Implementation of neural network algorithms for solving the problem of heat supply regulation

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Abstract. The article discusses a strategy for managing the supply of thermal energy, in which self-learning based on neural networks is used to predict the thermal regime of a building. Examples of the use of neural network technologies to improve the energy efficiency of technological and power plants at the stage of making a decision on their design and their operation are given. A further increase in the efficiency of heat supply provides for the transition to smart grids, which have qualitatively new characteristics of reliability and controllability. Smart grids make it possible to take into account specific consumer needs at any given time. To implement a scientific task, it is required, in particular, to reach the world average indicators of these characteristics. One of the ways to achieve them is accurate forecasting of heat energy consumption and construction of consumer profiles, which affects both technological processes and its economic efficiency of heat supply.

1. Introduction

Heat supply is a set of measures for generating heat, transporting it and distributing it to buildings and structures in order to ensure the thermal comfort of consumers located in them. The centralized heat supply system is a complex of installations, devices and units, the operating modes, which are interconnected in a continuous heat and power process. Therefore, it is necessary to regulate the heat supply at various stages [1].

Regulation of heat supply improves the quality of heat supply, reduces the excessive consumption of heat energy and fuel. An appropriate control method is selected in order to stabilize the heat load of consumers and generate heat with reduced cost at the station through heat networks. The method of using optimal control of heating of buildings was first in the world developed by Yu. A. Tabunshchikov and described in [2]. Among foreign authors, the works [3-6] are noted.

Depending on the place of implementation of regulation, there are central, group, local and individual regulation. There is also smart heat supply, which allows to reach the required temperature in the room without human intervention using a thermostat with a temperature sensor.

The purpose of the study is to assess the effectiveness of the use of neural network algorithms in the regulation of heat supply and to identify methods for the possible modernization of their mathematical apparatus. The importance of the study lies in demonstrating the advantages of neural network algorithms when solving a problem related to the regulation of heat release.
2. Methods and materials
The essence of the control methods can be understood from the heat balance equation:

\[ Q = \frac{G c (\tau_1 - \tau_2)}{3600} = \kappa \cdot F \cdot \Delta t \cdot n \]  

(1)

where \( Q \) is the quantity of heat, received by the heating device from the coolant and supplied for heated medium, kW / h; \( G \) is the flow rate of the coolant, kg / h; \( c \) is the heat capacity of the coolant, kJ / kg °C; \( \tau_1, \tau_2 \) is the coolant temperatures at the inlet and outlet, °C; \( n \) is time, h; \( \kappa \) is the heat transfer coefficient, kW / (m² °C); \( F \) is the heating surface, m²; \( \Delta t \) is the temperature difference between the heating and heated medium, °C [7].

The management of the release of thermal energy in the simplest case is based on the use of a pre-defined temperature schedule. The temperature graph of the heating system establishes the dependence of the temperature of the coolant in the supply line on the outside air temperature.

This concept of managing the release of heat energy does not allow us to properly take into account changes in the use of the room, changes in outdoor conditions (changes in solar radiation with variable clouds), etc. These circumstances lead to insufficient management of the release of thermal energy. On the one hand, this leads to a decrease in thermal comfort. On the other hand, this leads to an overexpenditure of thermal energy due to the occurrence of overflows. At the same time, the system requires significant commissioning efforts.

More advanced control systems with feedback. The use of indoor temperature correction in control systems increases the performance of heating controllers. Nevertheless, even such an extended concept of managing the release of heat energy for heating does not allow for optimal control. Since the heating system of the heat carrier, the heating system and the building itself (its structures, furniture, interior items) have a fairly high inertia. The correction response to an instantaneous change in the thermal state of the building is received with a long time delay.

The mathematical model of the thermal regime of a room as an object with distributed parameters has the form:

\[
\begin{align*}
\frac{\partial}{\partial t} (pV_t) &= -\frac{\partial \mathbf{v}}{\partial x_i} \\
\frac{\partial T}{\partial t} + \mathbf{v} \nabla T &= \text{div}\lambda \nabla T - \frac{1}{c_p} \\
\frac{\partial \rho}{\partial t} + \text{div}\rho \mathbf{v} &= 0 \\
\left(\frac{\partial H}{\partial t} = \text{div} \lambda \nabla T + C_{RJ} \frac{\partial T}{\partial y} + Q_{SOU}\right)_i \\
y &= 0 \left\{ q_{\text{cond}} = q_{\text{c,out,SF}} + q_{\text{R,out,SF}} + q_{\text{Sun,out,SF}} + q_{\text{ph,out,SF}} \right\}_i \\
y &= \delta \left\{ q_{\text{cond}} = q_{\text{c,in,SF}} + q_{\text{R,in,SF}} + q_{\text{Sun,in,SF}} + q_{\text{ph,in,SF}} \right\}_i \\
C_{\text{EQ}} \rho_{\text{EQ}} \frac{\partial T_{\text{EQ}}}{\partial t} &= \text{div} \lambda_{\text{EQ}} \nabla T_{\text{EQ}} + Q_{\text{EQ}}(x,y,z) \\
t &= 0 \{ T = T(x,y,z); T_1 = T_1(x,y,z); T = T(x,y,z); V_i = 0 \}
\end{align*}
\]

(2)

where \( T_{\text{EQ}} \) is the equipment surface temperature, °C; \( q_{\text{Sun,in,SF}} \) is the heat sources on the surface due to phase transitions, \( c_p \) is the volumetric heat capacity of air, \( \delta \) is the interlayer thickness, m, \( Q_{\text{SOU}} \) is the solar radiation absorbed by the surface, \( q_{\text{Sun,out,SF}} \) is the phase transitions on the surface.

The modes of heat consumption and heat energy production depend on a large number of factors. These are weather conditions, heat engineering qualities of heated buildings and structures, characteristics of the heat network and energy sources, etc. It is necessary to take into account the functional relationship of the heat supply system with other engineering systems, when choosing this models. For example, there is electricity-, gas-, and water supply.

The automation of the heat station makes it possible to maintain the required parameters of heat
The automatic heat supply control system is a system consisting of temperature sensors, a control valve, pumps, a controller, and communication equipment (if remote control of the system is required). The temperature outside and inside the house is analyzed, as well as the temperature in the supply and return pipelines with the help of installed sensors. This data is transmitted to the control cabinet controller. The controller analyzes the sensor readings and issues a command to the control valve in accordance with the specified schedule.

Improving the adequacy of the mathematical model of thermal management in the room is associated not only with its identification with the thermal characteristics of the room and the technological process in it, but also taking into account the reaction of the room to external climatic influences. The period of repeatability of external climatic influences is years. That fact creates great difficulties in the task of identifying a mathematical model. One way to solve this problem is to use a self-learning mathematical model.

The following algorithm for self-learning of mathematical models for managing heat and power consumption of buildings was proposed. In addition, a software block-emulator of readings of external meteorological conditions sensors is introduced into the heat energy consumption control system, which transfers the simulated readings of the sensors to the data processing program. In the initial period of system operation, the time between control cycles is used for self-learning of the system. For the period between control cycles, signals are processed not from real sensors of external meteorological conditions, but simulated readings. The system operates during training in the same way as during the control process, with the only difference that the system receives the input information from the simulator of external weather conditions sensors, and transfers the output information to the program that simulates the formation of the microclimate. The system is trained in stages. The initial stage takes place on simple mathematical models of microclimate formation, then the training models become more complex. As soon as the system begins fast transition from one mathematical model to another, the learning process on the models ends, and the system is transferred to the learning mode on a real object. The training time is reduced due to the fact that the frequency of control cycles increases by two orders of magnitude during the training period on mathematical models [2].

One of the options for the implementation of learning algorithms, including self-learning (unsupervised learning) is the use of so-called neural networks – artificial neural networks (ANN) [9].

An artificial neural network is a mathematical model based on the principles of biological neural networks.

The main structural unit of a biological neural network is a neuron – a highly specialized nerve cell. A neuron can receive information from another neuron or another organ, process it, store and transmit it further, also to another neuron or another organ. Neurons are combined into biological neural networks by means of branched connections. A biological neural network built on relatively simple neurons can be very complex itself since one neuron can be connected to many other neurons, and the total number of neurons (and connections) in the network can be large.

Like a biological neural network, an artificial neural network is built on relatively simple elements - artificial neurons. An artificial neuron receives input signals, processes them according to a specific algorithm and then transmits a specific output signal depending on the processing result. In an artificial neural network one artificial neuron can be connected to many others, similar to a biological
neural network. As a result, a very complex network can be implemented on relatively simple elements and algorithms.

An artificial neuron is a simplified model of a biological neuron. There are \( n \) input signals \( X_1 \ldots X_n \), which come from other neurons and are fed to the input of the adder \( \Sigma \). In this case, the signal from each neuron has a different significance (weight) and can be corrected by introducing a kind of correction factor \( W_1 \ldots W_n \) – the weight of each input signal. That is weight coefficients, the coefficients of communication between neurons. The signals corrected for the coupling coefficients are summed up and then fed to the calculator of the activation function \( \phi \). The calculator of the activation function generates one or another output signal \( Y \) depending on the given threshold value \( \theta \). Then output signal is transmitted to other neurons as an input signal.

One of the main advantages of neural networks over traditional algorithms is the ability to learn. From the point of view of a mathematical model, training an artificial neural network is finding the coefficients of connections between neurons. It is the values of the coefficients of connections between neurons (weight coefficients) that are the "knowledge" of the artificial neural network.

During training, a neural network is able to identify complex relationships between input and output data. With the known results of the response to the input signal, it becomes possible to adjust the weighting coefficients to reduce the error until the network can return the correct result. In the residential sector, temperature fluctuations of \( \pm 2 \) °C are permissible. The less often the prediction result deviates from the real temperature value, the more reliable the prediction and the more stable the neural network.

The neural network training process is based on minimizing the error function \([10]\).

The optimal control module receives predictions from modules describing the building and the outdoor climate as input parameters. This predictive data is used to develop an optimal sequence of heating control commands for the next 6 hours.

At each time step \( k \) (\( \Delta k = 15 \) min), the optimal control module processes the following input signals:
- current value of air temperature in the room \( T_{in}(k) \);
- the previous value of the air temperature in the room \( T_{in}(k-1) \);
- forecast (profile) of heat inputs with solar radiation through translucent enclosing structures during a fixed time interval (6 hours) \( G_{sol}(n+1) \ldots G_{sol}(n+6) \);
- forecast (profile) of outdoor air temperature during a fixed time interval (6 hours), averaged over the last 24 hours \( T_{out}(n+1) \ldots T_{out}(n+6) \).

At each next time step \( k \), the optimal control action (in this case, the heating power) \( P_{heat} \) is the command that minimizes the "cost function" \( J \).

The mathematical expression for the "cost function" used for the optimal control algorithm is as follows:

\[
J(P_{heat}, T_{in}, T_{setpoint}) = C_{heat} P_{heat} + C_{comf} (\exp (PMV(T_{in}, T_{setpoint}))^2 - 1) 
\]

(3)

where \( P_{heat} \) is the optimal control action – heating power, \( W \); \( PMV(T_{in}, T_{setpoint}) \) is the Fanger comfort index, predicted (expected) average assessment of the degree of thermal comfort; \( T_{in} \) is the room air temperature, °C; \( T_{setpoint} \) is the set room air temperature (setpoint), °C; \( C_{heat} \) is the weighting factor for the heat power indicator; \( C_{comf} \) is the weighting factor for the comfort index \([11]\).

3. Results and Discussion
Various options for initiating the initial values of the parameters of the trained neural network were investigated. The result showed that proximity of initial unconfigured network with the desired solution, results in faster optimisation of the algorithm (in a smaller number of learning steps). The failure in choosing an initial approximation can be compensated by a sufficiently large number of iterations. As the number of functions used increases, the number of iterations increases to achieve the
specified precision and time for each operation.

In the case of linear problems, other approaches to teaching neural networks are also possible. For example, the method of integral representations can be used. This approach uses non-standard neural network basic elements – solutions that are generated by neural network expansions of Cauchy data.

Mathematical models of the thermal regime of a room as an object with distributed parameters include mathematical models that describe the temperature field in the plan and along the height of the room and separately take into account radiant and convective heat exchanges in the room.

To optimize the thermal regime, it is necessary to have information on the dynamics of disturbing influences. In particular, information on changes in climatic factors is required (outside air temperature, wind speed and direction, solar radiation, etc.). The thermal characteristics of external fences, the degree of glazing of the facade, the number of people in the building are also significant, as well as the filling with furniture and other factors that affect the formation of the thermal regime. For short-term local weather forecasting, an adaptive model based on the influence of solar radiation and temperature changes associated with displacements of air masses can be used.

In this case, one of the main conditions for solving the problem of finding the structure of the model is taking into account the heat accumulated by the building (formula 2). It is possible to maintain the thermal regime of the building in a certain permissible region with a temporary discrepancy between heat gains and heat losses due to this heat. Methods for optimizing the thermal regime of buildings can be developed on the basis of the constructed model.

Building a neural network is a complex multi-level process. The learning dynamics defy mathematical analysis with chaotically changing input data. Many experiments were carried out with different design characteristics during the study: prediction step (\(\Delta t\)); number of network layers (\(X_n\)); number of neurons in each layer (\(NN\)); coefficient influencing the network learning rate (\(\eta\)) [12].

All numerical experiments were carried out on the basis of statistical weather data in the city of Chelyabinsk.

It was revealed that the accuracy of neural networks with a prediction step of 1 hour, having seven layers in their structure, is close to the accuracy of neural networks having six layers in their structure, up to hundredths.

The optimal control algorithm is aimed at optimizing thermal comfort and energy consumption over a fixed time interval (for the controller under consideration, the time interval is 6 hours). Optimization is carried out by minimizing the "cost function" taking into account both parameters – energy consumption and thermal comfort. Neural network algorithms are already being used to regulate heat release. Thus, the NEUROBAT self-learning heating control controller was developed as a joint project between CSEM (Center Suisse d'Electronique et de Microtechnique – the leading organization) and the engineering company ESTIA Ltd, an industrial partner of SAUTER and LESO-PB (Solar Energy and Building Physics Laboratory, Switzerland). Like traditional controllers, the NEUROBAT controller is interfaced with four temperature sensors [13].

4. Conclusion

The innovative nature of the concept of optimal predictive control based on the use of self-learning neural network algorithms not only ensures the optimization of operating costs, but also reduces the costs and labor intensity of commissioning.

The model can also be used to predict the weather in places with hot climates and be used to regulate refrigeration systems in a similar manner [14, 15].

The use of artificial neural networks made it possible to achieve self-learning of the model, which led to stable results when performing a large number of forecasts. For example, the average error is less than 0.5 degrees Celsius when forecasting with a step of 1 hour throughout the year. These algorithms can be used for building fundamentally new methods for regulating heat supply by building life support systems.
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