IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received October 6, 2019, accepted October 26, 2019, date of publication October 29, 2019, date of current version November 8, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2950341

An Indoor Temperature Prediction Framework Based on Hierarchical Attention Gated Recurrent Unit Model for Energy Efficient Buildings

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This work was supported in part by the National Natural Science Foundation of China under Grant 61702157, in part by the Postdoctoral Fund of Hebei Province of China under Grant B2017005002, and in part by the Tianjin Technical Expert Project of China under Grant 19JCTPJC51000.

ABSTRACT Indoor temperature is an important criterion for evaluating the operation quality of district heating systems (DHSs) and has a significant impact on improving the energy efficiency of heat exchange station regulation. Accurate prediction of indoor temperature is of great help to the precise control of heating systems. However, due to the thermal inertia and response delay characteristics of heating systems, there is a complex nonlinear relationship between indoor temperature and its many related factors. A hierarchical attention gated recurrent unit (HAGRU) neural network is innovatively proposed for predicting the indoor temperature of energy-saving buildings in which the indoor temperature is optimally regulated based on a newly designed smart on-off valve. The network is divided into two levels of attention model, which can realize the representation of a single influencing factor and the fusion of multiple feature inputs. Detailed simulation results show that the predictive accuracy of the proposed algorithm is 98.4%, which is significantly better than state-of-art algorithms, such as support vector machine (SVM), random forest regression (RFR), decision tree regression (DTR), gradient boosting regression (GBR), recurrent neural network (RNN), long short-term memory (LSTM) and gated recurrent units (GRU). Therefore, the proposed HAGRU algorithm has good nonlinear feature extraction and expression ability. The indoor temperature prediction results are used as feedback input to assist the control strategy of the heat exchanger station, which is conducive to the improvement of energy efficiency. In addition, the optimal selection of hyperparameters of the HAGRU algorithm is also analyzed in detail.

INDEX TERMS Indoor temperature prediction, HAGRU, attention mechanism, energy saving buildings, smart on-off valve.

I. INTRODUCTION

As an important infrastructure and livelihood project in northern China, district heating systems (DHS) have developed rapidly with the process of urbanization [1]. Heating systems consume a large amount of energy and cause serious environmental pollution, so it is urgent to improve energy utilization efficiency under the premise of satisfying users' heating comfort. Indoor temperature is one of the important indexes for evaluating DHS operation quality [2]. The accurate prediction algorithm of indoor temperature in energy-saving buildings is helpful for improving the control strategy of heat exchange stationCs and improving the operating efficiency of the DHS. It is of great significance to realize energy-saving operation under the premise of satisfying the thermal comfort of residential buildings [3]. Indoor temperature is used as the feedback input of the optimal energy-saving regulation of the heat exchanger station to realize the balance between heat demand and production in the heating system on the premise of fully satisfying the heat comfort of residents [4]. However, it is very

The associate editor coordinating the review of this manuscript and approving it for publication was Lei Guo.

difficult to collect each indoor temperature of the residential buildings in real time due to the constraints of economic cost and lack of appropriate sensors. It is well known that indoor temperature is affected by many factors during the heating season, such as meteorological parameters, operation parameters of heat exchanger stations, maintenance structure and thermal inertia of buildings. In addition, due to the thermal heat transfer effect, the indoor temperature between adjacent households will also affect each other. Green heating requires a more accurate indoor temperature prediction algorithm as a solid foundation, especially to improve the accuracy of indoor temperature prediction under the environment of complex multiparameter interactions.

As one of the key technologies of DHS, an accurate prediction algorithm of indoor temperature has important guiding significance for optimized regulation [5]. It has attracted many scholars' attention, and a large number of related studies have been published, which can be mainly classified as the following categories:

A. TRADITIONAL STATISTICAL MODELING METHOD

Aliberti *et al.* [6] proposed an innovative methodology for indoor temperature forecasting based on a nonlinear autoregressive neural network. Gustin *et al.* [7] developed an autoregressive model using exogenous inputs (ARX) to provide reliable short-term forecasts of indoor temperature. Hietaharju *et al.* [8] proposed a novel dynamic model for the temperature inside buildings to improve energy efficiency by providing predictive information on the heat demand, and the average modeling error during a 28 h prediction horizon was constantly below 5%. In Ref [9], [10], a mathematical model for indoor temperature calculation of a building that integrates a combined passive solar system was proposed. Moreno *et al.* [11] proposed a short-term indoor temperature prediction model based on knowledge discovery. Lee *et al.* [12] analyzed the thermal performance of buildings by a performance-based method using indoor temperature patterns. Refs [13], [14] studied the influence of the window-wall ratio on the indoor temperature in rural residential areas.

The inadequacy of traditional algorithms in representing the nonlinear characteristics of heating systems makes it difficult to improve prediction accuracy. Researchers later turned to machine learning to improve the expression of complex features.

B. MACHINE LEARNING

Machine learning, represented by artificial neural networks (ANNs), support vector machines (SVMs), genetic algorithms (GAs), extreme learning machines (ELMs) and other improved models, is a kind of data-driven feature extraction and representation algorithm that has been widely used in various kinds of prediction problems. ANN is an outstanding representative of the traditional machine learning algorithm, which is widely used to establish indoor temperature prediction models [15]–[17]. In Ref [18], a comparative study of ANN models for forecasting the indoor temperature in smart buildings was conducted. Magalhães *et al.* [19], [20] developed models for predicting the daily indoor temperature using an enhanced linear regression and ANN. Zamora-Martínez *et al.* [21] developed a predictive module based on ANN to produce short-term forecasts of indoor temperature and studied the development viability of predictive systems for a totally unknown environment by applying online learning techniques. Zamora-Martínez *et al.* [22] studied the indoor temperature prediction of a house based on ANN and presented the impact on forecasting performance of different covariate combinations. In Ref [23], an improved prediction model based on backpropagation neural networks (BPNN) was established to forecast indoor air temperature and relative humidity in advance. Yu *et al.* [24] evaluated the accuracy of indoor temperature prediction based on a generalized regression neural network (GRNN) algorithm. Li *et al.* [25] presented an indoor temperature prediction control method based on the Elman neural network. Poczęta *et al.* [26] presented the structure optimization genetic algorithm (SOGA) for predicting indoor temperature. Zhang *et al.* [27] proposed an integrated indoor prediction approach that aims to reduce excess heat loss. Dahlblom *et al.* [4] evaluated the principle for feedback control of heating systems based on actual indoor temperature measurements. Yan *et al.* [2] explored the influencing mechanism of outdoor temperature on indoor air temperature in residential buildings with heating systems during the heating season in three northern cities of China. Hagentoft and Kalagasidis [28] presented a convenient analytical model for a building connected to a district heating system that can be used to estimate both the reduction in heating power demand and the discomfort that follows based on the impact on indoor temperature. Wu *et al.* [29] developed a practical CHP-DHS model and multiregional coordinated operation strategy based on predictive control for planning and operating a CHP system. Zenglin *et al.* [30] studied an advanced indoor temperature controller system.

The classic ANN algorithm improves the accuracy of nonlinear feature expression compared with traditional statistical methods, but its shortcomings such as fewer network layers, difficulty in parameter tuning and inadequate prediction accuracy of nonlinear features, are also significant. With the rapid development of artificial intelligence technology, many kinds of prediction algorithms based on deep learning have attracted the attention of scholars [31]–[33]. Romeu *et al.* [34] presented an indoor temperature forecasting model based on pretrained deep neural networks. Candanedo *et al.* [35] studied the indoor temperature reconstruction problem by predicting the missing data from other measured variables using machine-learning techniques.

Deep learning has also been studied in other industrial Internet and Internet of things fields, such as Internet of vehicles [36]–[38] and it's energy management [39], [40], etc., which can usually achieve better accuracy than traditional machine learning algorithms. However, research on room temperature prediction algorithms based on deep learning is still rare. To improve the accuracy of indoor temperature prediction for existing energy-saving buildings, this paper first designs a smart on-off valve and proposes an indoor temperature prediction algorithm based on the HAGRU model. This algorithm provides a higher prediction accuracy of 98.4%, which can significantly improve the control strategy of heat exchange stations and is helpful in realizing green heating with energy savings and consumption reduction.

In general, the main contributions of our paper are demonstrated as follows.

First, a smart on-off valve for existing energy-efficient buildings is proposed, which can realize the independent regulation of indoor temperature and on-demand heating for each household. The hydraulic balance between households can be achieved through on-off regulation.

Second, an indoor temperature prediction algorithm based on HAGRU is proposed, which includes two attention GRU models. The first model realizes the self-attention prediction of a single feature, and the second model realizes the attention prediction of all feature vectors. Compared with existing state-of-the-art algorithms, this proposed algorithm has higher prediction accuracy.

Finally, the neighborhood indoor temperature as the feature input is proposed in the HAGRU algorithm for the first time due to the heat transfer between households in the DHS. The experimental results show that the prediction accuracy of this algorithm is much higher after introducing this feature.

The remainder of this paper is organized as follows: Section II demonstrates the basic principle of the smart on-off valve for energy-saving buildings. Section III presents the data description and feature selection. Section IV introduces the architecture and mathematical model of the proposed HAGRU algorithm in detail. Section V represents the experimental analysis, and performance evaluation Section VI presents the conclusion.

II. BASIC PRINCIPLE OF THE SMART ON-OFF VALVE

The hydraulic imbalance problem of traditional district heating systems leads to different heat acquisition by the households in each building, resulting in thermal imbalance, which makes the indoor temperature of the households near the heat exchange station higher and the indoor temperature of the households far lower. In addition, the imbalance problem also leads to pressure fluctuation in the heating pipe, which greatly restricts the stability of the heating system and reduces energy efficiency. Additionally, the inhomogeneity of indoor temperature greatly reduces the quality of heating, resulting in a high complaint rate. The imbalance problem also increases energy consumption, which makes the goal of green energy saving increasingly difficult to achieve. Therefore, it is urgent to solve the balance problem for the modern SDHS, which is an important basis and technical guarantee for energy saving, emission reduction and on-demand heating.

Considering energy-saving buildings, a wireless smart on-off valve to solve the hydraulic balance between households is designed in this paper. The system schematic diagram is shown in Figure 1, which mainly includes the following:

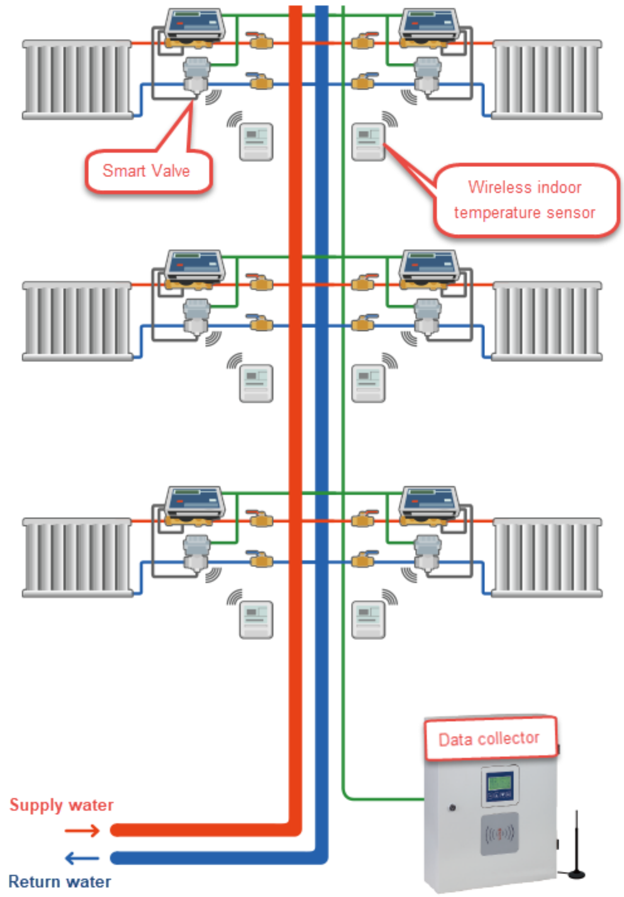

FIGURE 1. Schematic diagram of the indoor temperature control system based on a smart-valve.

1) Each household is equipped with a smart on-off valve, which is shown in **Figure 2**(a). The valve communicates with the indoor temperature sensor through a wireless link and automatically opens or closes the valve intelligently according to the user's indoor temperature setting goal. The smart-valve can realize remote online monitoring and real-time control.

(a) (b)

FIGURE 2. The IoT sensors, (a) smart on-off valve, (b) socket-type wireless indoor temperature sensor.

2) A heat meter for measuring the heat consumed by the household for change management;

3) A wireless indoor temperature sensor based on narrowband IoT (NB-IoT), as shown in **Figure 2**(b), has the shape of a traditional socket, which can realize remote communication with the data center. Additionally, it can cooperate with the smart on-off valve in real time and automatically control the open state of the smart-valve according to the setting target.

The smart on-off valve alleviates the problem of hydraulic balance to a certain extent. However, due to the complexity of the heating system, the indoor temperature of the household is affected by many factors. To optimize the operation parameters of heat exchanger stations, accurate prediction of indoor temperature is still a great challenge. Next, we analyze the influencing parameters of indoor temperature and determine the feature selection for the prediction algorithm.

III. DATA DESCRIPTION AND FEATURE SELECTION

The DHS is a complex nonlinear dynamic system. Energy-saving buildings have good maintenance structure and great thermal inertia; however, from a spatial point of view, heat sources, heat exchanger stations and buildings spread over a wide geographical range, coupled with the different pressures of the pipeline network, lead to different delayed responses of indoor temperature to outdoor temperature change or water supply temperature regulation.

The indoor temperature is one of the core indexes for evaluating the operation quality of the heating system, which mainly includes four related factors:

1) Meteorological parameters: outdoor temperature;

2) Building's thermal characteristics: maintenance structure, energy saving, radiator type (floor or radiator), historical indoor temperature;

3) Operating parameters of the heat exchanger station: first supply temperature, first return temperature, second supply temperature and second return temperature;

4) The indoor temperature of adjacent households: the indoor temperature of four adjacent households;

First, the maintenance structure, radiator performance, thermal inertia and other information of the building are essentially included in the operation history data of the buildings. Based on the data-driven method, we can mine the implicit features from the historical data of indoor temperature. The objective of this paper is to predict the indoor temperature, so we only need to make full use of the indoor temperature historical data, and without the analysis, the maintenance structure and radiator form characteristics of the building separately.

Our team set up a smart heating energy-saving monitoring system in Xingtai City, Hebei province, China, which makes use of many sensors on the supply side. The monitoring data are collected every 20 seconds and stored into the history database every 10 minutes; our designed smart on-off valve and indoor temperature sensors are installed on the user side, and these data are transmitted by the NB-IoT protocol once every 20 minutes. Additionally, the meteorological data parameters and weather forecast are collected from the Internet every 20 seconds and stored into the rational SQL server database every 10 minutes.

Different acquisition frequencies of various parameters lead to different time scales, which greatly affect the convenience of subsequent analysis. Therefore, we need to adjust the sampling frequency of different parameters to the same time scale for the model based on HAGRU. To simplify the analysis, the values of all parameters are scaled to hourly data.

$$\begin{cases} T_{in} = \frac{1}{N}\sum_{i=1}^{N} T_{in,i} & (i = 1, 2, 3) \\ T_O = \frac{1}{N}\sum_{i=1}^{N} T_{O,i} & (i = 1, \ldots, 6) \\ T_{1s} = \frac{1}{N}\sum_{i=1}^{N} T_{1s,i} & (i = 1, \ldots, 6) \\ T_{1r} = \frac{1}{N}\sum_{i=1}^{N} T_{1r,i} & (i = 1, \ldots, 6) \\ T_{2s} = \frac{1}{N}\sum_{i=1}^{N} T_{2s,i} & (i = 1, \ldots, 6) \\ T_{2r} = \frac{1}{N}\sum_{i=1}^{N} T_{2r,i} & (i = 1, \ldots, 6) \end{cases} \tag{1}$$

where

T_{in} represents the hourly indoor temperature (°C);
T_o represents the hourly outdoor temperature (°C);
T_{1s} represents the hourly first supply temperature (°C);
T_{1r} represents the hourly first return temperature (°C);
T_{2s} represents the hourly second supply temperature (°C);
T_{2r} represents the hourly second return temperature (°C);
N represents the sample size per hour.

The variables $T_{in,}T_o,T_{1s}$, T_{1r}, T_{2s}, and T_{2r} represent the single sample values of the corresponding parameters.

After the preprocessing of the original data, we obtain regular hourly statistics, which are shown in **Figure 3**.

As seen in **Figure 3**, the indoor temperature of several households fluctuates within ±1.5°C, and the water supply temperature and backwater temperature fluctuated within ±5°C. The outdoor temperature shows an obvious daily periodicity and a downward trend. The statistical characteristics of the data can be obtained by boxplots, which are shown in **Figure 4**. We studied the relationship between indoor temperature and the influencing factors. The scatter plot between nine factors, and indoor temperature is shown in **Figure 5**. We can see that there is a significant nonlinear relationship between indoor temperature and the related factors, which also creates a great challenge to accurately predicting indoor temperature. Second, we further analyze the correlation between indoor temperature and nine related factors. Because of the intrinsic complexity and large time delay of the heating system, the correlation between the indoor temperature data series and the influencing factors with different time delays should also be studied. In this paper, the Pearson correlation coefficient is used for correlation analysis, which is defined as the quotient of the covariance and standard

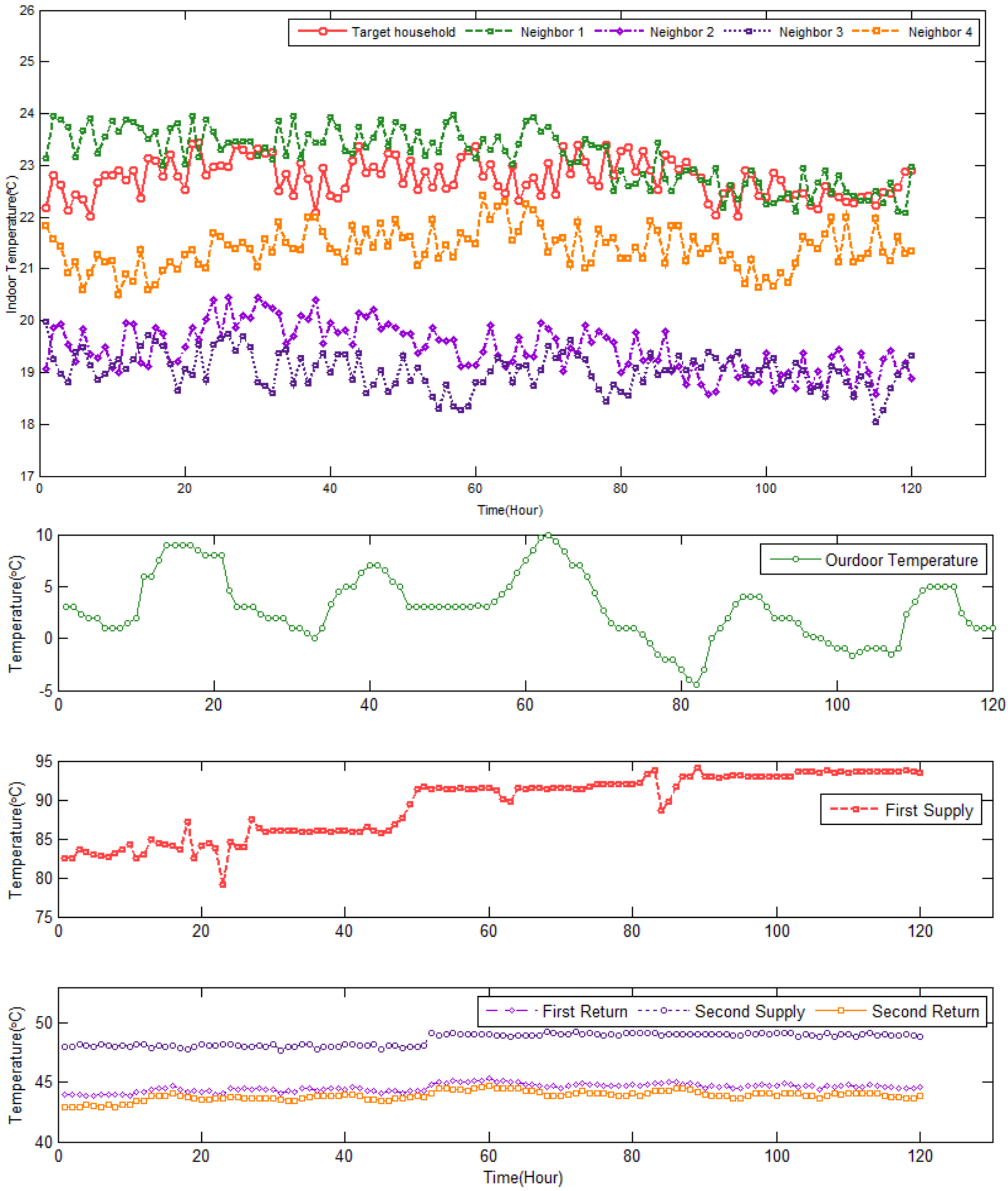

FIGURE 3. **The data curve for original factors.**

deviation between two variables.

$$\rho_{X,Y} = \frac{\mathrm{cov}(X, Y)}{\sigma_X \sigma_Y} = \frac{E\left[(X - \mu_X)(Y - \mu_Y)\right]}{\sigma_X \sigma_Y} \tag{2}$$

where

μ_X and σ_X represent the mean and standard deviation, respectively, for the X sample.

μ_Y and σ_Y represent the mean and standard deviation, respectively, for the Y sample.

In this paper, we study the correlation characteristics of delay from 1 hour to 24 hours. We can see the following information from the results, which is shown in **Figure 6**:

1) The correlation between indoor temperature and its historical data is the greatest. Even when the time delay is 24 hours, the correlation between the indoor temperature and its historical data is more than 0.8, which is also caused by the thermal inertia of energy-saving buildings.

2) In addition, the negative correlation value between indoor temperature and first supply temperature

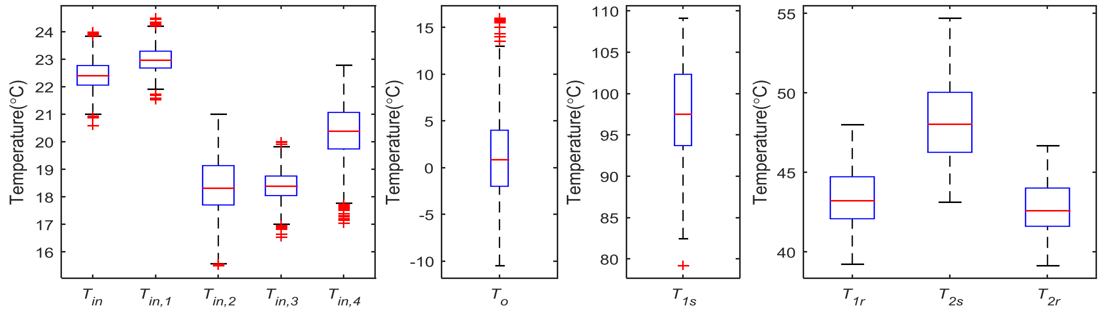

FIGURE 4. The boxplot of various historical data parameters (T_{in}: the indoor temperature of the middle household; $T_{in,1}$, $T_{in,2}$, $T_{in,3}$, and $T_{in,4}$: the indoor temperatures of four neighbors; T_o: the outdoor temperature; T_{1s}: the first supply temperature; T_{1r}: the first return temperature; T_{2s}: the second supply temperature; T_{2r}: the second return temperature).

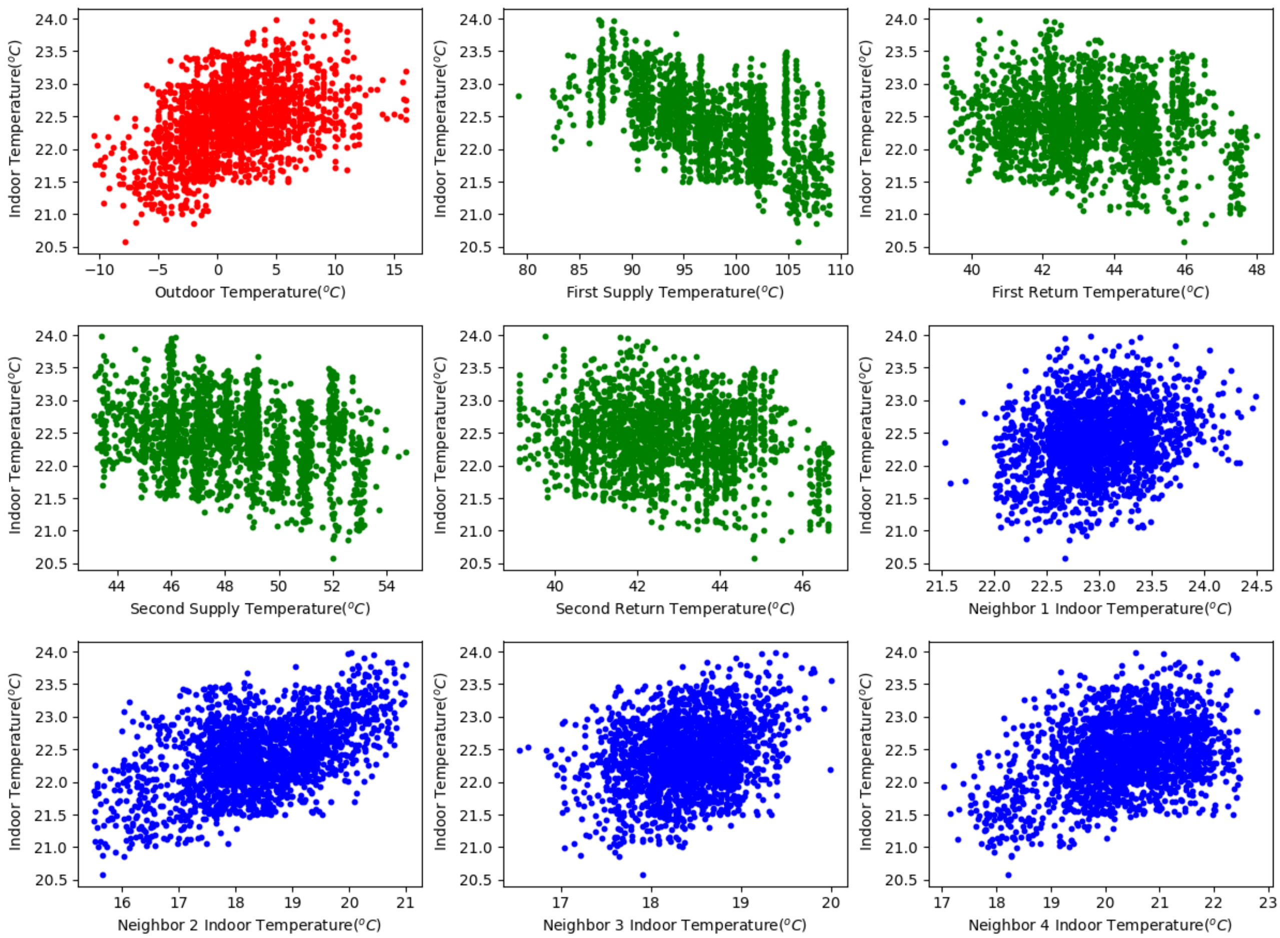

FIGURE 5. Scatter diagram of indoor temperature vs. the related factors.

exceeds −0.6. Correspondingly, the correlation value between the first return temperature and the indoor temperature is generally approximately −0.1, which indicates that the contribution of the first supply temperature to the indoor temperature is greater than the first return temperature. Similarly, the contribution of the second supply temperature and return temperature to the indoor temperature is also smaller.

3) There is a positive correlation between outdoor temperature and indoor temperature. When the outdoor temperature decreases, the indoor temperature of the household decreases. In contrast, when the outdoor temperature increases, the indoor temperature of the household increases.

4) Because of the heat transfer between buildings, the indoor temperature of the four neighboring households has a significant impact on the indoor temperature of the

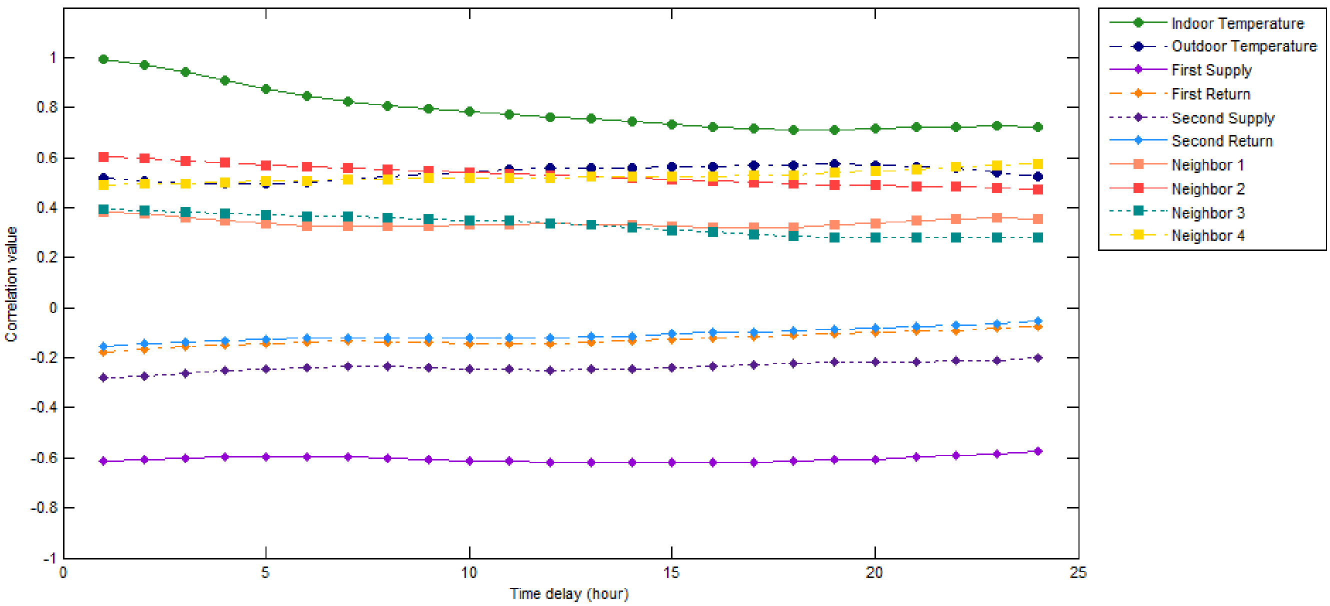

FIGURE 6. The correlation value between the indoor temperature and other factors with different time delays.

middle household. If the four neighboring households are heating normally, the indoor temperature of the household is more comfortable.

IV. METHODOLOGY AND ANALYSIS

A. THE ARCHITECTURE OF THE PROPOSED INDOOR TEMPERATURE PREDICTION ALGORITHM BASED ON HAGRU

As demonstrated in the previous section, the indoor temperature is affected by many related factors in DHS, such as the length of the pipeline from the heat exchange station to each building, and the maintenance structure and thermal inertia of buildings are also different, which makes the response of indoor temperature to other factors a complex nonlinear mapping relationship. Traditional prediction methods lack the ability to remember long-term features, so it is difficult to improve the prediction accuracy of such complex nonlinear problems. Fortunately, with the recent development of artificial intelligence technology, RNNs can obtain high-level feature representation of long time series and realize higher prediction accuracy. However, RNNs have the problem of vanishing and exploding gradient during reverse propagation: the gradient decreases gradually as time passes, the layer that receives small gradient updates stops learning, and the RNN forgets the knowledge it learned in a long sequence, so it has only short-term memory. In contrast, the exploding gradient problem leads to a gradual increase in the gradient, which leads to the oscillation and instability of the network model. LSTM introduces three gates, the forget gate, input gate and output gate, which can control the retention or discarding of information in the sequence, so it can obtain more long-term feature information than RNNs. GRU is simplified on the basis of LSTM using only two gated structures, a reset gate and an update gate, which reduces the computational complexity but has an equivalent performance with LSTM.

Therefore, this paper proposes an improved GRU-based indoor temperature prediction algorithm, which mainly includes the following:

1) adding an attention mechanism;
2) increasing the number of GRU layers.

The architecture and principles of the GRU model are shown in **Figure 7**. The forward calculation formula for GRU can be modeled as follows:

$$z_t = \text{sigmoid}\left(W_z \cdot [h_{t-1}, x_t]\right) \tag{3}$$
$$r_t = \text{sigmoid}\left(W_r \cdot [h_{t-1}, x_t]\right) \tag{4}$$
$$\tilde{h}_t = \tanh\left(W_h \cdot [r_t \odot h_{t-1}, x_t]\right) \tag{5}$$
$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \tag{6}$$
$$y_t = \text{sigmoid}\left(W_o \cdot h_t\right) \tag{7}$$

where

$\odot$ represents the dot product of a vector;
z_t represents the update gate;
r_t represents the reset gate;
y_t represents the output of the GRU at time t.

The nonlinear mapping functions sigmoid and tanh can be defined as follows:

$$\text{sigmoid}(x) = \frac{1}{1 + e^{-x}} \tag{8}$$
$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{9}$$

We assume that for time t, the output of the GRU is $\hat{y}_t$, the input is x_t, and the state at the previous time is S_{t-1}.

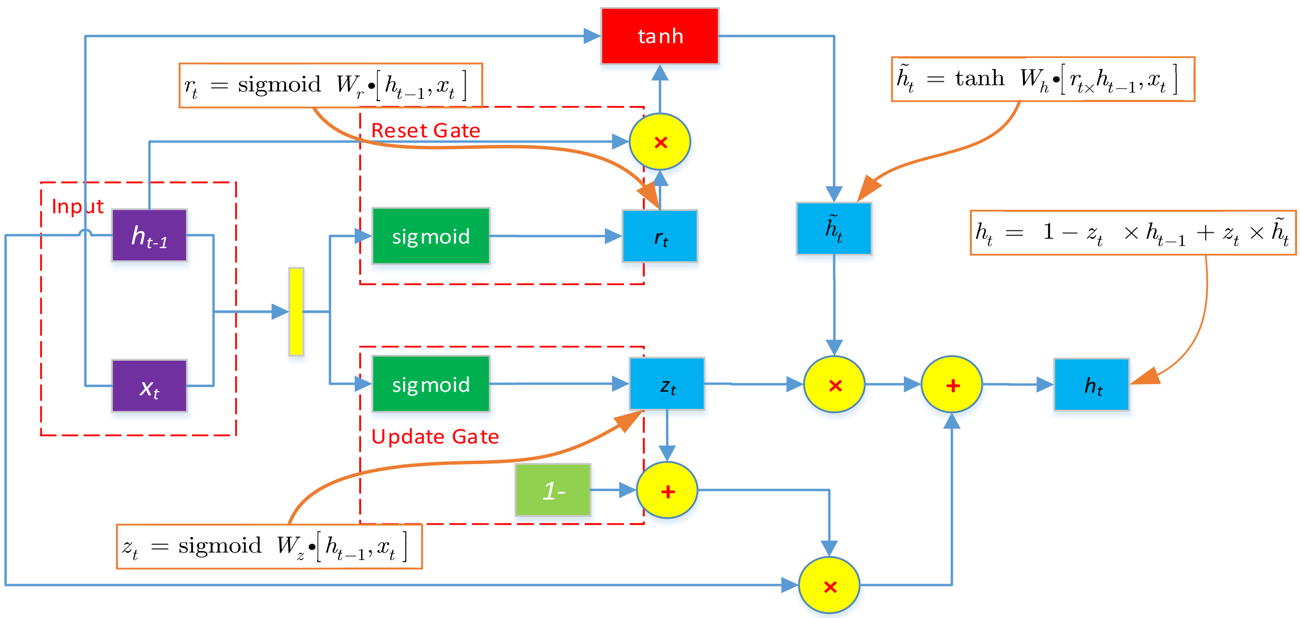

FIGURE 7. The architecture and the principle of GRU algorithm.

The backpropagation gradient calculation process of GRU mainly includes the following steps:

$$z_t = \text{sigmoid}\left(U_z x_t + W_z s_{t-1} + b_z\right) \tag{10}$$

$$r_t = \text{sigmoid}\left(U_r x_t + W_r s_{t-1} + b_r\right) \tag{11}$$

$$h_t = \tanh\left(U_h x_t + W_h s_{t-1} \odot r_t + b_h\right) \tag{12}$$

$$s_t = (1 - z_t) \odot h_t + z_t \odot s_{t-1} \tag{13}$$

$$\hat{y}_t = \text{softmax}\left(V s_t + b_v\right) \tag{14}$$

If the cross-entropy loss function is adopted, then the loss at time t is:

$$L_t = \sum_t \left(-y_t \odot \log\left(\hat{y}_t\right)\right) \tag{15}$$

The GRU can imitate the memory function of the brain when processing historical heating data. The output of its network model depends on the current input and the historical output, but it cannot distinguish the contribution of these characteristic data to the accuracy of indoor temperature prediction. Therefore, an attention mechanism is introduced into the GRU-based indoor temperature prediction algorithm. As the name implies, the attention mechanism is a unique signal processing mechanism of the human brain. The human brain scans the whole image quickly to obtain the focus area and then focuses on this area to obtain the main details of the target, ignoring other unimportant information. This is the ability of human beings to quickly screen out high-value information from massive data in long-term evolution, which greatly improves the processing efficiency and accuracy of visual information in the brain.

Similar to the selective visual attention mechanism of human beings, the attention mechanism of the AI algorithm is essential for quickly selecting more critical information for the current target from the input of many features, which is the core idea of the attention model. The attention mechanism is represented by weighted summation in mathematical form and can be understood as a similarity measure in the physical sense. Because of the different thermal inertia of buildings in the heating system and the various lengths of the pipeline from the heat exchange station, the response delay of indoor temperature is different, so the influencing degree of each part of the historical heating data on indoor temperature prediction is also different. The attention mechanism assigns different weights to each part of the time series related to the input factors. Its calculation method is based on the output sequence.

This paper proposes an indoor temperature prediction algorithm based on HAGRU, which is shown in **Figure 8**. It has two AGRU models based on the encoder-decoder. The bottom AGRU is a self-attention model that is used to predict the individually-related factors. The top AGRU of the fusion attention model combines all the relevant factors to predict future change in indoor temperature. The model assumes that the current decoder output is Y_t. The hidden layer on the decoder outputs is S_{t-1} at the previous time. The model outputs h_j with the hidden layer at each time of the encoder. The result calculated by the f_{att} operation is transformed into probability by *softmax*, which is the attention weight a we need. The new expression C of the input sequence is calculated as part of the decoder's current input by summing the weights of input with weight a, and Y_t is generated.

For related K d-dimensional features: h_i $(i = 1, 2 \ldots k)$, each feature has a different influence on indoor temperature prediction. The attention mechanism weight a_i is introduced

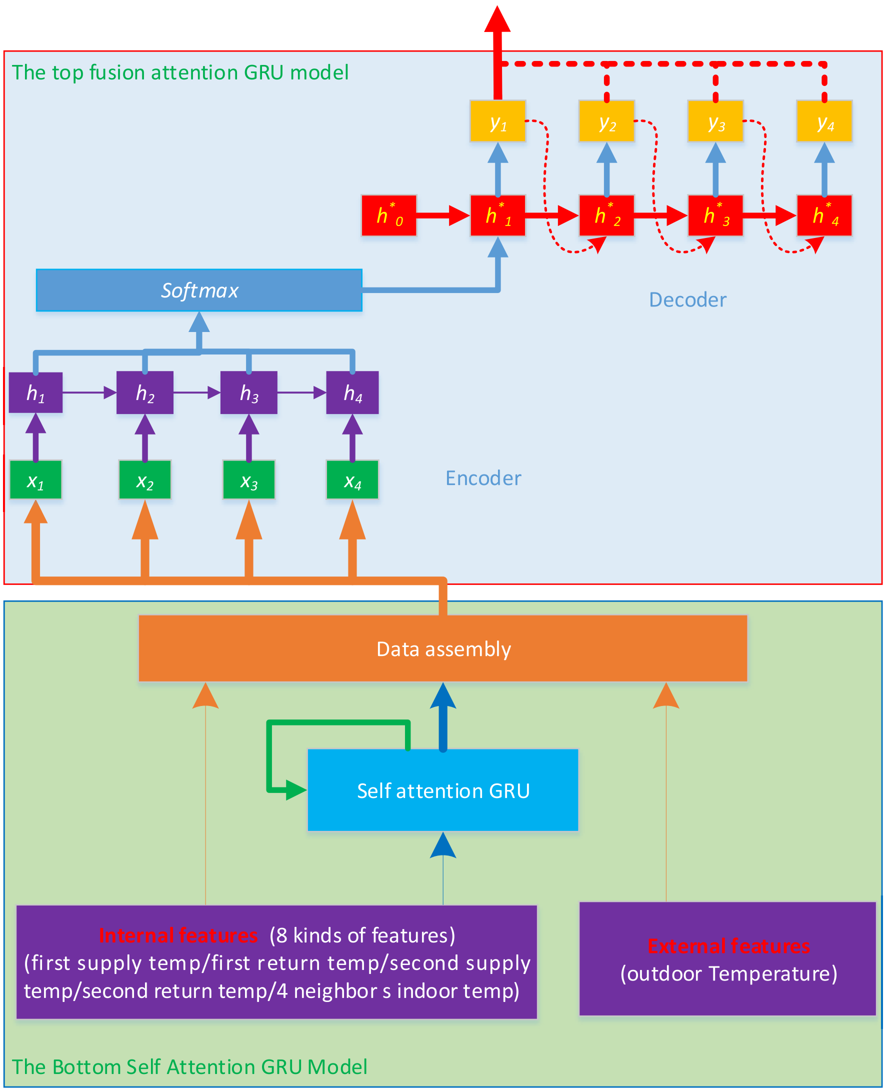

FIGURE 8. **The architecture of HAGRU for indoor temperature prediction.**

to integrate K vectors weighted average into a d-dimensional vector h^*, i.e.,

$$h^* = \sum_{i=1}^{k} a_i h_i \tag{16}$$

The steps for estimating the attention mechanism coefficient a_i are described as follows:

1) Design an evaluation function f_{att} and calculate a score S_i for each h_i according to the correlation degree between h_i and the attention vector. The larger the correlation value is, the larger the S_i is.

$$s_i = f_{att}(h_i) \tag{17}$$

2) For the K score S_i $(i - 1, 2 \ldots k)$, the final weight a_i is obtained by using the *softmax* function:

$$\begin{aligned} a_i &= \text{softmax}(s_i) \\ &= \frac{e^{s_i}}{\sum_{i=1}^{k} e^{s_i}} \end{aligned} \tag{18}$$

For the indoor temperature prediction algorithm based on HAGRU, the bottom self-attention focuses on h_i of the corresponding parameters individually, while the top attention focuses on the input vectors of all parameters. The evaluation function f_{att} is designed as follows:

$$\begin{aligned} s_i &= f_{att}(h_i) \\ &= activation\left(W^T h_i + b\right) \end{aligned} \tag{19}$$

where $W \in R^d$, $b \in R$, $si \in R$, and there are two types of *activation* functions: *tanh* and *ReLU*.

B. THE MATHEMATICAL MODEL OF INDOOR TEMPERATURE PREDICTION BASED ON HAGRU

The flowchart of the indoor temperature prediction algorithm based on HAGRU is shown in **Figure 9**. The bottom self-attention can be demonstrated as follows:

$$X_t = f_1(X_{t-1}, X_{t-2}, \ldots, X_1, X_0) \tag{20}$$

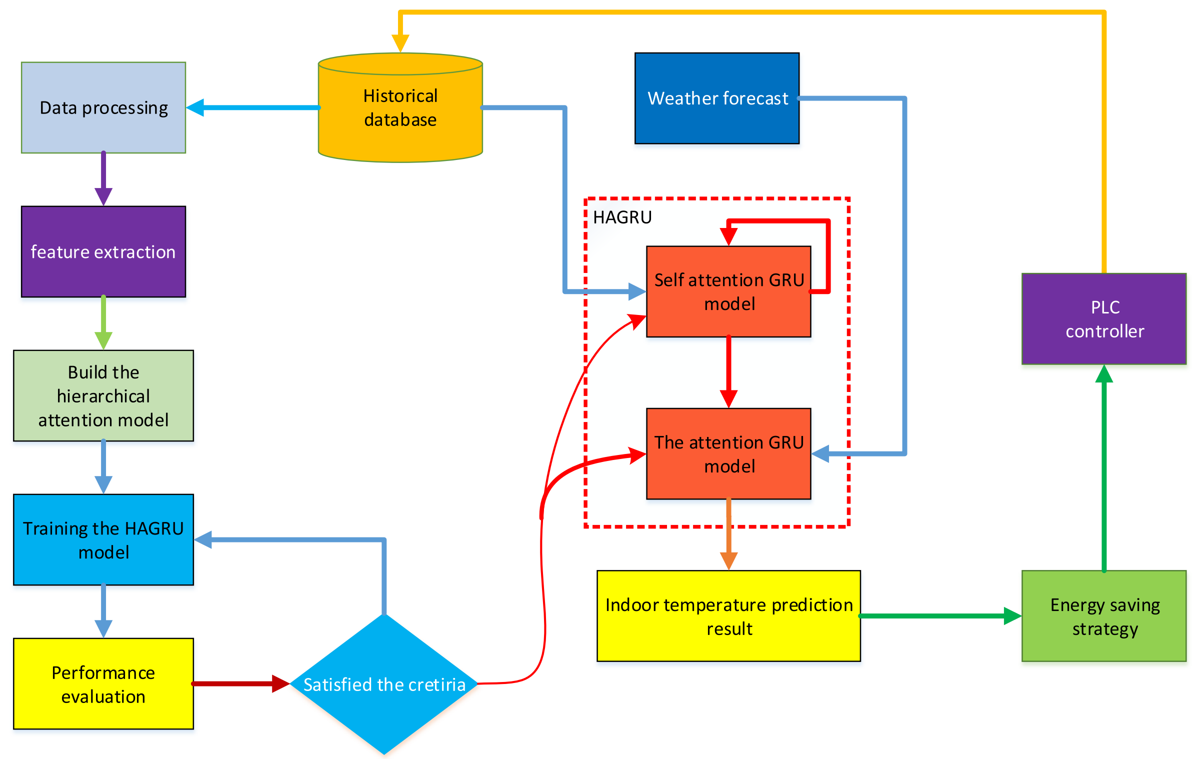

FIGURE 9. The flowchart of the indoor temperature prediction algorithm based on HAGRU.

where

X_t represents each feature value of time t;

X_{t-i} $(i = 0, \ldots t)$ represents each feature value of time *t-i;*

f_1 represents the bottom self-attention function;

According to the feature analysis of the previous section, the input of the HAGRU-based indoor temperature prediction algorithm in this paper includes nine features. The mathematical model of the top fusion AGRU algorithm can be expressed as follows:

$$T_{in}^{t} = f_2\left(T_{in}^{t-\mathrm{i}}, T_{1s}^{t-\mathrm{i}}, T_{1r}^{t-i}, T_{2s}^{t-\mathrm{i}}, T_{2r}^{t-i}, T_{o}^{t-i}, T_{o}^{t}, T_{in,j}^{t-i}\right) \quad (\text{where}, j = 1..4) \tag{21}$$

where

f represents the nonlinear map between the indoor temperature and related factors.

T_{in}^{t} represents the indoor temperature at t-time needs to be predicted.

T_{in}^{t-i} $(i = 1, 2, \ldots, n)$ represents a total of n historical data of indoor temperatures from time *t-1* to *t-n*;

T_{1s}^{t-i} $(i = 1, 2, \ldots n)$ represents a total of n historical data of the first supply temperature collected by the heat exchange station belonging to the household from time*t-1* to *t-n*.

T_{1r}^{t-i} $(i = 1, 2, \ldots n)$ represents a total of n historical data of first return temperatures collected by the heat exchange station belonging to the household from time *t-1* to *t-n*.

T_{2s}^{t-i} $(i = 1, 2, \ldots n)$ represents a total of n historical data of the second supply temperatures collected by the heat exchange station belonging to the household from time *t-1* to *t-n*.

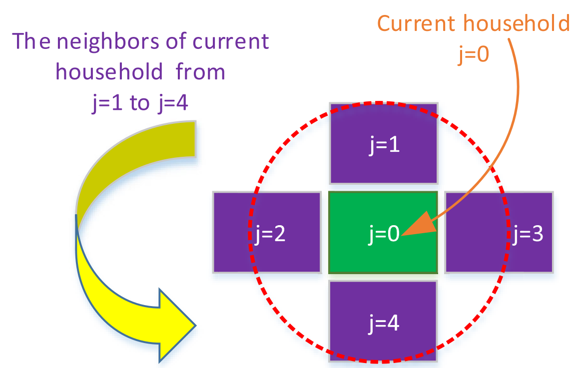

FIGURE 10. Diagram of the neighborhood of the current household.

TABLE 1. The optimal parameter selection of bottom-level self-attention GRU for the indoor temperature prediction algorithm.

Parameters	Value	Description
Learning rate	0.001	the value of learning rate
Hidden unit	50	the number of hidden cells
Step size	10	the value of the time step
Batch size	10	the value of the batch size
Iteration number	200	the number of iterations

T_{2r}^{t-i} $(i = 1, 2, \ldots n)$ represents a total of n historical data of second return temperatures collected by the heat exchange station belonging to the household from time *t-1* to *t-n*.

T_{o}^{t-i} $(i = 1, 2, \ldots n)$ represents a total of n historical outdoor temperatures collected by weather forecasting systems from time *t-1* to *t-n*;

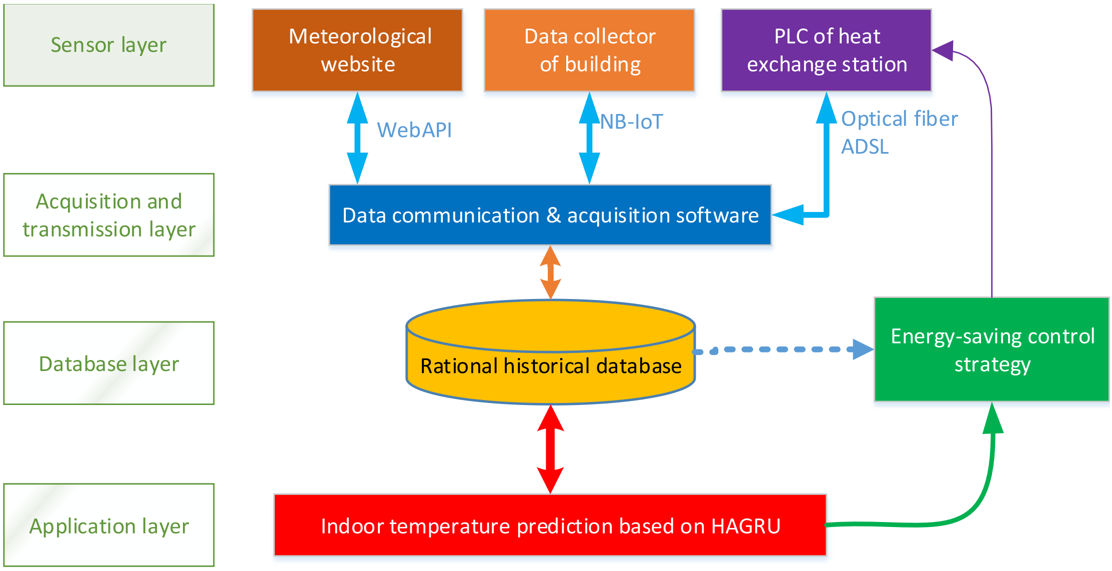

FIGURE 11. The architecture of the system.

TABLE 2. Comparisons of different parameters for the indoor temperature prediction algorithm based on AGRU.

Initial setting	Parameter	Value	Train RMSE	Train MAE	Train MAPE	Test RMSE	Test MAE	Test MAPE
hide_unit=20 time_step = 5 batch_size = 20 iter_count = 200	learn_rate	0.0001	0.346	0.267	0.014	0.746	0.568	0.028
		0.0006	0.452	0.349	0.018	0.554	0.467	0.023
		0.001	0.362	0.268	0.014	0.612	0.498	0.025
		0.002	0.300	0.233	0.012	0.804	0.636	0.032
		0.003	0.308	0.231	0.012	0.680	0.558	0.028
learn_rate=0.001 hide_unit=20 time_step = 5 iter_count = 200	batch_size	5	0.351	0.269	0.014	0.661	0.563	0.028
		10	0.417	0.316	0.016	0.596	0.493	0.024
		12	0.403	0.309	0.016	0.599	0.494	0.025
		15	0.438	0.335	0.017	0.781	0.646	0.032
		20	0.452	0.349	0.018	0.554	0.467	0.023
learn_rate=0.001 hide_unit=20 batch_size=20 iter_count = 200	time_step	7	0.412	0.311	0.016	0.637	0.535	0.027
		10	0.445	0.342	0.017	0.815	0.645	0.032
		12	0.425	0.319	0.016	0.645	0.523	0.026
		15	0.375	0.283	0.014	0.696	0.577	0.029
		20	0.359	0.268	0.014	0.598	0.478	0.024
learn_rate=0.001 time_step=20 batch_size=20 iter_count = 200	hide_unit	5	0.749	0.597	0.030	0.433	0.335	0.017
		7	0.646	0.509	0.026	0.546	0.418	0.021
		10	0.592	0.452	0.023	0.488	0.380	0.019
		12	0.515	0.393	0.020	0.615	0.497	0.025
		15	0.439	0.335	0.017	0.585	0.460	0.023

T_o^t represents the outdoor temperature at t-time predicted by the weather forecast.

$T_{in,j}^{t-i}$ $(i = 1, 2, \ldots, n, j = 1, 2, 3, 4)$ represents a total of n historical indoor temperature data for the jth neighbor of the current household from t-1 to t-n. For simplicity, if the current household number is $j = 0$, the number of the four adjacent households in the apartment will be from $j = 1$ to $j = 4$, as shown in **Figure 10**.

C. MEASURES TO AVOID OVERFITTING

To make the HAGRU algorithm have the best generalization performance and avoid overfitting, a batch normalization method is adopted in this paper. Because the input data are standardized in the preprocessing of the indoor temperature prediction algorithm with the adjustment of network parameters, the input data of the next layer is constantly changing, so the training of each layer needs to constantly change to adapt to this new data distribution, which makes the training difficult to converge. The batch normalization algorithm normalizes the input of each layer to ensure that the input data are stable to achieve the purpose of accelerating training.

V. EXPERIMENTS AND DISCUSSION

A. SYSTEM BACKGROUND AND SYSTEM ARCHITECTURE

Our team built a complete SDHS platform in Xingtai City, northern China, which includes the control of heat exchange stations on the supply side and the smart on-off valve subsystem on the demand side. The smart on-off valve system was installed in energy-saving buildings in several communities. Its main purpose is to provide feedback input for energy-saving regulation of heat exchanger stations.

Because of the abnormal data caused by equipment faults and electromagnetic interference in the heating field, we used the Kalman filtering algorithm to preprocess the data, which reduces the influence of random interference while eliminating abnormal values.

The system architecture designed in this paper is shown in **Figure 11**. It mainly includes four layers, the sensor layer, acquisition and transmission layer, database layer and application layer. A large number of sensors were installed in heat exchanger stations and households of heating systems, which belong to the sensor layer. Data acquisition software was responsible for real-time data acquisition, transmission, parsing and storage of the system, which belongs to the acquisition and transmission layer. The database layer mainly refers to relational databases, such as the SQL server or MySQL, which are in charge of the persistence of historical data. The prediction algorithm of indoor temperature based on HAGRU is located in the application layer, and the generation of an energy-saving control strategy is also the main content of the application layer.

B. DIVISION OF EXPERIMENTAL DATA

A cross-validation method was used to verify the performance of the proposed HAGRU algorithm. In the subsequent experiment, the dataset was split into three parts: a training dataset (70%), validation dataset (20%), and a testing dataset (10%). In actual forecasting scenarios, due to the time length of hourly weather forecasting, we usually used the HAGRU algorithm to predict indoor temperature from 24 hours to 168 hours, so the remaining data were used for training and validation.

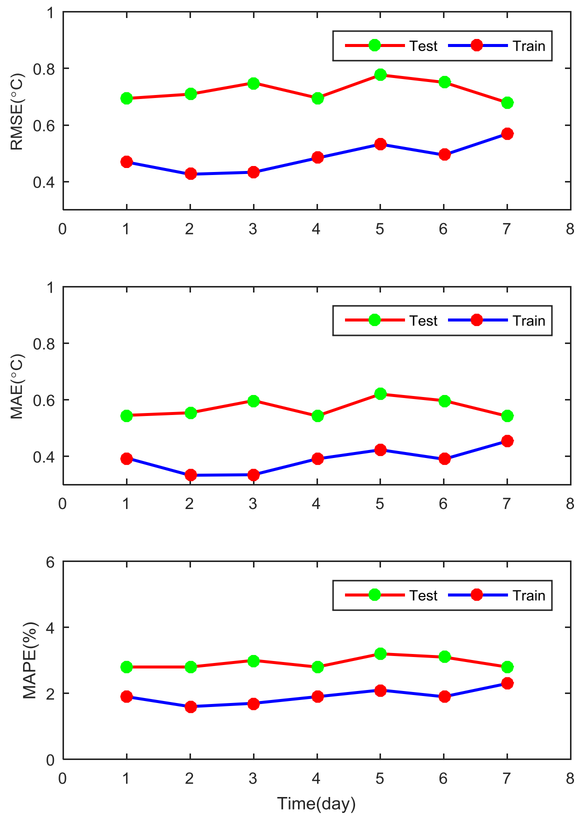

FIGURE 12. The performance of indoor temperature prediction based on the HAGRU algorithm for different prediction time horizons.

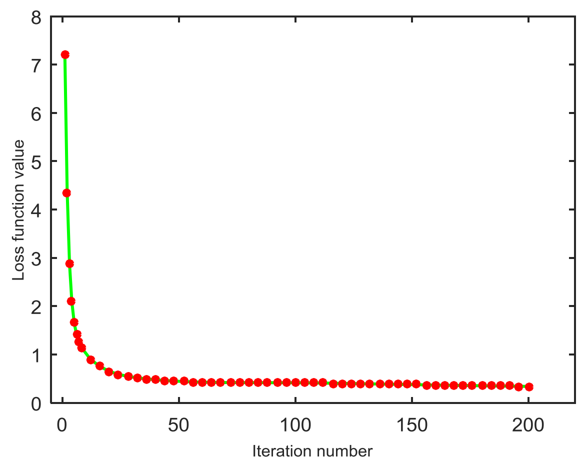

FIGURE 13. The loss function curve of the iteration process for HAGRU.

C. PERFORMANCE EVALUATION

The eight parameters, i.e., first supply temperature, first return temperature, second supply temperature, second return temperature and indoor temperature of four neighbors, were collected and stored in the database regularly by the DHS. The relevant 8 factors needed to generate the next prediction based on the self-attention GRU in advance, while the outdoor temperature data was obtained by weather forecasting for the

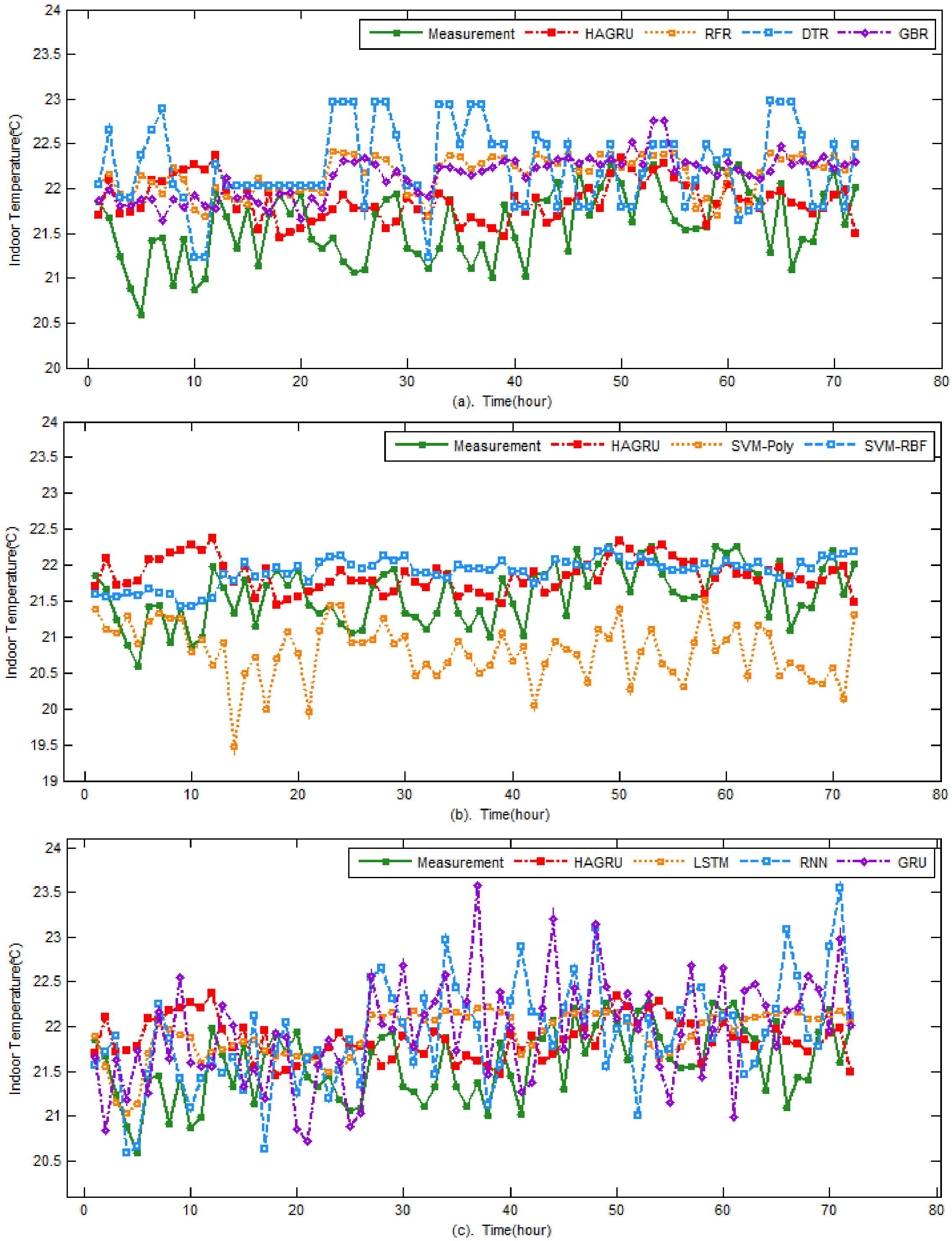

FIGURE 14. The performance comparisons between the proposed HAGRU algorithm and state-of-the-art algorithms.

next seven days or more. Therefore, the HAGRU algorithm uses a two-layer AGRU model: the bottom self-AGRU model to predict these eight parameters and then sends the prediction results to the top fusion AGRU model. Additionally, the outdoor temperature was directly sent to the top AGRU model.

The optimum parameters of the bottom self-attention GRU model are shown in Table 1. Because this self-attention GRU model only focuses on one relevant factor at a time, the optimal selection of hyperparameters of the self-attention GRU model was not analyzed in detail in this paper.

Thus, the fusion attention GRU model is the focus of this paper, and the main hyperparameters include the learning rate, hidden unit, step size, batch size and iteration number. In this paper, their initial values are selected from the same parameter values shown in Table 1, and the grid method is used to search for the optimal value of each parameter.

Based on the three evaluation indexes, *RMSE, MAE* and *MAPE*, Table 2 gives the performance statistics of AGRU under different values of the algorithm's hyperparameters in detail. As seen from the Table 2, when the learning rate was 0.0006, the *MAPE* index of the AGRU algorithm reached a minimum of 2.3% in the testing stage, and *RMSE* and *MAE* were also the minima. Similarly, when the batch size was 20, the AGRU algorithm reached the minimum value for the three evaluation criteria in the test process, and the optimal value of each parameter was determined one by one. All preferred values of the AGRU parameters are shown in Table 3.

TABLE 3. The final parameter selection for the indoor temperature prediction algorithm based on AGRU.

Name	Value	Description
Learning rate	0.0005	the value of learning rate
Hidden unit	15	the number of hidden cells
Step size	10	the value of the time step
Batch size	25	the value of the batch size
Iteration number	150	the number of iterations

In the training and testing process, the performance of the indoor temperature prediction algorithm based on HAGRU for different prediction time lengths with evaluation criteria such as *RMSE, MAE,* and *MAPE* are shown in **FIGURE 12**. The accuracy of the HAGRU algorithm in the training process was better than that in the testing stage, and the prediction accuracies in the interval from 24 hours to 168 hours were all better than 4%. Thus, this HAGRU algorithm has low sensitivity to prediction time lengths, i.e., it has good stability.

The evolution curve of the loss function of the HAGRU algorithm in the training process is shown in Figure 13. As the number of iterations increased, the gradient of the loss function decreased rapidly, and the algorithm approximated the local optimum quickly in the initial stage. When the number of iterations increased to approximately 100, the renewal amplitude of the loss function decreased, and a fine search was carried out near the optimal value of the solution space, which shows that the optimization efficiency of the proposed algorithm is very high, and the intrinsic characteristics of the data can be obtained in a relatively short time.

D. COMPARISONS WITH OTHER ALGORITHMS

To evaluate the performance of the indoor temperature prediction algorithm based on HAGRU proposed in this paper, the comparisons between the proposed HAGRU algorithm and the state-of-the-art algorithms such as SVM-poly, SVM-RBF, RFR, DTR, GBR, RNN, LSTM and GRU, were conducted in detail. For simplicity, the predicted length of time for indoor temperature was 72 hours. The performance results with the *RMSE, MAE*, and *MAPE* indicators are shown in Table 4. We can see that the performance of the HAGRU algorithm outperformed other algorithms and that the *MAPE* index reached the smallest value of 1.6%.

TABLE 4. Comparisons of indoor temperature prediction performance with other state-of-art algorithms.

Algorithms	RMSE	MAE	MAPE
SVM(poly)	0.966	0.816	0.037
SVM(RBF)	0.558	0.451	0.022
RFR	0.735	0.635	0.029
DTR	0.824	0.703	0.033
GBR	0.804	0.707	0.034
RNN	0.541	0.446	0.025
LSTM	0.528	0.433	0.024
GRU	0.516	0.422	0.021
HAGRU	0.458	0.372	0.016

The predicted indoor temperature curves of HAGRU and other algorithms are shown in Figure 14. We can learn from Figure 14 that the prediction accuracy of the indoor temperature prediction algorithm based on HAGRU is better than that of other algorithms.

VI. CONCLUSION

Due to the complex nonlinear dynamic characteristics of district heating system and various influencing factors, it is a challenging task to accurately predict the indoor temperature of energy-saving buildings with smart on-off valves. In order to obtain the multi-scale and time delay nonlinear feature representation of indoor temperature, an indoor temperature prediction framework based on HAGRU is proposed in this paper. The algorithm has two-level GRU models. At the same time, the attention mechanism is designed and introduced to automatically obtain the influence weights of the data at different historical moments on the future indoor temperature, which can further improve the prediction accuracy of indoor temperature and provide more accurate feedback input for the optimization and regulation strategy of heat exchange station. Compared with state-of-the-art algorithms, such as SVM-poly, SVM-RBF, RFR, DTR, GBR, RNN, LSTM and GRU, the proposed HAGRU prediction framework has the best MAPE accuracy of 98.4%. In addition, this paper analyzes the parameters of the HAGRU algorithm in detail and uses batch normalization to avoid overfitting problems.

In the next step, we will expand from a household to a building or community to study the indoor temperature prediction algorithm for collaborative control among multiple heat exchanger stations.

ACKNOWLEDGMENT

The authors would like to thank the Associate Editor and anonymous reviewers for their valuable comments that have helped improving the presentation of this paper.

Nomenclature

AGRU	attention gated recurrent unit
AI	artificial intelligence
ANN	artificial neural networks
ARX	Autoregressive using exogenous inputs
BPNN	back propagation neural networks
CHP	Combined heat and power
DHS	district heating system
ELM	Extreme Learning Machines
GA	Generic algorithm
GBR	Gradient Boosting Regression
GRNN	Generalized Regression Neural Network
GRU	Gated Recurrent Unit
HAGRU	Hierarchical Attention Gated Recurrent Unit
IoT	Internet of Things
LSTM	Long Short Term Memory
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MLR	Multiple Linear Regression
NB-IoT	Narrow Band Internet of Things
RFR	Random Forest Regression
RMSE	Root-Mean-Square Error
RNN	Recurrent Neural Networks
SDHS	Smart District Heating System
SOGA	Structure Optimization Genetic Algorithm
SVM	Support Vector Machine

REFERENCES

[1] X. Chen, L. Wang, L. Tong, S. Sun, X. Yue, L. Zheng, and S. Yin, "Energy saving and emission reduction of China's urban district heating," *Energy Policy*, vol. 55, pp. 677–682, Apr. 2013.

[2] H. Yan, L. Yang, W. Zheng, and D. Li, "Influence of outdoor temperature on the indoor environment and thermal adaptation in Chinese residential buildings during the heating season," *Energy Buildings*, vol. 116, pp. 133–140, Mar. 2016.

[3] J. Zhao, Y. Wu, and N. Zhu, "Check and evaluation system on heat metering and energy efficiency retrofit of existing residential buildings in northern heating areas of China based on multi-index comprehensive evaluation method," *Energy Policy*, vol. 37, pp. 2124–2130, Jun. 2009.

[4] M. Dahlblom, B. Nordquist, and L. Jensen, "Evaluation of a feedback control method for hydronic heating systems based on indoor temperature measurements," *Energy Buildings*, vol. 166, pp. 23–34, May 2018.

[5] N. Henry, A. A. Dahlan, A. M. Nasib, A. A. Aziz, and Sumeru, "Indoor temperature control and energy saving potential of split unit air conditioning system using fuzzy logic controller," *IAENG Int. J. Comput. Sci.*, vol. 43, pp. 402–405, Dec. 2016.

[6] A. Aliberti, F. M. Ugliotti, L. Bottaccioli, G. Cirrincione, A. Osello, E. Patti, A. Acquaviva, and E. Macii, "Indoor air-temperature forecast for energy-efficient management in smart buildings," in *Proc. IEEE Int. Conf. Environ. Elect. Eng.*, Jun. 2018, pp. 1–6.

[7] M. Gustin, R. S. McLeod, and K. J. Lomas, "Forecasting indoor temperatures during heatwaves using time series models," *Building Environ.*, vol. 143, pp. 727–739, Oct. 2018.

[8] P. Hietaharju, M. Ruusunen, and K. Leiviskä, "A dynamic model for indoor temperature prediction in buildings," *Energies*, vol. 11, no. 6, p. 1477, Jun. 2018.

[9] A. V. Djordjević, J. M. Radosavljević, A. V. Vukadinović, J. R. M. Nikolić, and I. S. B. Protić, "Estimation of indoor temperature for a passive solar building with a combined passive solar system," *J. Energy Eng.*, vol. 143, no. 4, Feb. 2017, Art. no. 04017008.

[10] J. M. Radosavljević, M. R. Lambic, E. R. Mihajlovic, and A. V. Djordjevic, "Estimation of indoor temperature for a direct-gain passive solar building," *J. Energy Eng.*, vol. 140, Mar. 2014, Art. no. 04013007.

[11] M. V. Moreno, A. F. Skarmeta, A. Venturi, M. Schmidt, and A. Schuelke, "Context sensitive indoor temperature forecast for energy efficient operation of smart buildings," in *Proc. IEEE 2nd World Forum Internet Things*, Dec. 2015, pp. 705–710.

[12] J. Lee, S. Kim, J. Kim, D. Song, and H. Jeong, "Thermal performance evaluation of low-income buildings based on indoor temperature performance," *Appl. Energy*, vol. 221, pp. 425–436, Jul. 2018.

[13] S. J. Fu, H. Liu, and Y. H. Ha, "Analysis of the influence of window-wall ratio on the indoor temperature in rural residential," *Building Energy Efficiency*, vol. 43, pp. 55–58, Jul. 2015.

[14] M. Liangdong, S. Nina, Z. Jili, and Z. Tianyi, "The influence of doors and windows on the indoor temperature in rural house," *Procedia Eng.*, vol. 121, pp. 621–627, 2015.

[15] Z. Afroz, G. Shafiullah, T. Urmee, and G. Higgins, "Prediction of indoor temperature in an institutional building," *Energy Procedia*, vol. 142, pp. 1860–1866, Dec. 2017.

[16] L. Mba, P. Meukam, and A. Kemajou, "Application of artificial neural network for predicting hourly indoor air temperature and relative humidity in modern building in humid region," *Energy Buildings*, vol. 121, pp. 32–42, Jun. 2016.

[17] N. Attoue, I. Shahrour, and R. Younes, "Smart building: Use of the artificial neural network approach for indoor temperature forecasting," *Energies*, vol. 11, no. 2, p. 395, Feb. 2018.

[18] S. Alawadi, D. Mera, M. Fernández-Delgado, and J. A. Taboada, "Comparative study of artificial neural network models for forecasting the indoor temperature in smart buildings," in *Smart Cities*, vol. 10268, E. Alba, F. Chicano, and G. Luque, Eds. Cham, Switzerland: Springer, 2017, pp. 29–38.

[19] S. M. C. Magalhães, V. M. S. Leal, and I. M. Horta, "Predicting and characterizing indoor temperatures in residential buildings: Results from a monitoring campaign in Northern Portugal," *Energy Buildings*, vol. 119, pp. 293–308, May 2016.

[20] S. M. C. Magalhães, V. M. S. Leal, and I. M. Horta, "Modelling the relationship between heating energy use and indoor temperatures in residential buildings through Artificial Neural Networks considering occupant behavior," *Energy Buildings*, vol. 151, pp. 332–343, Sep. 2017.

[21] F. Zamora-Martínez, P. Romeu, P. Botella–Rocamora, and J. Pardo, "On-line learning of indoor temperature forecasting models towards energy efficiency," *Energy Buildings*, vol. 83, pp. 162–172, Nov. 2014.

[22] F. Zamora-Martínez, P. Romeu, P. Botella–Rocamora, and J. Pardo, "Towards energy efficiency: Forecasting indoor temperature via multivariate analysis," *Energies*, vol. 6, pp. 4639–4659, Sep. 2013.

[23] X. Shi, W. Lu, Y. Zhao, and P. Qin, "Prediction of indoor temperature and relative humidity based on cloud database by using an improved bp neural network in Chongqing," *IEEE Access*, vol. 6, pp. 30559–30566, 2018.

[24] D. Yu, A. Abhari, A. S. Fung, K. Raahemifar, and F. Mohammadi, "Predicting indoor temperature from smart thermostat and weather forecast data," in *Proc. Commun. Netw. Symp.*, Apr. 2018, Art. no. 9.

[25] X. Li, T. Zhao, J. Zhang, and T. Chen, "Predication control for indoor temperature time-delay using Elman neural network in variable air volume system," *Energy Buildings*, vol. 154, pp. 545–552, Nov. 2017.

[26] K. Poczęta, A. Yastrebov, and E. I. Papageorgiou, "Forecasting indoor temperature using fuzzy cognitive maps with structure optimization genetic algorithm," in *Recent Advances in Computational Optimization*, vol. 655, S. Fidanova, Ed. Cham, Switzerland: Springer, 2016, pp. 65–80.

[27] L. Zhang, O. Gudmundsson, J. E. Thorsen, H. Li, X. Li, and S. Svendsen, "Method for reducing excess heat supply experienced in typical Chinese district heating systems by achieving hydraulic balance and improving indoor air temperature control at the building level," *Energy*, vol. 107, pp. 431–442, Jul. 2016.

[28] C.-E. Hagentoft and A. S. Kalagasidis, "Effect smart solutions for district heating networks based on energy storage in buildings. Impact on indoor temperatures," *Energy Procedia*, vol. 78, pp. 2244–2249, Nov. 2015.

[29] C. Wu, W. Gu, P. Jiang, Z. Li, H. Cai, and B. Li, "Combined economic dispatch considering the time-delay of district heating network and multi-regional indoor temperature control," *IEEE Trans. Sustain. Energy*, vol. 9, no. 1, pp. 118–127, Jan. 2018.

[30] Z. Zenglin, W. Pute, H. Wenting, and Y. Xiaoqing, "Research of an advanced indoor temperature controller system," *J. Converg. Inf. Technol.*, vol. 8, p. 592, May 2013.

[31] Q. Zhu, J. Chen, L. Zhu, X. Duan, and Y. Liu, "Wind speed prediction with spatio–temporal correlation: A deep learning approach," *Energies*, vol. 11, no. 4, p. 705, 2018.

[32] A. Koesdwiady, R. Soua, and F. Karray, "Improving traffic flow prediction with weather information in connected cars: A deep learning approach," *IEEE Trans. Veh. Technol.*, vol. 65, no. 12, pp. 9508–9517, Dec. 2016.

[33] Q. Hu, R. Zhang, and Y. Zhou, "Transfer learning for short-term wind speed prediction with deep neural networks," *Renew. Energy*, vol. 85, pp. 83–95, Jan. 2016.

[34] P. Romeu, F. Zamora-Martínez, P. Botella–Rocamora, and J. Pardo, "Time-series forecasting of indoor temperature using pre-trained deep neural networks," in *Artificial Neural Networks and Machine Learning—ICANN*, vol. 8131, V. Mladenov, P. Koprinkova-Hristova, G. Palm, A. E. P. Villa, B. Appollini, and N. Kasabov, Eds. Berlin, Germany: Springer, 2013, pp. 451–458.

[35] L. M. Candanedo, V. Feldheim, and D. Deramaix, "Reconstruction of the indoor temperature dataset of a house using data driven models for performance evaluation," *Building Environ.*, vol. 138, pp. 250–261, Jun. 2018.

[36] Z. Ning, P. Dong, X. Wang, M. S. Obaidat, X. Hu, and L. Guo, "When deep reinforcement learning meets 5G vehicular networks: A distributed offloading framework for traffic big data," *IEEE Trans. Ind. Informat.*, to be published.

[37] Z. Ning, P. Dong, X. X. Wang, and J. Rodrigues, "Deep reinforcement learning for vehicular edge computing: An intelligent offloading system," *ACM Trans. Intell. Syst. Technol.*, vol. 25, p. 1, May 2019.

[38] Z. Ning, Y. Feng, M. Collotta, X. Kong, X. Wang, and L. Guo, "Deep learning in edge of vehicles: Exploring trirelationship for data transmission," *IEEE Trans. Ind. Informat.*, vol. 15, no. 10, pp. 5737–5746, Oct. 2019.

[39] Z. Ning, J. Huang, X. Wang, J. J. P. C. Rodrigues, and L. Guo, "Mobile edge computing-enabled Internet of Vehicles: Toward energy-efficient scheduling," *IEEE Netw.*, vol. 33, no. 5, pp. 198–205, Sep./Oct. 2019.

[40] X. Wang, Z. Ning, X. Hu, L. Wang, L. Guo, and B. Hu, "Future communications and energy management in Internet of vehicles: Toward intelligent energy-harvesting," *IEEE Wireless Commun.*, to be published.

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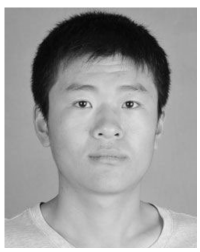

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