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MODELING HEATING DYNAMICS IN THE ROOM USING COMSOL MULTIPHYSICS

Abstract

In this study, a physical model of indoor air temperature change dynamics has been developed, considering heat transfer and convection. The system was modeled in COMSOL Multiphysics and tested in MATLAB, where the influence of external temperature, room area, number of radiator sections and air flow velocity were analyzed. The results showed a strong correlation between room temperature and external temperature (0.92), while weaker dependence was observed on the temperature of a radiator (0.2), height (0.1) and area of the room (0.11). However, number of sections and size of the radiator have the least impact on the room temperature (0.07). Additionally, initial temperature of the room does not have any significant correlation with final room temperature. The correlation, observed in simulations enabled us to develop transfer function of controlled object in MATLAB/Simulink. Nonlinear relay, used in resultant model, is used to turn actuator on and off to control room temperature. The results of the study can be used to create neural network to simulate the physical behavior of the room temperature in different initial conditions.

Keywords: room temperature control system, COMSOL Multiphysics, MATLAB, transfer function, reinforcement learning.

Introduction

Today comfortable living and working totally depend on automatic systems of the building services. These systems are used in different types of buildings: houses, commercial and industrial buildings. Global energy crisis and high attention to energy consumption efficiency make highly comfortable and efficient automatic building control systems strongly important [1].

In order to automatically maintain the indoor microclimate, sensors and actuators are used, which interact to create comfortable living conditions for humans. The sensors measure air temperature, humidity, and carbon dioxide levels and transmit the collected data to the control unit. After processing the received data, this unit decides on the further operation of heating, ventilation and air conditioning [2–7].

The rapid development of telecommunication technologies, the Internet of Things, and artificial intelligence allowed the systems not only to increase the efficiency of indoor climate control systems, but also to increase the accuracy and speed of these systems [8]. The use of artificial intelligence and the Internet of Things makes it possible to respond to any changes in the environment, predict the consequences of these changes, and take preventive measures to eliminate these undesirable consequences through rapid processing and transmission of huge amounts of data [9–11].

Automated temperature control systems are becoming a backbone part of modern buildings, whether they are private homes, office buildings or industrial structures, helping to maintain comfort and reduce their energy consumption. According to the International Energy Agency (IEA), up to 40% of all energy in buildings is spent on heating, air conditioning and ventilation (HVAC), which increases the field of activity for the introduction of smart control systems that can reduce these costs by 20–30% [12–13].

When developing such systems, it is important to take into account many factors: building design features, regional climate, equipment characteristics, and even user preferences, for example, in regions with harsh winters, users will pay special attention to thermal insulation and integration of heating systems with renewable energy sources such as solar panels and heat pumps [14–16]. Automated temperature control systems are used not only in residential and office buildings, but also in specialized facilities such as hospitals, laboratories, and server rooms, where stable temperature is critically important because it affects operation of equipment and even human health, as well as reducing likelihood of errors and improving system reliability [17]. The development of automated systems plays an important role not only for individual users, but also for the whole society, contributing to the creation of "smart" cities and reducing negative impact on the environment [18–20].

One of the ways to solve the problem of automation of energy consumption and climate control in buildings is to create accurate mathematical models that predict indoor climate changes [21]. Another promising area is the use of artificial intelligence, which, based on the trained sample and the results of previous selections made by the system, is able to predict the future state of the system based on current state and choose actions to improve the future state. Modern research shows that machine learning algorithms, especially reinforcement learning, can significantly improve the efficiency of such systems.

The main problem of implementing microclimate management systems in buildings using reinforcement learning is the risks of financial, moral and technical damage in the process of AI training in a real building. In addition, the resulting model will be suitable for use only at the building where it was trained. Therefore, the most accurate digital model of a real room is needed, which will allow simulating various scenarios of the system operation [22–23].

There are three main approaches to modeling building energy consumption: white-box, black-box, and grey-box models [24]. In general, models for predicting building energy consumption are mathematical methods, often based on physical principles. In the early stages of development of such models, the main focus was on physical (white-box) approaches, which were widely used to calculate the energy performance of buildings [25].

With the progress in machine learning algorithms and artificial intelligence, alternative forecasting methods focused on data analysis, the so-called "black box" models, began to actively develop. Later, a hybrid approach appeared – "grey box" models, combining both physical equations and the processing of empirical data [26]. Each of these approaches has both advantages and limitations.

White box models are based on fundamental physical laws, such as the conservation of energy and mass. Their important advantage is the high opportunity to interpret the results using physical laws, which makes such models especially useful for analysis and verification. However, their correct work requires detailed full information about the building, which is often difficult to obtain [27].

Black box models are based on historical data on energy consumption and do not require deep knowledge of the physics of the building. They are highly flexible, can adapt to new data and constantly improve as they accumulate new data from environment [28]. However, their disadvantage is their high sensitivity to the quality of the input data.

Gray box models combine elements of both of the above approaches. They partially use physical principles, but in a simplified form, and at the same time actively use data analysis methods.

This approach allows to increased efficiency without significant loss of accuracy and explain ability [25, 29].

When creating models for predicting building energy consumption, uncertainties inevitably arise, which can be conditionally divided into three categories: the human factor, building properties, and climatic conditions.

During modeling building energy consumption certain uncertainties occur. They can be classified in three group: human, building and weather factors. Human factors uncertainties are related to perception of people of environmental conditions in the building and cannot be predicted accurately Building uncertainties related to the geographic placement of building, materials of the wall and its degree of obsolescence. The final uncertainty factor is weather, which has very high impact on HVAC system itself and two mentioned parameters [30–31].

In this work, in order to create an accurate digital model, the COMSOL Multiphysics was used to simulate the dynamics of the air temperature of the room in different conditions, as it was validated in [32]. The influence of air temperature and capillary pressure on the properties of building materials was analyzed in the COMSOL Multiphysics environment, which helped to evaluate their thermal characteristics [33]. These data can be useful in designing new buildings and selecting suitable materials for heating systems, including underfloor heating [34–36]. As a result, the physical model of the room was created, which makes it possible to analyze the dynamics of indoor air temperature under various initial conditions, such as room size, initial air temperature, temperature and radiator size. This will become the basis for further development of AI, which will be able to adapt the microclimate of the building effectively.

Materials and methods

To study the dynamics of indoor temperature changes in this paper, the physical model was developed, which is based on numerical methods for calculating heat transfer and convection processes using the COMSOL Multiphysics software package. This model takes into account the following parameters: room area, number of radiator sections, ceiling height, radiator temperature, outdoor air temperature, and indoor air flow velocity. Determining the degree to which these factors are taken into account considering dynamics of indoor temperature changes will improve the accuracy of simulating the dynamics of temperature changes using a neural network. Modeling of heat transfer and convection is based on solving a system of equations describing the movement of heat flows in a room and on the surfaces of heated objects, which are the subject of research in the discipline of heat and mass transfer. To model such processes, the finite element method is used, which allows taking into account the geometry of rooms, the interaction of air flows, and heat transfer processes in gases and solids.

On the other hand, the dynamics of temperature change can be considered as an object of control and has the properties of an inertial link of the first order, to which the research methods used in the theory of automatic control can be applied.

Finally, since the dynamics of indoor temperature changes, although a nonlinear process, can generally be linearized and predicted with good accuracy, a digital model based on neural networks can be built that will be able to predict the final temperature and steady-state time based on the training sample, depending on the input parameters.

Mathematical model of the control object

We will construct heat balance equation for air in the room with window and radiator and consider the air in the room as control object. The control parameter will be the air temperature T near the wall opposite the radiator, since the room is a fairly large object and some temperature gradient will be observed in it. For simplicity, let's assume the dependence of the air temperature on the outside temperature Tamb and on the power of the heat flow the radiator g0, as shown in equation (1).

$$T = f(\mathrm{T}_{amb}, \mathrm{g}) \tag{1}$$

Duo to the law of conservation of energy, part of the power P_1 goes to heating the air, part P_2 is dissipated by transferring heat the walls of the room, as shown in equation (2–3).

$$P_1 = c\frac{dT}{dt} \tag{2}$$

$$P_2 = \frac{1}{p}S(\mathrm{T}-\mathrm{T}_{amb}) \tag{3}$$

where p is the coefficient of resistance of the walls of the room to heat loss, which depends on the material and thickness of the walls, m^2K/W, S is the area of the walls. Let us consider that the sum of both powers is equal to the product of the power of the heat flow from the radiator and the area of this radiator, as shown in equation (4).

$$\mathrm{gS}_0 = c\frac{dT}{dt} + \frac{1}{p}\mathrm{S}(\mathrm{T}-\mathrm{T}_{amv}) \tag{4}$$

where S_0 is the surface area of the radiator. Let us write the equation for the static mode of the system (5):

$$\mathrm{gS}_0 + \frac{S}{p}T_{amb\,0} = \frac{S}{p}T_0 \tag{5}$$

where $T_{amb\,0}$ is the outside air temperature at time t=0, T_0 is the indoor air temperature at time t=0. Next, we will consider not absolute values, but their deviation and substitute them into the main equation (5) to get (9):

$$T = T_0 + T' \tag{6}$$

$$g = g_0 + g' \tag{7}$$

$$T_{amb} = T_{amb\,0} + T'_{amb} \tag{8}$$

$$(\mathrm{g}_0 + \mathrm{g}')\mathrm{S}_0 = c\frac{d(\mathrm{T}_0+\mathrm{T}')}{dt} + \frac{1}{p}S((\mathrm{T}_0+\mathrm{T}') - (T_{amb\,0} + T'_{amb})) \tag{9}$$

Which gives us the following equation (10):

$$\mathrm{c}\frac{dT'}{dt} + \frac{S}{p}T' = g'S_0 + \frac{S}{p}T'_{amb} \tag{10}$$

From the other hand to make the heat balance equation closer to the reality, we have to add ventilation heat and load heat (11).

$$C_p \rho V\frac{dT}{dt} = Q_{radiator} + Q_{vent} + Q_{load} - Q_{losses} \tag{11}$$

where C_p – specific heat capacity of air (J/kgK), V – air density (kg/m³), V – room volume (m³), T – indoor air temperature (K), $Q_{radiator}$ – radiator heat dissipation capacity (W), Q_{losses} – heat loss through ventilation (W), Q_{losses} – internal heat input from people, equipment and lighting (W), Q_{losses} – heat loss through walls, window and door (W).

Heat loss through ventilation takes into account air consumption and temperature differences.

$$Q_{vent} = \rho C_p G(\mathrm{T}_{vent} - T_{inter}) \tag{12}$$

where: G – ventilation air consumption (m^3/s); $R = \frac{cp}{S}$ – supply air temperature (K)

Now if we compare equations (10) and (11) we will see that constant value c depend on heat capacity of air, volume of room and density of air. The value Q_{losses} is determined by walls coefficient p, area of walls S and change of temperature T' as shown in equation (3). Radiator heat value depends on heat flow and surface area of radiator. We need to add ventilation heat which will be described by air flow velocity in the room v. So we get $Q_{vent} = C(T_{vent} - T)$, where $C = \rho C_p S_{vent} v$. Taking into account $T_{vent} = T_{amb}$ and S_{vent} – is ventilation window in the room, the equation (10) will be rewritten as following (13).

$$c\frac{dT'}{dt} + \frac{S}{p}T' + CT' = g'S_0 + \frac{S}{p}T'_{amb} + CT'_{amb} \tag{13}$$

Let R and K be as following $R = \frac{cp}{S}$, $K = \frac{S_0 p}{S}$ and $L = \frac{Cp}{S}$ so in the end we will get the following equation (14):

$$R\frac{dT'}{dt} + T' + LT' = Kg' + T'_{amb} + LT'_{amb} \tag{14}$$

Control theory model

The radiator exerts the control effect, the external temperature exerts the disturbing effect. After the Laplace transformation we obtain (15):

$$RT'(s)s + T'(s) + LT'(s) = Kg'(s) + T'_{amb}(s) + LT'_{amb}(s) \tag{15}$$

We obtain the transfer function for the control action. Then, the disturbing action must be equal to 0 (16).

$$W_u^{CO} = \frac{T'(s)}{g'(s)} = \frac{K}{Rs+1+L} \tag{16}$$

We obtain the transfer function for the disturbing action. Then, the control action must be equated to 0 (17).

$$W_F^{CO} = \frac{T'(s)}{T'_{amb}} = \frac{1+L}{Rs+1+L} \tag{17}$$

The parameters of the control object (CO) R, K and L can be determined from experiments or simulations.

Results and discussion

In the COMSOL Multiphysics environment, a room with a radiator was modeled to simulate the dynamics of air temperature changes in various conditions, as shown in Figure 1. The following variables were set as input parameters: room area S (20–40 m^2), ceiling height H (2.5–3 m), temperature of the Trad radiator (273–303 K) and air flow velocity in the room (0.01–0.1 m/s). The output variable is the air temperature near the middle of the wall opposite the radiator at human height. The number of sections N of the radiator was calculated using empirical equation (18).

$$N = 1.2 \cdot SH \cdot \frac{Q_s}{Q_0} \tag{18}$$

where Q_s – heat amount needed to heat up 1 m^3 of air taking into account heat loss and Q_0 is heat amount of one section of radiator at certain temperature according to standard requirements for heating residential buildings. Width of the wrad aluminum radiator is calculated by multiplying the width of one section of radiator by calculated number of radiators. The height of radiator is constant

0.6 m. If Q_s will be 40 W/m^3 and Q_0 will be 200 W then number of radiators take values 12–29, width of radiator – (0.97–2.33 m) for given room areas.

A total of 41,850 simulations were run for 3,600 seconds, yielding a total of 2,511,000 rows of data. A correlation matrix was constructed to determine the dependence of the temperature over an hour on the specified input parameters.

Figure 1 shows a physical model of the room created in COMSOL Multiphysics in order to analyze the temperature distribution in the space with a radiator. As shown in Figure 1, the temperature near the radiator has high values close to the temperature of a radiator itself, about 343 K. Warm air flows tend to the ventilation and upward and cool down, which is clearly demonstrated in this figure.

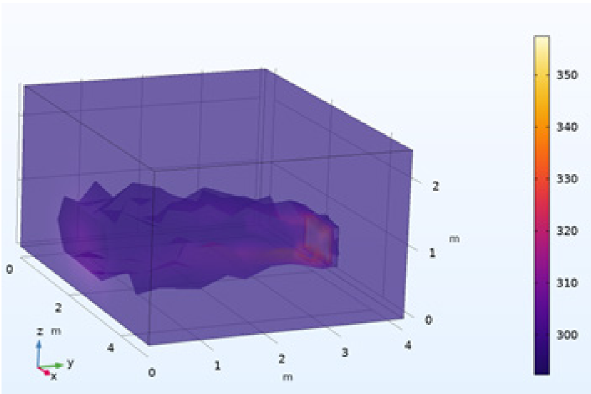

Figure 1 – Physical model of the room in COMSOL with radiator

Figure 2 presents the correlation matrix of data obtained from air temperature simulations under various initial conditions. The analysis reveals 92% correlation between outdoor temperature and the final indoor temperature, Tmax, which aligns with results shown in [24–25]. Additionally, strong correlations are observed between room size, the number of radiator sections, and radiator width. This is due to how air circulation and radiator heat output influence temperature distribution – larger rooms take longer to heat up, while bigger radiators provide more heat output. In contrast, ceiling height has a significantly smaller impact on the final air temperature, showing only a 30% correlation, indicating a relatively low influence of convection processes within the room.

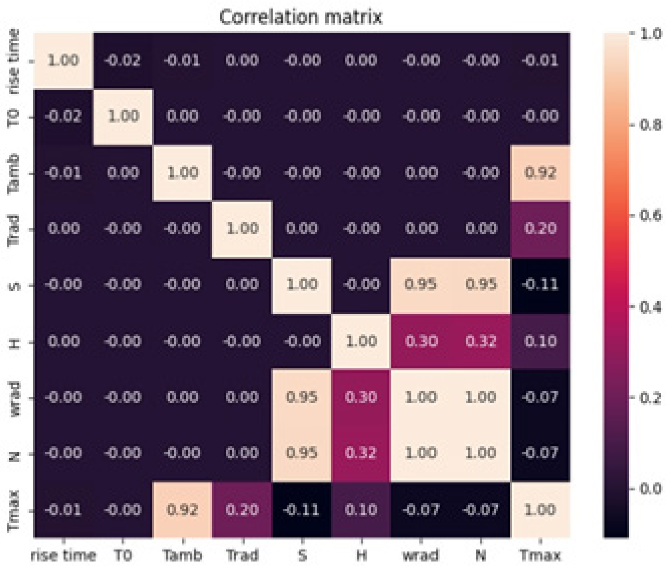

Figure 2 – Correlation matrix of variables of the room temperature

Parameters such as the area of the room (S) strongly correlates (0.95) with the size of the radiator (wrad) and the number of sections, the height of the room (H) also shows a moderate correlation (0.30–0.32) with the size of the radiator (wrad) and the number of radiator sections (N), which is justified by the standard requirements for a comfortable temperature in the heated room. Small negative correlations were also found between the final temperature and the size of the radiator and the number of its sections (about 7%) because the number of section and size of the radiator were precalculated for sizes of the room using equation (18). In addition, the room temperature is inversely proportional to the room area by 11% and depends on the radiator temperature by 20%. Thus, correlation analysis helps to determine the most significant input parameters which can be used to build the model of an automatic temperature control system, including ambient temperature, radiator temperature and size, room area and height, as well as temperature dynamics. The most uncertain parameter is the rise time, which is calculated from graphs of temperature versus time, and is the most important parameter in modeling, but its dependence on the above parameters is practically absent, which may indicate that this parameter depends on other parameters and cannot be determined analytically.

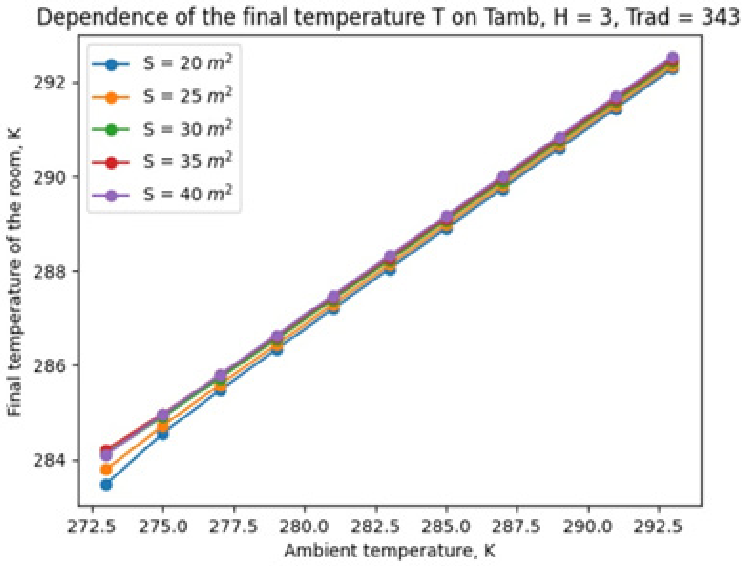

Figure 3 – Dependence of final temperature of the room temperature at height 3 m, radiator temperature 343 K in room with different area S

Figure 3 shows the dependence of the final room temperature on the ambient temperature for various area values. All the lines on the graph follow linear trend, which indicates a direct dependence of the final temperature on the ambient temperature, which agrees with experimental data.

The time constant R (rise time) is determined from the graph and is the abscissa of the intersection point of the tangent to the room temperature graph at point zero and the horizontal line passing through the final room temperature. The rise time for different rooms areas at radiator temperature 343 K and height of the room 3 m shown in Figure 4.

Figure 4 shows the dependence of heating time on ambient temperature for different areas (S) of the system. Each line on the graph represents data for a specific area of the system, ranging from 20 m2 to 40 m2. The figure shows that the heating time of the system is not linear and shows significant fluctuations depending on the ambient temperature.

As an example, consider heating the room of 25 m2 in size, with a ceiling height of 3 m. The flow power is 3690 W/m2 at an air flow rate of 0.01 m/s, with a radiator temperature of 343 K and an outside air temperature of 281 K. Figure 5 shows a graph of the temperature change in the room. At the beginning, there is a sharp increase in temperature from 276 K to 288 K in the first 600 seconds, after which the temperature stabilizes around 288 K with slight fluctuations. This type of change may indicate the process of heating the system and then switching to a stationary mode. Minor fluctuations are caused by external processes and at higher amplitude could be described using second order differential equation with damper.

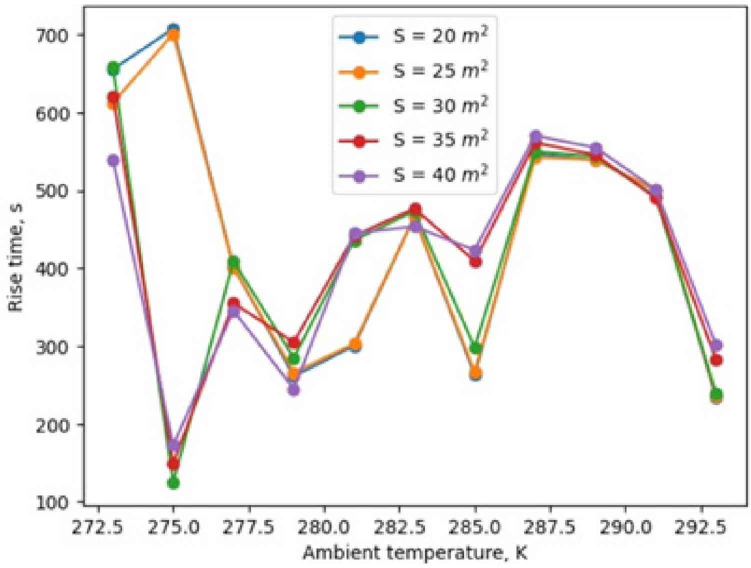

Figure 4 – Rise time at different areas of the room at height 3,
radiator temperature 343 K

The mathematical expression for the transient response will look as shown in equation (19), as the transfer function of the room is an aperiodic link of the second order:

$$h(\mathrm{t}) = \mathrm{K}\left(1 - \mathrm{e}^{-\frac{t}{R}}\right) \tag{19}$$

K is obtained from the following equation (20):

$$K = \frac{T_{fin} - T_0}{gS_0} \tag{20}$$

The coefficient R is determined from the graph, it is equal to the time during which the tangent to the graph, passing through the initial temperature T_0, will intersect T_{fin}. In this case applying described method we will get following value of R=100.

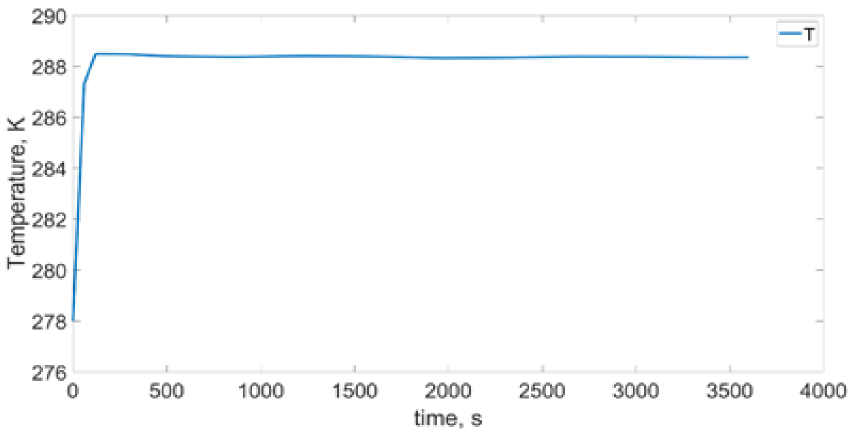

Figure 5 – Example of a graph of room temperature changes

Thus, the final transient response will look like the following equation (21):

$$h(\mathrm{t}) = 0.0034\left(1 - e^{-\frac{t}{100}}\right) \tag{21}$$

And the transfer function for the control action and the disturbing action will look like the following equations (22–23):

$$W_u^{CO} = \frac{T'(\mathrm{s})}{g'(\mathrm{s})} = \frac{0.0034}{100s+1} \tag{22}$$

$$W_F^{CO} = \frac{T'(\mathrm{s})}{\mathrm{T}'_{amb}(\mathrm{s})} = \frac{1}{100s+1} \tag{23}$$

Development of an automatic control system in the MATLAB/Simulink development environment

In the MATLAB/Simulink environment, we will construct a nonlinear system for automatic control of the room temperature, as shown in Figure 6. Figure 7 shows the self-oscillations that occur during automatic temperature control. This circuit is designed to control the parameters of the smart home, including temperature, lighting, and power consumption/ the system uses dynamic filters of the first order, which allow taking into account the inertia of processes. The temperature is controlled though a heat transfer unit, and the lighting is adjusted depending on the input data and external conditions.

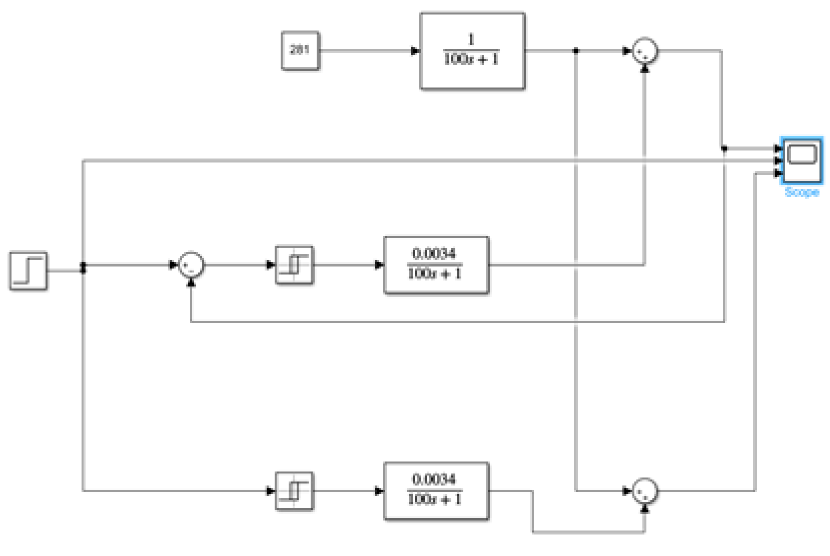

Figure 6 – Schematic diagram of a nonlinear room temperature control system

Figure 7 shows the dynamic of temperature changes in a room with and without a control system. The blue line indicates the desired temperature to be maintained in the room, which is represented by a Heaviside function with a final value of 285 K. As can be seen from the figure, in the absence of a monitoring system, the room temperature rises above the desired value. Using the relay characteristic turns off the radiator, which leads to a decrease in temperature and the creation of an auto oscillating process.

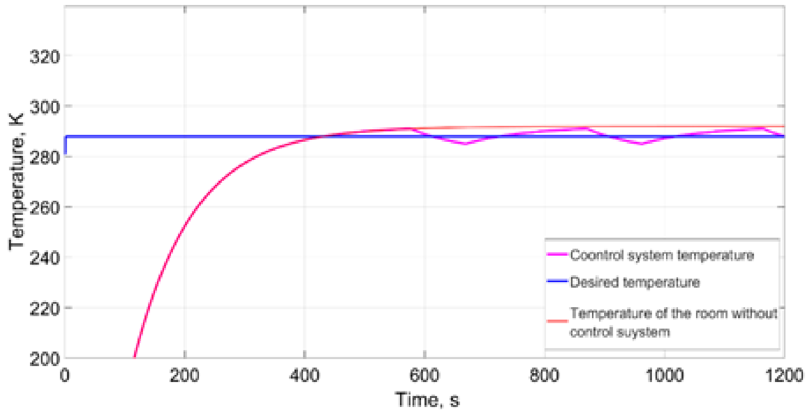

Figure 7 – Time diagram of self-oscillation in the control system

Conclusion

This paper shows the development of a model of a control object, which is the indoor air temperature. The research is aimed at creating an accurate model that simulates indoor air temperature at various parameters. For this purpose, a physical model was created in the COMSOL Multiphysics development environment and 41,850 simulations were performed and 2,511,000 rows of data were obtained. The data shows a 92% correlation of the final room temperature after an hour with the outside temperature of the space, as well as a correlation with the size of the room and the size of the radiator. The data obtained were used to develop a model of the control object and simulations of a nonlinear automatic control system were carried out. The results show important non-linear parameter R (rise time), which did not show dependence on other given parameters but has very high impact on model of control system. The results obtained show the possibility of further creating a neural network that simulates indoor air temperature based on physical simulations in COMSOL to create a highly efficient automatic control system.

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COMSOL MULTTIPHYSICS КӨМЕГІМЕН БӨЛМЕНІҢ ЖЫЛЫТУ ДИНАМИКАСЫН МОДЕЛЬДЕУ

Аңдатпа

Бұл жұмыста жылу берілу мен конвекция үдерістерін ескере отырып, бөлмедегі ауа температурасының өзгеру динамикасының физикалық моделі жасалды. Жүйе COMSOL Multiphysics бағдарламасында модельденіп, MATLAB ортасында сынақтан өткізілді. Зерттеу барысында сыртқы температураның, бөлменің ауданының, радиатор секцияларының саны мен ауа ағыны жылдамдығының әсері талданды. Нәтижелер бөлме температурасы мен сыртқы температура арасындағы жоғары корреляцияны (0,92) көрсетті. Сонымен қатар, радиатор температурасына (0,2), бөлменің биіктігіне (0,1) және ауданына (0,11) әлсіз тәуелділік байқалды. Радиатор секцияларының саны мен оның жалпы көлемі бөлме температурасына ең аз әсер ететіні анықталды (0,07). Бастапқы бөлме температурасы мен соңғы температура арасында елеулі байланыс анықталмады. Модельдеу нәтижесінде байқалған корреляциялар MATLAB/Simulink ортасында басқарылатын жүйенің беріліс функциясын құруға негіз болды. Алынған модельде қолданылған сызықтық емес реле бөлмедегі температураны басқару мақсатында радиаторды қосу және өшіру үшін пайдаланылады. Бұл зерттеу нәтижелері әртүрлі бастапқы шарттар жағдайында бөлме температурасын болжау үшін нейрондық желі моделін құруда қолданылуы мүмкін.

Тірек сөздер: бөлме температурасын бақылау жүйесі, COMSOL Multiphysics, MATLAB, тасымалдау функциясы, нейрондық желілерді күшейту арқылы оқыту.

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МОДЕЛИРОВАНИЕ ДИНАМИКИ НАГРЕВА В ПОМЕЩЕНИИ С ИСПОЛЬЗОВАНИЕМ COMSOL MULTTIPHYSICS

Аннотация

В данной работе была разработана физическая модель динамики изменения температуры воздуха в помещении с учетом теплопередачи и конвекции. Система была смоделирована в COMSOL Multiphysics и протестирована в MATLAB, где было проанализировано влияние внешней температуры, площади помещения, количества секций радиатора и скорости воздушного потока. Результаты показали сильную корреляцию между температурой в помещении и внешней температурой (0,92), в то же время наблюдалась более слабая зависимость от температуры радиатора (0,2), высоты (0,1) и площади помещения (0,11). Количество секций и размер радиатора оказывают наименьшее влияние на температуру в помещении (0,07). Кроме того, начальная температура помещения не имеет существенной корреляции с конечной температурой в помещении. Корреляция, наблюдаемая при моделировании, позволила разработать передаточную функцию управляемого объекта в MATLAB/Simulink. Нелинейное реле, используемое в результирующей модели, применяется для включения и выключения радиатора с целью управления температурой в помещении. Результаты исследования могут быть использованы для создания нейронной сети для моделирования динамики изменения температуры в помещении при различных начальных условиях.

Ключевые слова: система контроля температуры в помещении, COMSOL Multiphysics, MATLAB, передаточная функция, обучение с подкреплением.

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