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Temperature Prediction in a Public Building Using Artificial Neural Network

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***Abstract*—The paper proposes an approach to predict the temperature in the rooms of a public building. The model of the building is described by the average temperatures in its rooms, the characteristics of external walls and heating elements. Weather conditions are determined by the temperature, speed and direction of the wind. The state of the thermal unit is described by the temperature of heat agent at the inlet and outlet of a heat supply system, as well as the flow rate. To build a predictive model, it is necessary to identify a nonlinear dependence of the temperature inside the room on these parameters. This problem is solved using a recurrent artificial neural network. The network based on gated recurrent unit was selected as the base for the network architecture in this approach. The features of this structure allow to take into account the sequence of data without using excessive parameters. To train the model and predict temperature values, measurement sequences of different lengths were used to determine the most effective model. The number of blocks corresponds to the length of the time series. The state of the network on the last block is a predicted temperature.**

Keywords—prediction, artificial neural network, temperature mode modeling

I. Introduction

In order to reduce thermal energy consumption and ensure comfortable working conditions, it is important to predict room temperature in a public building depending on the heating mode and external conditions (outdoor temperature, wind speed and direction). The traditional approach to solving this problem is based on the study of local (at the room level) and global (for the whole building) heat loss. Building a model of heat transfer processes in a building supports more accurate management of heat supply systems to comply with sanitary standards and reduce heat agent consumption [1, 2].

The heat and energy balance of buildings is determined, first of all, by the intensity of heat transfer due to the heat conduction mechanism. Moreover, during the winter period, changes in weather conditions significantly affect the values of heat transfer parameters of the exterior walls of buildings [3, 4]. Additional difficulties revealed using intermittent heating as a tool to decrease energy consumption. In this case, with periodic prolonged decreases in the room temperature, the heat transfer parameters for internal walls and ceilings can also change. Finally, it is not possible to assess the structure of walls and ceilings in terms of the number of layers and material parameters, which leads to the use of certain conditional values of the parameters for any buildings.

Thus, we can assume that the classical approach, which is based on the full description of the heat transfer process and the corresponding balance ratios, allows to perform a general assessment of the condition of the building in terms of heat loss. However, in order to predict the temperature of rooms under unsteady heating conditions and changing weather conditions, it is necessary to consider corrections for the heat transfer parameters, the thermal inertia of the rooms and the entire building or use a different approach.

In case when it is possible to observe the temperature in the building, environmental conditions, as well as the parameters of the heating system, the task of predicting the room temperature can be posed as the classical problem of multi-parameter non-linear regression. An artificial neural network deep learning method could be used as a solution.

II. State of the Art

Machine learning and deep learning methods are widely used to study the thermal characteristics of buildings and the control process of Heating Ventilation and Air Conditioning (HVAC) systems. Thus, Ferreira P. M. et al [5] use neural networks in combination with genetic algorithms to control the HVAC system in order to achieve the desired level of comfort heat level and energy saving in the building of the university campus. Moreover, as noted in their review articles Enescu [6], Moon J. W. et al. [7], Afram A. et al. [8], the attention of researchers focuses on issues of economic efficiency of heat supply and on supporting comfortable conditions, mainly for residential building, the operation mode of which differs significantly in compare to public buildings.

In the paper of Liang and Du [9], a neural network is used to control an HVAC system in order to maintain the comfortable temperature. In the papers of Moon J. W. et al. [10], Castilla M. et al. [11], approaches to manage thermal mode using artificial neural networks in a separate room are considered. However, the possibility of scaling the solution for the entire building is not considered. The study of Sablani S. S.

et al [12] is aimed at obtaining the values of the heat transfer parameters of building structures using ANN.

Accordingly, the use of artificial neural networks is based on a fully-connected network architecture, which does not have practical application in the case of a large building. Moreover, Moretti M. et al. [13] show that to build effective predict models, the role of the network architecture and the length of the time series of the measured parameters that is used in training the model is significant. This result is crucial for the current study.

III. Classical method for temperature prediction in a room

A. *Thermal characteristics of a building*

The state of the building regarding its thermal characteristics is determined by the corresponding parameters of its walls. To describe the model of a building it is important to take into account the layers of various materials for walls [14, 15] as well as the other significant parts of the heat transfer process.

The following significant characteristics are considered:

- thermal conductivity coefficient;
- heat transfer coefficient;
- heat capacity of the material;
- surface area;
- layer thickness;
- area of heating elements;
- area of window openings.

To determine the nature of heat transfer between rooms and the environment, aggregate unite coefficient K, which reflects the characteristics described above. To assess the thermal characteristics of walls, the mathematical model of a building's thermal regime, described in [14], is used as a basis.

In addition to outdoor temperature, it is also necessary to consider the wind. The influence of wind on the microclimate is applicable both to a specific room and to the entire building [16, 17] and should be taken into account in the model.

B. *Assumptions*

The heat received and absorbed for each room is not specified by its source, but is taken as the total amount of heat.

Heat transfer between rooms and within a building are not taken into account.

Elements of the heating system for each room are not divided into separate structural elements and are not determined by specific parameters.

C. *Model of the thermal mode of a building*

The following room parameters are considered as source data:

- outdoor temperature and wind direction;
- average room temperature;
- the amount of heat received by a room.

To control the energy balance, the total amount of heat that the building received from a heating system is used. Based on the temperature difference at the inlet and outlet of the heat agent in a heating unit, the amount of heat for individual rooms is allocated:

$$Q_c = \sum Q_i,\ i = 1, n \qquad (1)$$

- Q_c – total amount of heat received by the building;
- Q_i – the amount of heat for the i-th room;
- n – is the number of rooms in a building.

Data are received from temperature sensors located indoors and outdoors of a building with a predetermined interval.

D. *Calculation method*

Thus, the task of the assessing boundaries of the change in thermal characteristics is the problem of linear regression:

$$Q_c = \sum K_{ij}(T_i - T_j),\ i = 1, n,\ j = 1, m_i \qquad (2)$$

- Q_c – total amount of heat received by a building;
- K_{ij} – the thermal characteristic of the overlap connecting the spaces i and j;
- T_i – average temperature in the i-th room;
- T_j – the outdoor temperature corresponding to the outside wall with its direction taking into account;
- m_i - the number of external walls of the i-th room;
- n - the number of rooms in a building.

IV. Temperature prediction using a recurrent ANN

Obviously, the classical approach allows only a rough estimate of the room temperature. It is made without taking into account changes of the main dynamic parameters. At the same time, it is the dynamics of weather conditions and heating regime that significantly affect the nature of the change in temperature in the room.

The proposed approach takes into account the dynamics of changes in the state of walls, heating elements, heat agent and the effect of these changes on the room temperature.

We rely on the data from the monitoring of temperature in a building and heating elements, outdoor temperature, wind speed and direction, temperature and flow rate of the heat agent. In this case, the temperature prediction in the rooms of a building can be provided based on of solving the problem of multi-parameter nonlinear regression. Because of the features of the initial data, we believe that the corresponding prediction can be performed using an artificial neural network (ANN).

A. ANN architecture

In the study, we used the architecture of the Gated Recurrent Unit (GRU) [18, 19], which is the modification of the Long-Short-Term Memory (LSTM) network. The features that are the difference between GRU and LSTM are the combination of modules responsible for forgetting and processing the input to a single update gate. In addition, there is no hidden state in the GRU. Based on this, calculations in the GRU are faster, because of fewer parameters and fewer variables to consider.

The network architecture allows to take into account changes in the state of an object over time. The architecture of the GRU is shown in Fig. 1 [20], where the structural parts are:

- x_t – the vector of input values;
- $\tilde{h}_t$ – the candidate vector of the state of the module t;
- h_t – the current state of module t;
- σ, tanh – activation functions.

Vectors z_t, r_t, $\tilde{h}_t$, h_t are to be calculated:

$$z_t = \sigma\,(W_z \cdot [h_{t-1}, x_t] + b_z) \tag{3}$$

$$r_t = \sigma\,(W_r \cdot [h_{t-1}, x_t] + b_r) \tag{4}$$

$$\tilde{h}_t = tanh\,(W_h \cdot [r_t * h_{t-1}, x_t] + b_r) \tag{5}$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t \tag{6}$$

W, U, b – unit parameters.

The update gate (r_t vector) is responsible for retrieving information from a past state. The reset gate (r_z vector) controls the replacement of the module state with a new one or its modification.

B. Architecture adjustment

This ANN allows using the history of observations of the state of an object and the dependence of the predicted temperature on additional factors that are not explicitly accounted in the model to obtain the result:

- effective temperature relative to the direction and speed of the wind for each wall;
- change in heat transfer characteristics depending on the wall temperature.

The use of GRU modifications of the LSTM network is due to the fact that the internal state is acceptable to be considered as the target value of the network.

Input data are tuples that describe the state of the room, heating system and the environment at a certain time stamp.

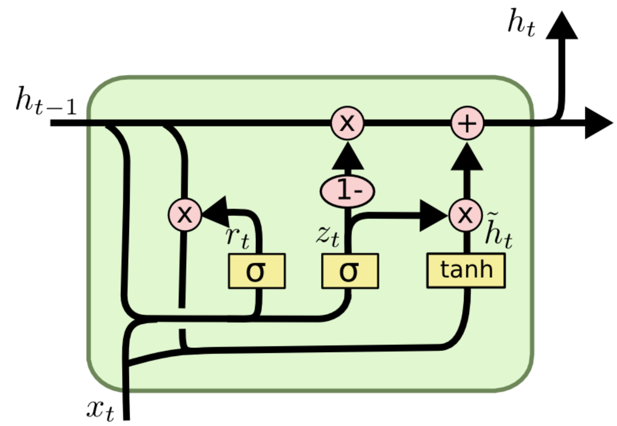

Fig. 1. GRU architecture

The network uses GRU with in and out gates. The number of blocks depends on the required number of time steps, one block per step.

The network state is the current predict value obtained based on already processed data. This value is updated at each subsequent processing of the input data for the next time step.

The updated valve in this task omits situations in which there are minor changes in the state of the room model, while the reset valve responds to sudden changes, for example, weather conditions or a significant decrease in room temperature due to an opened window or malfunctions in the heating system.

The predicted temperature in the corresponding room is determined by the last state of the ANN and is the output of the network.

C. Parameters of the ANN input data

To obtain the predicted temperature at time t, when processing k time steps, the following parameters are taken into account:

- T_{inside} – temperature in a room;
- T_{bat} – temperature of a heating element;
- $T_{outside}$ – outdoor temperature;
- $Wind_s$ – wind speed;
- $Wind_d$ – wind direction;
- T_{in} – temperature of inlet heat agent;
- T_{out} – temperature of outlet heat agent;
- Q – heat agent flow;
- $Wall_d$ – wall direction;
- S_{bat} – area of heating elements;
- V_r – room volume;

- τ – time step;
- k – length of time series.

The parameters $Wall_d$, S_{bat}, V_r are constant and do not change with the next input x_t. The remaining parameters are dynamic and reflect the change in the state of the room over time.

D. *ANN training*

The process of learning a neural network is performed by the backpropagation method. Each input tuple is the state of an object at particular time. The value of the room temperature at the last time step is the target. It is used to assess the accuracy of the ANN in the learning process.

To establish the initial state of the ANN when training the model for the next room, you can use the values that were obtained when working with a room of the same class according to the classification of rooms by deviation from temperature norms [15, 21, 22].

V. COMPUTATIONAL EXPERIMENT

A. *Input data*

To study the effectiveness of the proposed approach, the main emphasis was placed on studying the influence of weather conditions on the dynamics of changes in room temperature.

An important feature is that on generation of the temperature regime, the position of the room is taken into account. To generate the temperatures of the training collection, we used the data of sensors in a separate room with corrections for the corresponding class.

To enlarge original data from sensors we generated sets of pseudo-random indoor temperatures based on initial data. Random outliers reflecting events leading to short-term temperature drops (open windows and / or doors) were included in the sets. Data on wind speed and direction for each time step were obtained from the weather conditions archive. The data generation period is an interval of 1 hour. In fig. 2 is shown the graph of changes in temperature in the room and the environment.

To perform a computational experiment, we used the data generated corresponding to daily measurements in December 2019 with a specified period, total of 744 records.

The temperature of the heat agent for the mentioned period were not changing significantly. The values are at the inlet from 78 °C to 89 °C and at the outlet from 39 °C to 53 °C.

B. *GRU parameters*

To build the solution, a structure was chosen in which the number of indoor units is equal to the number of time steps used for prediction. The internal parameters in the blocks are initialized with pseudo-random numbers with a uniform distribution on the interval [0, 1].

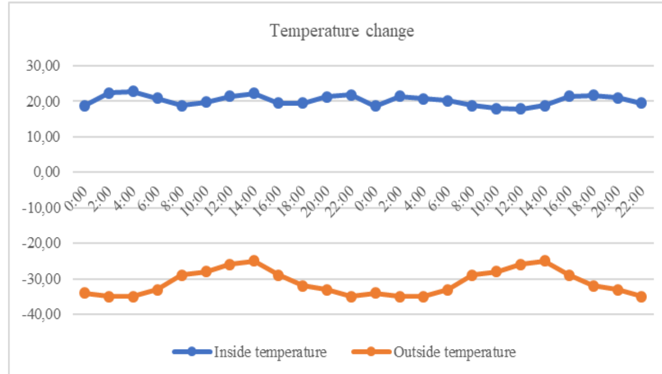

Fig. 2. Temperature change

C. *ANN training*

In order to determine the most effective predictive model, when forming the training and testing samples, sequences of 6, 12, 24, 48, 72, 96, 120 steps in length were selected. The initial data were normalized on the interval [0, 1].

For the training of the predictive model, the following training parameters were fixed:

- the number of epochs – 10000;
- coefficient of learning speed - 0.001;
- number of parameters – 14;
- output dimension – 1.

D. *Prediction*

In the table 1 the standard deviation of the predicted data from the actual temperature measurements for each of the models.

TABLE I. MEAN AND STANDARD DEVIATION OF THE PREDICTED VALUES FROM THE ACTUAL TEMPERATURE MEASUREMENTS

Time series length	Mean temperature, °C	Standard deviation
6	21.2	3,48
12	21.4	3,04
24	21.3	4,96
48	20.9	5,09
72	21.5	5,43
96	20.1	8,08
120	21.3	2,76

According to the results of the computational experiment, the most accurate results were obtained by the model with a time series length of 120. However, a short-term prediction based on only 12 hours produces comparable results in accuracy, which can find its application in certain scenarios.

Significant variation of predicted values for k = 96 is related to a short sharp change in external conditions. It is notable thing that the model showed stability with respect to random emissions of indoor temperature.

VI. Conclusion

According to the results, the effectiveness of the method for predicting temperature in the premises of a public building using ANN is shown. The solution allows to produce modes of intermittent heating in order to decrease overall heat agent consumption in various outdoor conditions. Future work will focus on developing the approach that takes into account the influence of the presence of people in the room on the temperature and humidity.

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