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Development of a Module to Measure Losses Through Building Envelopes for the Smart Energy-Saving Ventilation Automatic Control System

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Abstract : Modern smart technologies are becoming a new trend in construction. Simple and precise methodologies must be developed to process data and predict further trends of relevant parameters. This article describes algorithms that will allow operating the heating and ventilation smart control system with minimal time and resource contributions.Applying these systems in practice will allow increasing the energy efficiency of buildings and structures.

Keywords : Automatic control system, ventilation, heating, heat loses, building envelopes, energy efficiency, energy-saving systems, energy audit.

1. INTRODUCTION

Increasing the energy efficiency of used resources is urgent for any facility. It plays a significant role in the field of power industry and power consumption, *e.g.*, in the life of any human being. It means that increasing energy efficiency is of constant relevance and it induces constant development of new state-of-the-art technologies intended to achieve some balance between resources used and efficiency.

One of the primary fuel and energy resources used by humanity for its needs is thermal energy. The heat is used to solve multiple tasks in industry, power-engineering, construction and other process and production tasks. In everyday life, thermal energy is used to heat premises in buildings. According to the Federal State Statistics Service (Rosstat), 226.4 million Gcal of energy were produced in the Russia's Central Federal District in 2015. The losses of thermal energy are officially claimed to be 24.7 million Gcal, or 10.9% [1].

One of the primary tasks in thermal engineering of buildings is to determine actual thermal losses and measure the thermal energy consumed for heating, air conditioning and ventilation, which is complicated by no monitoring systems in most facilities that would otherwise allow getting actual data, including those concerning the losses through building envelopes. For example, the total heat consumption for a building consuming 500 Gcal of thermal energy per annum will be 900,000 rubles per year, for a 1 Gcal average price of 1,900 rubles. The losses through doors, walls and windows will be about 60%, which is approximately 540,000 rubles. If it is possible to control the roofing, the percentage of considered losses is increased to 85%, so there is an opportunity to control almost all expenses for heating. Considering the poor condition of residential and non-residential buildings in the country, the ventilation and heating smart control system will make it possible to find new opportunities for energy saving.

To create a ventilation and heating smart control system, a facility shall be energy audited [2-3]. The first step in any energy audit is analyzing the design documentation. This allows determining the system's geometry, actuating mechanisms in the system and optimal system parameters, with minimal material and labor efforts. In addition, the design documentationanalysis suggests minimal restraints for those residing in the building. However, experience

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has proven that the method of design documentationanalysis may be insufficient to reflect the actual conditions. This may be associated with multiple reasons, such as mistakes made in construction and assembly activities, failures to observe design documentation and further failures to reflect these deviations in the as-built documentation, the system age and other factors.

The second step of energy audit is practical: using measuring instruments to take readings in various installation locations of the suggested system.This will allow calibrating the future automation system during the fist stage and achieving the distribution of ventilation flows in the buildings. In case of single calibration, there is a chance that some factors that may occur during actual operation will not be considered.As a consequence, the system's operating conditions will not be optimal. To avoid such conditions, the system shall be regularly adapted, which requires specialist's attendance and possible shut-down of the ventilation system. This approach may require substantial material and capital expenses and will result in non-optimal use of automation system capabilities.

To analyze the quantitative parameters of thermal losses through the building envelope, integrated complex modeling of the facility under study shall be done. Thermal modeling is a method of experimental study of thermal processes based on their physical similarity and mathematical description of processes occurring in the modeled facility. As a rule, the studies by using the thermal modeling methods are undertaken in laboratory conditions.This is caused by the fact that there are many heat exchanging processes occurring during operation, that are frequently hard to consider both physically and mathematically [4-7].

The thermal modeling is intended to mathematically describe the processes occurring within the measured facility and calculate primary thermal and physical parameters based on experimentally obtained data. In this case, the thermal modeling is aimed at a vertically oriented envelope – a building wall, a heating boiler wall, a furnace wall, or any other item [8-9].

Another important aspect in creating automatic control systems consists in establishing forecasting systems. Forecasts are made by using the following forecasting methods :

1. Extrapolation methods are based on a suggestion that future events are defined by past events. For example, the demand-in-time variance analysis suggests three components: trend; seasonal variations; random changes.The trend describes the general development tendency; seasonal variances show how the demand varies depending on the season; and random changes are the changes of random factors that are hard to be defined. In the conditions of instability and uncertainty of external factors, the extrapolation methods are rarely used.
2. The methods of expert estimation are based on statistical processing of estimates obtained by interviewing highly qualified specialists in respective narrow fields.These include such methods as the Delphi method, the methods of collective idea generation, sequential sampling, paired comparison, scoring, estimating of probabilities, and row ranking. All these methods are based on various designed algorithms for assessing subjective opinion of experts (specialists). The Delphi method suggests interviewing the expert group members and further circular familiarization of group members with the opinion of their colleagues and those who are interested in expertise results in order to achieve grouped consensus. The collective idea generation method (brainstorming) suggests a discussion where any opinions, ideas and suggestions can be made, including the most counter intuitive ones. After the interview, its quality is assessed, and expert opinions are processed.
3. The cause-and-effect methods are based on using regression mathematic methods and connectionist models (CM). Regression models are based on making statistical equations to determine the values of some variables and to assess the effect on the value sought. For example, a regression model is developed to forecast the demand depending on the level of prices and advertisement expenses. CMs have become widely spread recently as compared to regression models, since they allow getting more consistent results by revealing non-linear relations between parameters. CMs allow revealing non-evident and substantial systemic links when modeling complex systems. By using CMs, the following uncertain factors can be considered when measuring the sales volume: behavior of competitors; season; changes in market shares; advertisement intensity, etc.

2. STUDY

The input data for thermal modeling include the following parameters: envelope height, width, material of construction, indoor and ambient air temperature, inside and outside surface temperature, thickness of materials used in the envelope, the envelope thickness and data sheets and documentation for the facility.

Based on the developed thermal model, envelopes are computer-modeled to calculate thermal flows taking place in each envelope. In calculations, it is suggested that the envelope is thermodynamically balanced/saturated, and the thermal flow through a wall inside the premise equals to the thermal flow on the outside surface.

According to the Newton-Richmann law [10], at the air/wall boundary, the thermal flow will be:

$$q_a = \alpha_a(T_{aa} - T_{aw}) = (\alpha_{ra} + \alpha_{ca})(T_{aa} - T_{aw}) \tag{1}$$

where : α_a = heat output coefficient at the air/wall boundary;

T_{aw} = wall temperature in the premise, K;

T_{aa} = air temperature in the premise, K;

According to [11], for vertically oriented surfaces in the premise on the wall surface, the convective heat output coefficient α_{ca} can be assessed under the following formula:

$$\alpha_{ca} = 1.66(T_w - T_c)^{1/3}, \tag{2}$$

where : T_w = temperature of a warm object, K;

T_c = temperature of a cold object, K.

The heat output coefficient with radiation α_{ra} in this case can be calculated by using the Stefan-Boltzmann equation [12]:

$$q_{ra} = \varepsilon\sigma(T_w^4 - T_c^4) = \alpha_{ra}(T_w - T_c)$$

where : ε = reduced radiation coefficient;

σ = Stefan-Boltzmann constant

$\sigma = 5.67.10^{-8}\ W/(m^2.\ K^4)$;

$$\alpha_{ra} = \varepsilon\sigma(T_w^2 + T_c^2)(T_w + T_c)$$

For building envelopes, the total heat output coefficient on the outside surface is a sum of convection and radiation coefficients [10] and it will equal:

$$\alpha_a = \alpha_{ra} + \alpha_{ca} = 1.66\left(T_{aa} - T_{aw}\right)^{1/3} + \varepsilon\sigma(T_{aa}^2 + T_{aw}^2)(T_{aa} + T_{aw})$$

When substituting formulas (4) in (1), we get the final expression to calculate the thermal flow q on the wall's internal surface, *e.g.*, in the premise:

$$q_a = \alpha_a(T_{aa} - T_{aw}) = 1.66\left(T_{aa} - T_{aw}\right)^{4/3} + \varepsilon\sigma(T_{aa}^4 - T_{aw}^4) \tag{5}$$

According to the thermal flow calculated under the formula (5), the amount of thermal energy lost by the heating boiler wall for a unit of time is calculated. The resulting amount of heat equals the integral for the studied surface of the boiler wall:

$$Q = \iint_S \left(\frac{5}{3}\left(T_{aa} - T_{aw}\right)^{4/3} + \varepsilon\sigma(T_{aa}^4 - T_{aw}^4)\right)dxdy,$$

where x and y are the dimensions of the measured surface.

For a plane-parallel wall, the integral will be a sum of thermal flows over the entire surface under study.

$$Q = \sum_S \left(1.66\left(T_{aa\_xy} - T_{aw\_xy}\right)^{4/3} + \varepsilon\sigma(T_{aa\_xy}^4 - T_{aw\_xy}^4)\right) \tag{6}$$

By obtaining the amount of thermal energy lost through the envelope per second, and knowing the distribution of losses for each element (surface pixel), we can reduce thermal losses though walls by point application of various thermal protections.

To forecast thermal losses through envelopes, it is reasonable to use the solutions based on neural networks. Currently, neural networks are used to solve a large number of various tasks: forecasting in economics and applied areas, diagnosing patients in medicine, processing and analyzing various images, analyzing social data, identifying handwritten and hardly readable texts, etc. Among other things, neural networks are applied in non-destructive testing [13-14].

The artificial neural network is a software or hardware solution built upon the functioning principle of biological neural networks. A neural network can be considered as a system of simple processors (artificial neurons) interconnected by multiple mutual links. Each processor regularly receives signals and transmits them further to other processors. Processors have a simple internal memory for operations obtained during learning, e.g., neural networks are not programmed in a conventional sense, but learn through specific examples and accesses. The learning capability is one of the most important advantages of neural networks as compared to traditional algorithms.

To develop and implement solutions based on neural networks, universal software or expansions of popular software are used (Matlab, Statistica, etc.). These software products feature basic operations to create, manipulate and train neural networks, which allows solving various complicated real tasks. Also, neural networks show relatively low errors and high level of reliable prediction if a correct training and creation methodology has been chosen.

Most frequently, the structure of such networks includes a sequence of layers: input signals go to the first layer and then pass through all layers to the last one where they arrive to the output. Internal layers of the neural network are usually referred to as hidden. The simplest implementation of a neural network is perceptron (Figure 1).

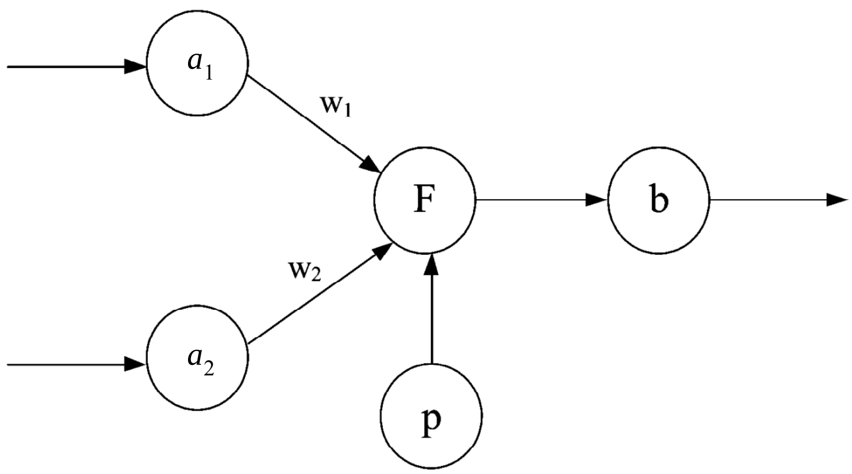

Fig. 1. Simple perceptron with two inputs, a shift and one output.

Signals a_1 and a_2 are supplied to the output, then the incoming signals are multiplied by their weight coefficients w_1 and w_2, respectively. The output signal b remains zero until its value exceeds a threshold limit p. The equation of a neuron with shift will be as follows:

$$b = f(a_1 w_1 + a_2 w_2 + p)$$

By adjusting the shift and weight, the neural network can be trained to perform specific work. Furthermore, the neural network itself can change its parameters to achieve the required result. An example of a most frequently used three-layer neural network is given in Figure 2.

To create a dynamic thermal model of an envelope, measurements shall be made at some intervals. By applying the suggested methodology for several times in different conditions, the thermal flow can be calculated for each measurement and envelope's thermal and physical characteristics, which increases the accuracy of data obtained. Based on the specific number of measurements, it is possible to create an envelope's thermal model that can be applied in the future without additional measurements and will allow analyzing the history of the envelope and each defect individually.

To create a dynamic thermal model, a neural network can be used, having the number of inputs equal to the number of images necessary to make calculations with the required accuracy. Experience [15-16] has proven that 2 to 32 surface measurements of the unit under study shall be made to achieve certainty and accuracy. The number of outputs is determined by tasks that must be solved. To create a thermal model and calculate each pixel, only one output is required – the result of thermal modeling for the selected pixel.

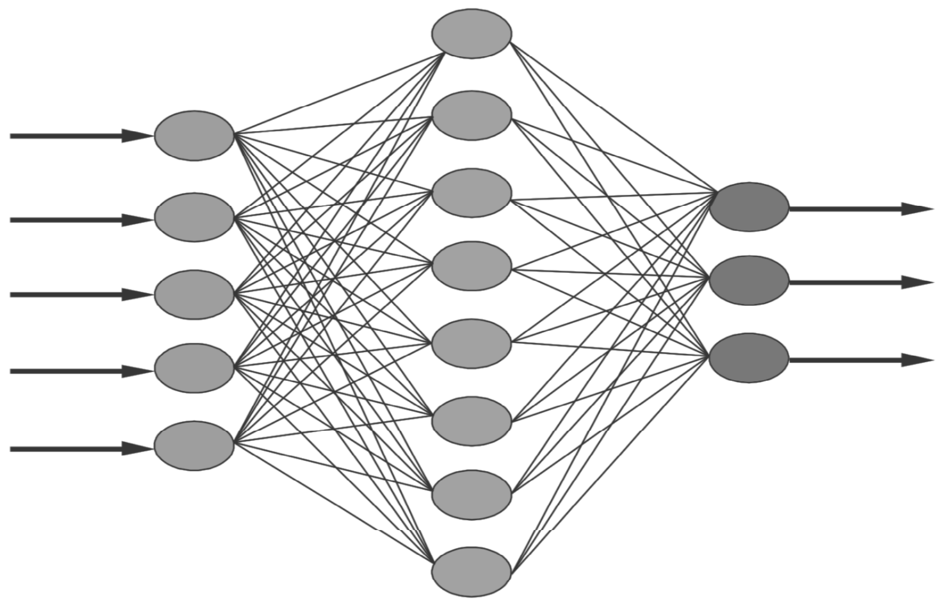

Fig. 2. Example of a three-layer neural network with 5 inputs and 3 outputs.

In such a manner, the neural network that will allow creating an envelope's thermal model shall include 20 outputs and one input. Inputs receive data for the thermal flow through each element of the thermal model of the envelope under study in different time points and for different shifts – external measurement conditions. A forecasted value of the thermal flow through this element in specific conditions can be obtained at the output, depending on the shift. This process shall be done successively for each element in the thermal model.

As an alternative for regular calibration, an adaptive self-learning ventilation control system can be used that analyzes the existing system and performs commissioning. When using the self-learning system, the analysis is provided by the same sensors that will be used in further operation.

Let us consider the logic of such a self-learning system in more detail. Let us take a one-storey building with several premises and a ventilation system installed, as an example. Suggest that according to the terms of reference, we need to control an arbitrary number of parameters in each premise, the control consisting in maintaining the parameters within the specified limits (such as temperature when using air-heating systems). The control is implemented through proportional-integral-derivative control (PID-control). The PID-controller is intended to timely control the actuators depending on the feedback signal (temperature sensor readings in our case). The self-learning system is intended to select coefficients of proportional, integral and derivative components Kp, Kd, Ki). The self-learning function consists in the fact that the system constantly brings refreshed data and system coefficients into a compliance table by recording coefficients with respective external factors (weekday, season, ambient temperature) into the database. During its operation, the system constantly checks the existing external and internal factors and operation parameters for their compliance with any of the existing records in the compliance table, and in case of coincidence, it applies tabular coefficients as effective ones and utilizes them in operation. This approach is referred to as the use of precedents and is one of the most effective methods in building smart self-learning systems.

In general, the PID-controller logics is represented in Figure 3.

The self-learning system PID-controller using precedents acts similarly, but when finding and applying correct precedents, it saves computational capacities and software and hardware resources of control instruments (Figure 4).

We can make a conclusion that two approaches to self-learning (neural networks and precedent-based systems) shall be combined in order to build a ventilation control smart system.

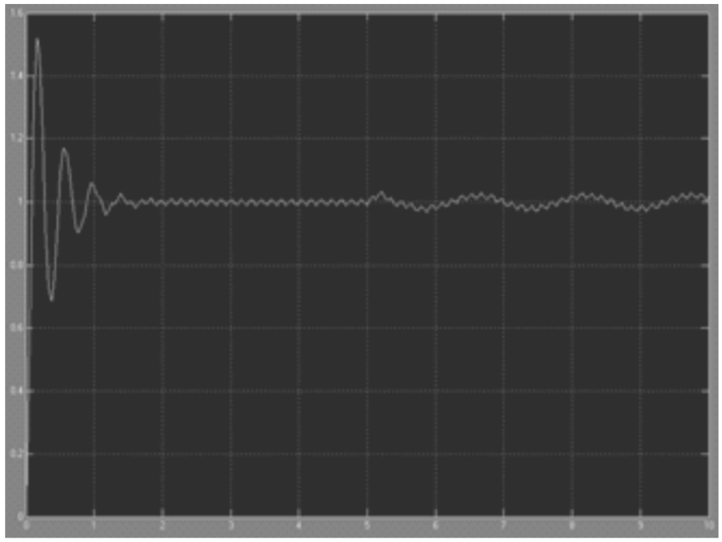

Fig. 3. Standard PID-controller solution-seeking model.

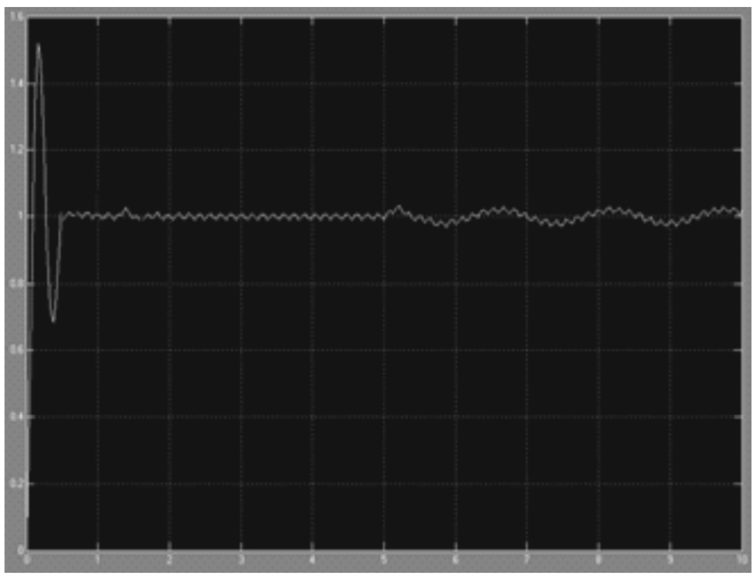

Fig. 4. Precedent-based PID-controller.

3. CONCLUSION

To build a thermal model of an envelope for a building or a structure, the unit under study shall be preliminary examined. It is important to develop a correct and consistent structure of the study that will enable measuring the necessary data with the accuracy sufficient for further operation. Another relevant point in the study is precise planning, since repeated measurements of the envelope surfaces under examination are required to create a dynamic model.

In case of multiple repetition with recording of temperature and time parameters, it is possible to create a comprehensive time thermal model of the envelope than can be used for integrated assessment of the thermal protection in various periods and various input data. To create an automatic heating and ventilation control system, it is required to control microclimatic parameters in the premise and calculate the amount of heat energy losses through building envelopes. This will enable forecasting future changes in control with higher precision, foreseeing unexpected losses of heat energy, and will allow the system to self-learn during operation.

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