entering the heat exchanger, while B defines the output after heat exchange, when the fluid is transferred further into the system. Block H defines the process of fluid circulation between the boiler and the heat exchangers. This block models the change in flow and the return of the fluid back to the system.

The last main component of the basic heating system is the $\mathrm{M_{Control}}$ model of control system. This block implements the heating process control subsystem, which takes into account temperature parameters and mass fuel consumption to minimize costs (fuel cost). This control model can be attributed to proportional-integral (PI) models with dynamic signal processing. Let us present the $\mathrm{M_{Control}}$ model of control system in the following form:

$$\mathrm{M_{Control}} = (\{\mathrm{T_{exp}}, \mathrm{T_{avg}}\}, \{S, GV\mathrm{L}, \mathrm{VOMFR}, \mathrm{NGD}, \mathrm{IB}, SB\}, \{\mathrm{mdot\_fuel}, \mathrm{fuel\ cost}\}) \tag{8}$$

where $\mathrm{T_{exp}}$ – set (expected) room temperature, $\mathrm{T_{avg}}$ – current average room temperature, S – adder, GVL – gas supply valve dynamic delay block, VOMFR – gas mass flow rate determination block through the valve, NGD – natural gas density inversion block, IB – integrator block, SB – scale blocks, signal scaling blocks, mdot_fuel – fuel mass flow rate, fuel cost – fuel cost.

The model of heating control system for the base model is shown in Fig. 4.

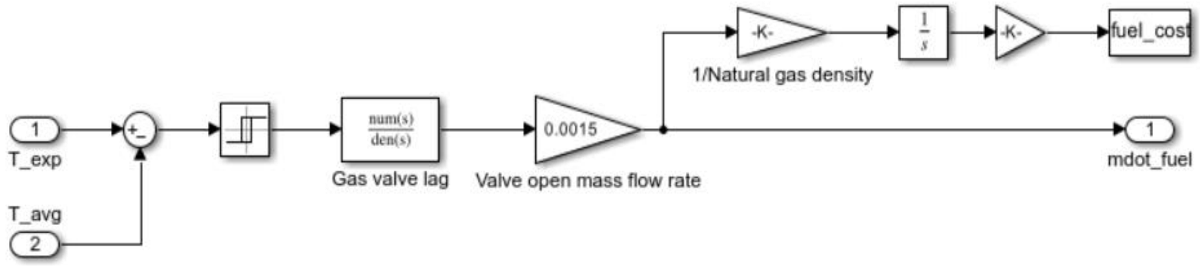


Fig. 4. Model of heating control system

The inputs of this model are T_{exp} and T_{avg} (Temperature expected and Temperature average). T_{exp} is the expected temperature that the system should maintain (set by the user or the program). T_{avg} is the average current temperature (for example, read from sensors). These two signals are fed to the adder to calculate the error (deviation from the desired temperature).

The outputs of this model are mdot_fuel – mass fuel consumption. This value is used to analyze the system operation and fuel cost – fuel costs, which are calculated as a function of fuel consumption and its cost.

The adder block (indicated in the diagram as +) calculates the difference between the values of T_{exp} and T_{avg}. The resulting value determines how much the actual temperature differs from the desired one. This error is the basis for further regulation of the natural gas flow rate:

$$Error = T_{exp} - T_{avg} \tag{9}$$

The next stage is the dynamic processing of this signal through a gas supply valve delay model, which takes into account the time characteristics of the system described by the transfer function:

$$w(s) = \frac{num(s)}{den(s)} \tag{10}$$

This functionality is represented by the GVL – Gas Valve Lag block.

The VOMFR block scales the signal from the valve to determine the gas mass flow rate through the valve. In the proposed model, the coefficient value for this block is 0.0015.

The NGD (1/Natural Gas Density) block represents the inversion of the natural gas density and allows you to take into account the properties of the gas (density) to convert the mass flow rate into the corresponding thermal energy.

An additional integrator block (1/s) integrates the signal corresponding to the gas flow rate to calculate the accumulated amount of fuel used (or energy transferred to the system).

Blocks with SB coefficients scale signals based on system characteristics (in the figure marked as -K-). The first coefficient determines the energy efficiency of the gas, while the second coefficient determines the cost of fuel per unit of energy.

Thus, the controller implemented in the basic version [9] is a proportional control that estimates the actual temperature of the house relative to the target temperature, with an error of 2 °C and a hysteresis of 4 °C. In this case, the concept of hysteresis defines the effect when the system has a different reaction to changes in the input value depending on whether this value increases or decreases. This means that the controller will open the valve to connect the heater when the temperature drops below 2 °C from the set point, and close the valve when the temperature exceeds the target by 2 °C.

Thus, the basic heating model in a Smart Home is described, which will be compared with the proposed heating optimization system in the Smart House. This approach will assume the preservation of the same conditions for both models, which will allow a correct assessment of the effectiveness of the proposed system compared to the traditional one. The modeling will be carried out on the basis of the same building information modeling model in Matlab, which will provide a comparison according to the same parameters.

Defining the optimization problem for heating optimization

The basic heating control model in the Smart Home considered in the previous section defines proportional-integral control with dynamic signal processing. However, an obvious drawback is the rather frequent switching of the system operating modes, which can lead to excessive energy consumption and faster wear of the equipment. This is explained by the fact that the basic model is focused on a quick response to temperature changes, but does not take into account the long-term stability of the system. As a result, it provides an insufficiently smooth control mode and an increased number of fluctuations in the ambient temperature.

To solve these problems, in the following sections it is proposed to use a system with fuzzy logic inference. Let us formulate the problem of optimizing heating control in the Smart Home.

The problem of optimizing heating control can be represented through a mathematical objective function that must be minimized [10]. The goal of this problem is to simultaneously reduce fuel costs and reduce temperature fluctuations in rooms.

Let the input variable for the control system be the temperature in the Smart House$T_{house}(t)$, as well as the set temperature $T_{desired}$, which determines the comfortable temperature for the selected room. The task is to control the heat output $Q_{heat}(t)$, which is regulated through the boiler or other heating sources, in order to minimize two criterion indicators.

The first criterion is the cost of fuel. The cost of fuel depends on how much fuel is consumed to maintain the set temperature in the Smart House. This can be expressed in terms of fuel consumption $\dot{m}_{fuel}(t)$ for a certain time period T. The cost of fuel is defined as the integral of fuel consumption per unit of time, multiplied by the cost of a unit of fuel C_{fuel}. Mathematically, this can be written as:

$$C_{total} = \int_0^T \dot{m}_{fuel}(t) \cdot C_{fuel} dt \quad (11)$$

This is the first criterion that we aim to minimize.

The second criterion is to reduce the frequency of temperature fluctuations in the Smart Home. Temperature fluctuations occur due to frequent switching on and off of the boiler, which leads to significant temperature differences in the room. This can be described by a function that measures the rate of change of the thermal power $Q_{heat}(t)$. The smoothed power change is an important aspect to ensure a stable temperature in the room. For this, a metric that integrates the derivative of the thermal power can be used, i.e.:

$$S_{smoth} = \frac{1}{T}\int_0^T |\frac{dQ_{heat}(t)}{dt}| dt \quad (12)$$

The smaller this value, the smoother the system works, and therefore, the smaller the temperature fluctuations. Thus, the optimization problem as a whole is to minimize the combination of these two criteria:

$$\min J = w_1 \cdot C_{total} + w_2 \cdot S_{smoth} \quad (13)$$

where w_1 and w_2 are weighting factors that determine the priority of each of the criteria. Weighting factors can be adjusted depending on what the overall optimization criterion is more focused on (for example, if fuel economy is more important, then w_1 will be larger).

In this problem, a fuzzy logic inference system is used to determine the optimal heating power $Q_{heat}(t)$ depending on the current temperature deviation $\Delta T = T_{house}(t) - T_{desired}$ and the rate of temperature change. Based on these inputs, the fuzzy system determines whether it is necessary to increase or decrease the heating power to stabilize the temperature in the Smart House. Thus, the problem is a multi-objective optimization problem, where it is necessary to simultaneously reduce fuel consumption and stabilize the temperature in the room, using a fuzzy control system for smoother regulation of the heating power.

Architecture and functioning of the heating optimization system in a smart home based on fuzzy logic and integration with cloud services

In order to solve the problem of maintaining the optimal temperature in a Smart Home, a heating optimization system is proposed. Its key feature is the modular structure and the involvement of fuzzy logic in the optimization process.

In the proposed system, all blocks are divided into three modules that differ in their functioning. In particular, such modules as the control and user interaction module, the physical parameters tracking module, and the decision-making module are highlighted.

The central component of the entire system is the user control and interaction module. Functionally, this module is responsible for two main tasks: coordinating the operation of the entire system and communicating with the user. Structurally, the control and user interaction module consists of a controlling block and a communication interface for interacting with the user. In the context of the proposed system, the controlling block is a block that controls and coordinates the operation of the remaining components. It is responsible for initializing other blocks, controlling their activity, and checking the performance of tasks. In the proposed system, the control unit initializes other system units at the beginning of operation, periodically checks the activity of the remaining units, and also listens to incoming messages from the units of the artificial intelligence module.

Structurally, the user control and interaction module also includes a user communication block. Thanks to integration with cloud services, this unit provides the possibility of extended functionality, allowing users to access the system and manage it from any point of connection to the network. The main purpose of this block is to organize an interface for transmitting and receiving messages from the user via the cloud infrastructure.

Another module of the proposed system is a physical parameters tracking module. This module consists of the following blocks: block of detection of people presence, outdoor temperature measurement block, indoor temperature measurement block and outdoor humidity measurement block. All these blocks have one goal, which is to determine the physical parameters of the environment (external and internal).

The third module in the proposed system for optimizing the use of heating in a Smart Home based on fuzzy logic is a decision-making module. This module performs the intelligent functions of the entire system. It will use the information collected by the previous module and transmitted by the control unit to evaluate all variables and determine the most appropriate output signal for the current situation. Two types of blocks are defined in this module: a fuzzy logic decision block and a system status block.

The fuzzy logic decision block is a key element of the heating control system. It includes a fuzzy control system that processes data received from the physical parameter tracking module blocks and generates the appropriate control action that is transmitted to the system. Within the block, rules and membership functions for various variables are defined to ensure the correct execution of control actions. The block receives data from the sensor blocks to perform its function. The mechanism of operation of the fuzzy logic decision block involves periodic activity, which includes the absence of constant generation of output signals for controlling the heating system (only when necessary).

The system status block is responsible for setting the control action defined by the fuzzy block and notifying the control block that the action has been performed in the physical system. Despite its simplicity of operation, its role is extremely important, because it changes the state of the system. This block operates cyclically: it constantly listens to messages from the fuzzy logic decision block and performs its task each time it is needed.

The structure of the heating optimization system in a smart home based on fuzzy logic and integration with cloud services is shown in Fig. 5.

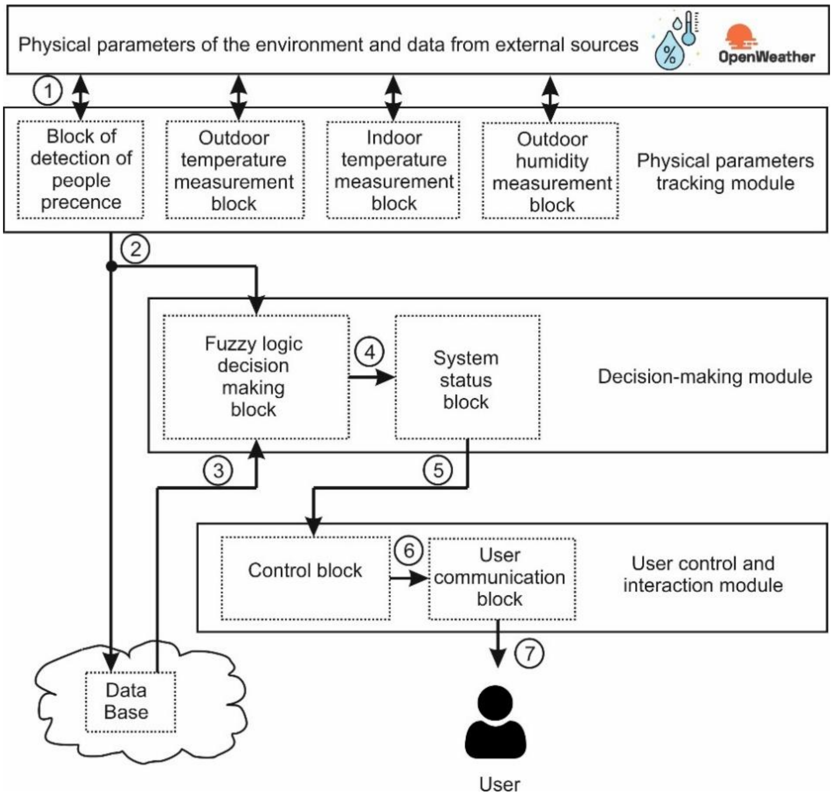


Fig. 5. The structure of the heating optimization system in a smart home based on fuzzy logic and integration with cloud services

Implementation of proposed solution

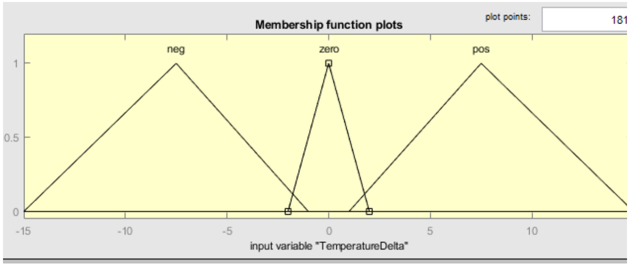
In order to evaluate the proposed solutions, a prototype of a heating optimization system in a Smart Home based on fuzzy logic was designed. The JADE (Java Agent Development Framework) framework was used to implement the functioning of the designed system [11].

The main goal of the system is to monitor and analyze key parameters in a smart home, such as temperature, humidity, and the number of people in the room. These parameters are collected by blocks that track physical parameters, processed, and decisions are made based on them using fuzzy logic.

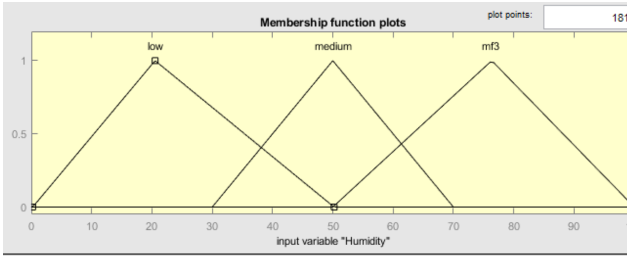
Since there are no real sensors in this system, their functions are simulated in matlab (and getting from external sources). For example, the values of the external temperature are modeled by variables in matlab and double check with OpenWeatherMap [12], which are dynamically updated. The external temperature changes according to a sinusoidal law with given parameters of amplitude, frequency, phase, and offset.

Implementation of the fuzzy logic inference block

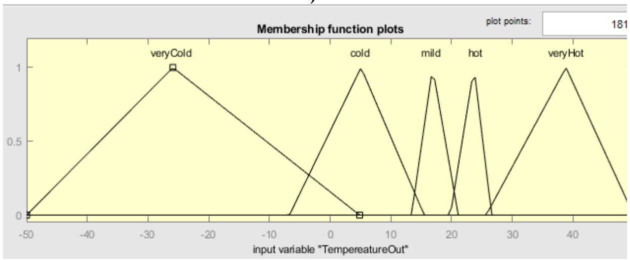
The fuzzy logic inference block is implemented in the Matlab software environment. Its operation is based on a fuzzy logic inference system of the Sugeno type, which provides the formation of a clear output (on/off). The proposed system operates on four input variables: temperature difference (TemperatureDelta), external humidity (Humidity), external temperature (TemperatureOut) and the presence of people in the room (PeoplePresence). Each of these variables is represented by trapezoidal membership functions, which allows taking into account their influence in a fuzzy system with flexibility and accuracy. The graphs of the membership functions are shown in Fig. 6.



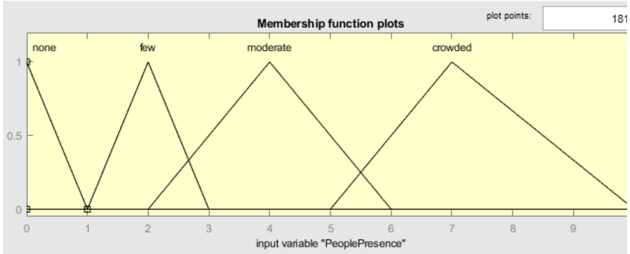
a)



b)



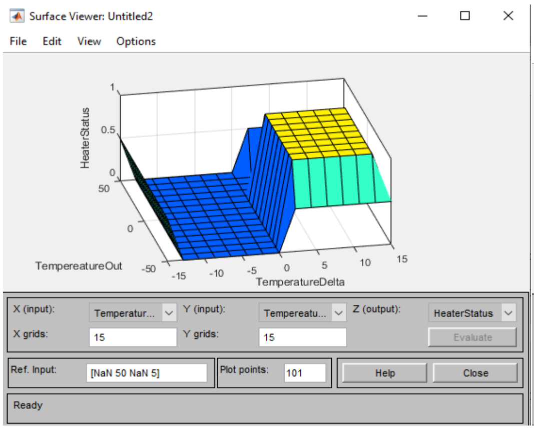
c)



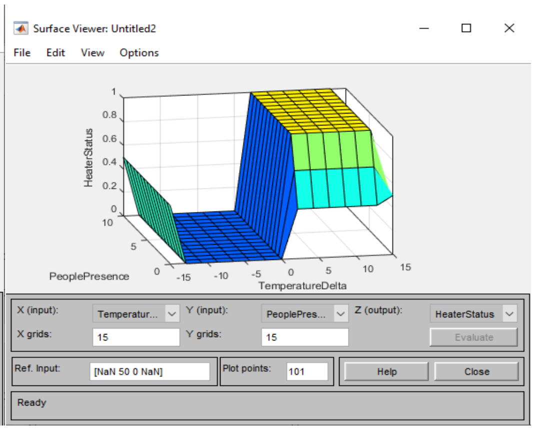
d)

Fig. 6. Membership function: a) TemperatureDelta; b) Humidity; c) TemperatureOut; d) PeoplePresence

The core of the system consists of 21 rules that were empirically developed. These rules are the basis for the functioning of fuzzy logic, which determines how the variable HeaterStatus (heater status) reacts to combinations of input parameters. Surfaces illustrating the dependencies between the output variable and the input variables are shown in Fig. 7.



a)



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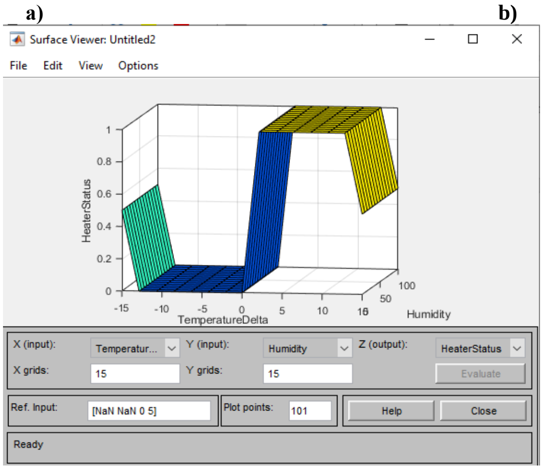

c)

Fig. 7. Surfaces illustrating the dependencies between the output variable HeaterStatus and the input variables: a) TemperatureOut and TemperatureDelta; b) PeoplePresence and TemperatureDelta; c) TemperatureDelta and Humidity

From the surfaces shown in Fig. 7, it can be noted that when the temperature difference is large and the outside temperature is low, the heater is actively working (HeaterStatus is close to 1). As the outside temperature increases or the temperature difference decreases, the heater starts to turn off, and HeaterStatus decreases to 0. This demonstrates a logical principle: when the outside weather is warm or the inside temperature is almost at the optimum level, heating becomes unnecessary. It can also be seen that if the temperature difference is large, even with a large number of people, the heater continues to work, but its intensity is reduced compared to the case when there are no people in the room (there is no need to heat an empty room).

Evaluation of the efficiency of the heating system using optimization criteria

According to the goal of the work, which was to optimize resource consumption in the heating system of the Smart Home, a control system was modeled, which included two models: basic and based on fuzzy logic. The efficiency of the system was evaluated using two optimization criteria.

Two models were compared: the basic control model and a model using fuzzy logic. The goal was to determine how much each of these models provides efficiency and stability of temperature control. Two indicators that met predefined criteria were used for the analysis. The first indicator assessed the total costs (fuel cost) for maintaining a given temperature level, and the second indicator analyzed the frequency of temperature fluctuations (smoothness of temperature changes), which indicates the comfort of conditions.

For this, Matlab software was used, which allows you to model complex systems and analyze the results. The simulation covered a time period of 50 hours, during which temperature changes were simulated in conditions close to real ones.

The estimation of fuel consumption by the basic heating system and the proposed heating optimization system in the Smart Home based on fuzzy logic is presented in Fig. 8.

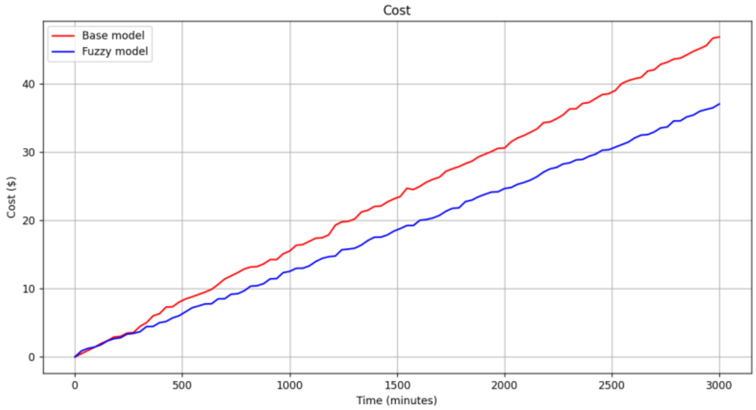

Fig. 8. Estimation of fuel consumption by the basic heating system and the proposed heating optimization system in the Smart Home based on fuzzy logic

Fig. 9 shows a graphs of temperature changes when implementing the basic heating control system and the proposed heating optimization system in the Smart Home based on fuzzy logic. The resulting graph shows the temperature change inside the houses depending on time. The red line, corresponding to the basic model, demonstrates large and sharp temperature fluctuations that look irregular. This indicates less effective regulation. In contrast, the blue line, representing the fuzzy model, looks much more stable. The temperature changes more smoothly, with smaller deviations, which indicates better smoothing of fluctuations and more efficient operation of this model.

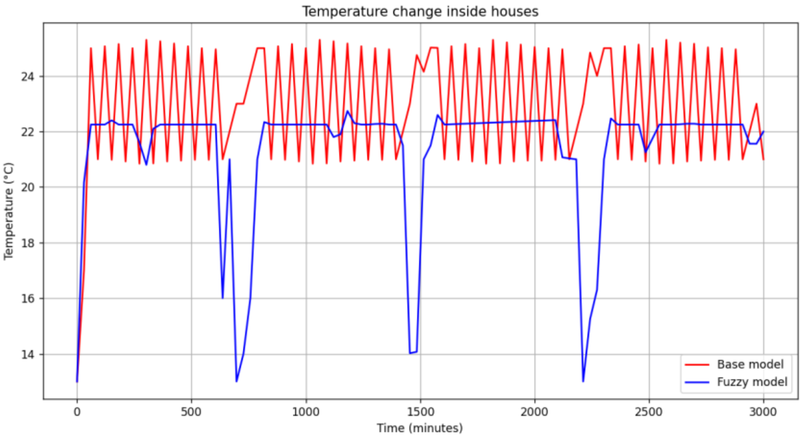

Fig. 9. Temperature change graph when implementing the basic heating control system and the proposed heating optimization system in a Smart Home based on fuzzy logic

Let us calculate the effectiveness of optimizing heating control in a Smart Home. To do this, we will determine the percentage change in two indicators that meet the specified optimization criteria (equation 13) – the cost of fuel and the frequency of temperature fluctuations in the Smart Home. The percentage change for the first criterion (cost of fuel) will be determined by the following formula:

$$\Delta C = \frac{C_{base} - C_{fuzzy}}{C_{base}} \cdot 100\% \quad (14)$$

where C_{base} is the total cost in the base (non-optimized) system, C_{fuzzy} is the total cost in the system with fuzzy logic.

The percentage change according to the second criterion (smoothness of control) is determined based on the calculation of the number of boiler starts. The number of starts was calculated as the average number of starts per hour. Thus, for each of the systems, the average number of starts was calculated for each of the 50 hours of system operation. These values are expressed as S_{base} and S_{fuzzy}.. Then the percentage change according to the second criterion (smoothness of control) is determined based on the following formula:

$$\Delta S = \frac{S_{base} - S_{fuzzy}}{S_{base}} \cdot 100\% \quad (15)$$

Thus, according to the fuel consumption estimation graphs (fig. 8) for the basic heating system and the proposed heating optimization system in the Smart Home based on fuzzy logic, the value of ΔC will be $\Delta C = (46 - 37)/46) * 100\% = 19{,}57\%$.

Тоді як відповідно до графіків зміни температури при реалізації базової системи керування опаленням та пропонованою системою оптимізації опалення у Розумному будинку на основі нечіткої логіки значення ΔS складатиме $\Delta S = (17 - 6)/17) * 100\% = 64{,}70\%$.

According to equation 13, let us calculate the value of J_{base} :

$$J_{base} = w_1 \cdot C_{base} + w_2 \cdot S_{base} \quad (16)$$

where the values w_1 and w_2, which are the weighting coefficients that determine the priority of each of the criteria, are set at 0.7 and 0.3, respectively (priority is given to reducing fuel consumption).

As a result, we obtain the value of $J_{base} = 0{,}7 * 46 + 0{,}3 * 17 = 37{,}3$.

Similarly, we determine the value of J_{fuzzy} :

$$J_{fuzzy} = w_1 \cdot C_{fuzzy} + w_2 \cdot S_{fuzzy} \quad (17)$$

As a result, we will obtain the value $J_{fuzzy} = 0{,}7 * 37 + 0{,}3 * 6 = 27{,}7$.

Finally, we determine the efficiency gain using the following formula:

$$\Delta J = \frac{J_{base} - SJ_{fuzzy}}{J_{base}} \cdot 100\% \quad (18)$$

Thus, the result was 25.7%, which indicates that the optimization task has been achieved by a quarter compared to the basic version of the system.

Conclusions

As a result, heating optimization system in a smart home based on fuzzy logic and integration with cloud services was developed and modeled. The aim of the work was to determine how effective the use of fuzzy logic is in comparison with the basic heating control model. For this purpose, two criteria were analyzed: fuel consumption and the frequency of temperature fluctuations, which allow assessing the efficiency of the system.

The implementation of the fuzzy logic system block was performed using the Matlab software environment. The operation of two heating systems was simulated: based on the basic model and based on the proposed fuzzy logic inference system. Two indicators were used for the analysis that met the predefined criteria. The first indicator assessed the total energy consumption to maintain a given temperature level, and the second indicator analyzed the frequency of temperature fluctuations (smoothness of temperature changes), which indicates the comfort of the conditions.

According to the results obtained, the use of fuzzy logic significantly improves the stability of the temperature in the house, which is important for the comfort of residents. The basic system, which does not take into account variable factors with such a level of flexibility, leads to large and sharp temperature fluctuations, which can create discomfort and increase energy consumption. In contrast, the model with fuzzy logic demonstrates smoother and more stable temperature regulation, which allows you to significantly reduce energy costs.

According to the calculations, the sum of the percentage changes for both criteria showed a significant improvement. Fuel consumption in the model with fuzzy logic decreased by 19.57%, which indicates significant energy savings. There was also a significant decrease in the frequency of temperature fluctuations - by 64.70%, which has a positive effect on the comfort of living in the house. Given these indicators, the efficiency of the system with fuzzy logic turned out to be much higher. For a comprehensive assessment of efficiency, a general J-index was calculated, which takes into account both optimization criteria with certain weighting factors. The results showed that the overall efficiency of the system with fuzzy logic increased by 25.7%, which is a significant achievement compared to the baseline system. This proves that the use of fuzzy logic allows optimizing the operation of the heating system, reducing fuel consumption and increasing the comfort of conditions in the Smart Home.

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