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AI Control Methodology Applied in Geothermal District Heating System

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ABSTRACT

Geothermal energy systems provide an eco-friendly, cost-effective solution for district heating, driving urban decarbonization and sustainable development. Geothermal district heating systems are complex, nonlinear systems influenced by various factors including weather conditions, system design, user behavior, building types, and thermal losses. Current operational strategies mainly rely on weather compensation adjustments, resulting in suboptimal thermal performance and low energy efficiency. This challenge necessitates smart system optimization that balances energy efficiency with real-time performance through predictive control. This study develops a Long Short-Term Memory (LSTM) neural network incorporating meteorological data, system operational parameters, and indoor temperature measurements. Time series values of these parameters serve as input features to capture system thermal lag and building thermal inertia. The modeling process consists of three key steps: 1) Training the model using meteorological data and system operation data as inputs and indoor temperature as target variable; 2) Setting the indoor temperature control interval and calculating the appropriate water supply temperature; 3) Calculating the operating status of system components including submersible pumps, heat pumps, and circulation pumps. The model has a good prediction effect on room temperature, with a MAE of 0.08℃ for the training set and 0.24℃ for the testing set. For the selected typical geothermal heat central, after optimizing the supply water temperature through the model, a 27% energy-saving effect can be achieved while ensuring the thermal comfort of users.

1 INTRODUCTION

Building energy consumption accounts for approximately 40% of the global annual energy consumption and a considerable proportion of direct and indirect carbon dioxide emissions [1]. District heating systems (DHS) are key infrastructure for ensuring indoor thermal comfort for residents in winter. In northern China, energy consumption for heating in urban areas accounts for 36% of the total building energy consumption, accompanied by severe air pollution problems [2]. Geothermal energy is a sustainable, cost-effective and environmentally friendly energy source. It has been successfully used for heating in countries such as China, Iceland, United States, France, Canada, Japan, New Zealand and Turkey.

The geothermal heating system is a complex nonlinear system, and its operation is influenced by multiple factors such as weather changes, system design, user behavior, building type and heat loss. Heat transfer in actual built environments is a transient process, especially in extreme circumstances such as large daily temperature differences, where the steady-state assumption is no longer applicable. Sun [3] evaluated the feasibility of geothermal district heating in the Yangbajain geothermal area of the Tibet region, taking into account the thermal inertia of buildings and outdoor temperature changes, and conducted steady-state and dynamic simulations using MATLAB. The results show that modern buildings have more stable heating performance due to their large thermal mass. Traditional building thermal performance simulation software (such as eQuest, DesignBuilder) relies on detailed physical models (such as envelope materials, thickness etc.), which are often difficult to obtain and computationally complex and time-consuming, making it hard to handle the complex thermal processes within buildings [4].

District heating (DH) systems are undergoing a significant transformation, evolving towards the fourth generation (4GDH) and fifth generation (5GDH) systems that offer lower water temperatures and higher efficiency. Digitalization and machine learning (ML) are regarded as the key technologies for achieving this transformation [7]. By utilizing the meteorological data, system operation parameters and indoor temperature information collected by the SCADA platform, and establishing an artificial intelligence model at the heat central level, more accurate and personalized water supply temperature prediction can be achieved. In recent years, with the popularization of Internet of Things (IoT) sensors and data acquisition technologies (such as SCADA systems),

DHC systems have accumulated a large amount of operational data, providing a foundation for ML applications [8]. To accurately predict the heating load, Chung et al. [5] proposed the Parallel CNN-LSTM Attention Model (PCLA), which combines the convolutional neural Network (CNN), Long Short-Term Memory network (LSTM), and attention mechanism to extract and learn the spatiotemporal features of the input data in a parallel manner. Xue et al. [6] proposed the Feature Fusion LSTM (FFLSTM) model. The core idea is that historical data at different time scales contribute differently to current load forecasting.

Considering the difference in peak-valley electricity prices and the thermal inertia of buildings, artificial intelligence models can identify the thermal inertia characteristics of buildings, rationally arrange heating strategies, avoid peak electricity consumption periods, and reduce energy consumption and operating costs. Ultimately, by integrating the trained artificial intelligence model into the SCADA system, the automated operation of the geothermal heating system is achieved. The system can intelligently adjust the operating status of each key equipment (such as heat pumps, submersible pumps, circulating pumps, etc.) to ensure the efficient and stable operation of the heating system. This not only enhances user comfort but also significantly improves energy utilization efficiency, promoting the development of geothermal energy towards a smarter and greener direction.

2 METHODOLOGY

2.1 Control Strategy for Cascade Utilization

As shown in Figure 1, the geothermal cascade utilization heating system includes submersible pumps, heat pumps, circulating pumps, etc. In the primary loop, the temperature of the geothermal water drops to 37℃ after heat exchange through the primary heat exchanger. After entering the secondary heat exchanger, the temperature further drops to 15℃. In the secondary loop the user end is floor heating, and the supply and return water temperatures are 45/35℃. In addition, the geothermal energy is the base load and other forms of energy as peak shaving loads, including ground source heat pumps, gas boilers, air source heat pumps, sewage source heat pumps, electric boilers with heat storage, industrial waste heat, and solar thermal energy etc.

The priority order for energy consumption control of heat sources in geothermal energy systems is geothermal energy > heat pump > peak shaving energy. The heat pump is only activated when the primary heat exchanger is not sufficient to meet the terminal demand. When primary heat exchanger and heat pumps fail to meet the requirements, the peak shaving energy e.g. gas boiler is activated.

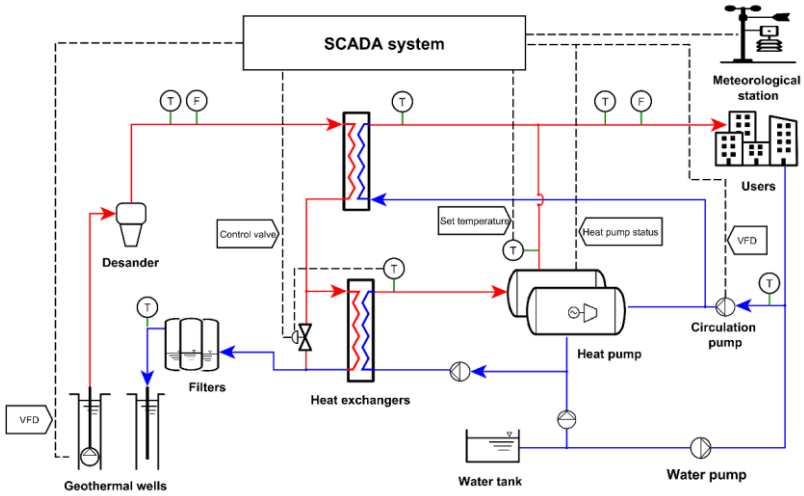


Figure 1 Schematic diagram of the geothermal district heating SCADA system

2.2 Neural network

2.2.1 Artificial intelligence modeling

This research takes artificial intelligence technology as the core and combines actual operation data to establish an intelligent geothermal heating control system.

The modeling process is divided into three key steps:

1. Model training: Use meteorological parameters (such as outdoor temperature and humidity), system operation parameters (secondary supply and return water temperatures, pump flowrate etc.) as features, and indoor temperature as target to train the LSTM neural network model;
2. Target inversion: Set an indoor temperature range (such as 18 to 24℃), and based on the prediction model, inversely deduce the optimal secondary supply temperature required to meet the thermal comfort requirements.
3. Equipment status reasoning: Based on the system's thermodynamic model, determine the optimal operating conditions and control strategies for equipment such as submersible pumps, heat pumps, and circulating pumps.

Relying on the meteorological data, system operation parameters and indoor temperature data collected by the IDH platform, a time series prediction model based on Long Short-Term memory network (LSTM) is constructed to explore the thermal lag characteristics of the system and the thermal inertia law of buildings, Figure 2.

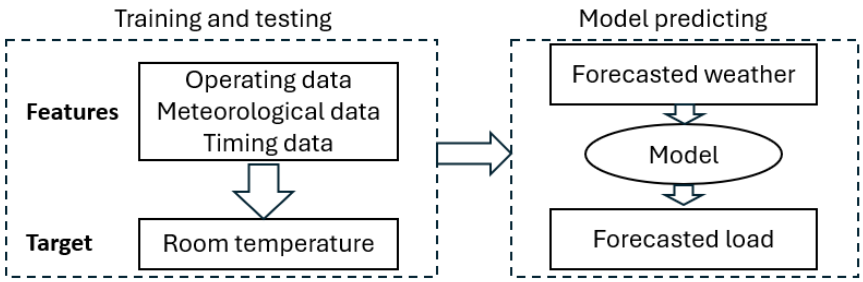


Figure 2 The process of artificial intelligence modeling

Based on the above model, further considering the electricity price structure, combining the building's thermal inertia with the system's response characteristics, a building off-peak electricity heat storage model is established. Through intelligent regulation and control, the heating capacity is enhanced during the off-peak electricity price period, achieving time-shifted storage of thermal energy and improving energy economy.

2.2.2 Data processing

The currently collected data includes the operation data of the heat central (supply water temperature, flow rate, return water temperature etc.), meteorological data (outdoor temperature, light, wind direction, wind speed, etc.), and indoor temperature data, Figure 3. In data processing, data is preprocessed through abnormal data identification, missing data filling and feature engineering.

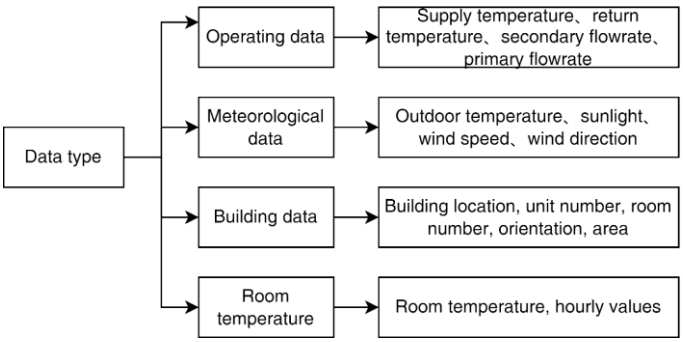


Figure 3 Data collection classification

Mean Absolute Error (MAE) is used as the evaluation index of the model.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \qquad \text{Eq.1}$$

- n Indicates the quantity of the sample
- y_i Represents the true value of the i-th sample
- $\hat{y}_i$ Represents the predicted value of the i-th sample

3 CASE STUDY

3.1 Geothermal station

This study selected 15 geothermal heat centrals A-O, and the system forms include direct utilization and cascade utilization. In this section, the geothermal heat central J is taken as an example to illustrate. The heat central J is in Xiong'an New Area, Hebei Province, China. Xiong'an has a temperate continental monsoon climate, and the heating period starts from November 15 and ends on March 15, totaling 2,904 hours. The outdoor dry bulb temperature during the 2024-2025 heating season is shown in Figure 4. The minimum temperature during the heating season is -14.5℃, and the maximum temperature is 21℃. The SCADA flow chart is shown in Figure 5. There are 5 geothermal wells in the station, including 3 production wells and 2 reinjection wells. The geothermal water outlet temperature is 65℃, and the geothermal water flowrate of each well is approximately 90 m^3/h. The system form is a typical geothermal cascade utilization. It is equipped with two heat pump units, two primary heat exchangers, two secondary heat exchangers, and five secondary network circulation pumps. The outdoor calculated temperature for heating is -7℃. The designed supply water temperature for the secondary network is 45℃, the return water temperature is 35℃, and the indoor designed temperature is 22℃.

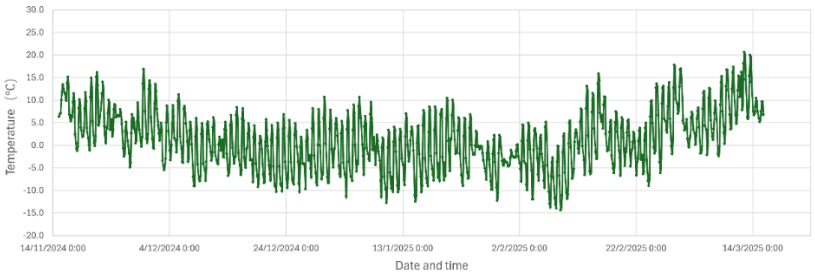


Figure 4 Outdoor hourly dry bulb temperature

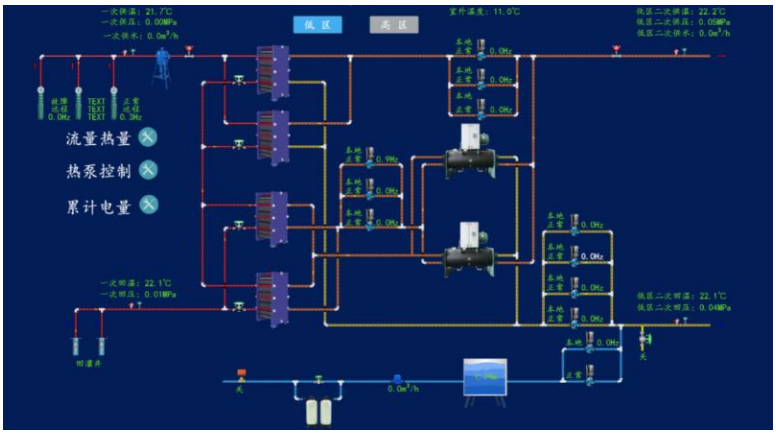


Figure 5 SCADA system of Heat central J

The system operation data includes data from the heat central, meteorological data and user data. Table 1 has captured some operation data, including the supply water temperature of the secondary network, the return water temperature, the flow rate of the secondary network, local meteorological data and the average indoor temperature of 10 selected users (HLXY11403-HMY51402) within the community. The user type is residential users, and the terminal form is floor radiant heating. The actual heating area for the 2024-2025 heating season is 182,832.18 square meters. The distribution of indoor temperature data is shown in Figure 6, with a temperature distribution range of 18.3℃ to 30.5℃ and a median temperature of 25℃. The difference in indoor temperature is related to the building structure, water distribution of the secondary network, user location and user habits. According to China's national standard GB5073-2012, it is generally calculated that maintaining an indoor temperature between 18 and 24℃ offers better comfort and energy efficiency. The median heating room temperature in the community of the heat central J during the 2024-2025 heating season exceeds the recommended range, and there is a problem of hydraulic balance in the secondary network.

Table 1 Operation data of heat central J

Date and time	Secondary supply temp. (℃)	Secondary flow (m3/h)	Secondary return temp. (℃)	Outdoor temperature	Weather conditions	Humidity	Wind speed	Wind direction	Average total cloud cover	Average room temperature
11/15/2024 0:00	36.5	724.4	30.6	7.8	Thick fog	95	0.1	0	1	22.51
11/15/2024 1:00	36.8	720.5	30.5	7.6	Thick fog	97	0.4	130	1	22.52
11/15/2024 2:00	36.5	723.3	30.6	7.9	Thick fog	98	0.9	123	1	22.53
11/15/2024 3:00	36.8	726.1	30.6	6.5	Thick fog	98	0.5	254	1	22.53
11/15/2024 4:00	36.5	728.8	30.6	6.3	Thick fog	98	0.1	0	9	22.52
11/15/2024 5:00	36.5	729.6	30.7	5.7	Thick fog	98	0.7	121	36	22.52
11/15/2024 6:00	36.5	730.4	30.6	6.2	Thick fog	98	0.5	272	1	22.51
11/15/2024 7:00	36.8	731.1	30.6	6.3	Thick fog	98	1.4	316	1	22.49
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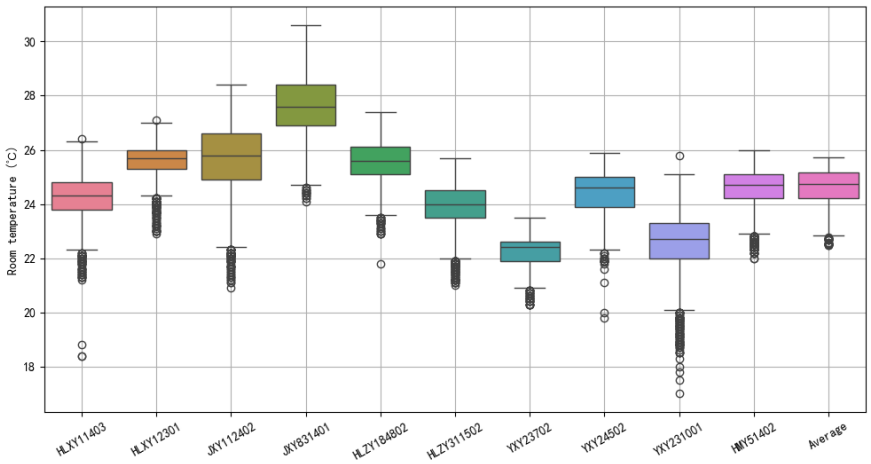


Figure 6 Indoor temperature distribution map of 10 selected users

3.2 Results of the neural network model

This paper proposes a long short-term memory (LSTM) neural network model based on the attention mechanism for room temperature prediction in heating systems. The basic features include secondary network supply temperature, return temperature, flowrate, outdoor temperature, wind speed, wind direction angle, weather conditions and indoor temperature. Among them, the weather conditions are not numerical data and are encoded in One-Hot. To enhance the predictive ability of the model, derivative features are introduced. Derivative features are new features generated by computing, transforming or combining the original data, such as heat supply, change rate of heat supply, temp. difference, change rate of flowrate, change rate of outdoor temperature, timing feature. For instance, the heat supply capacity is derived from the basic features of secondary network supply temperature, return temperature and flow rate, reflecting the system's heat load.

This study compared different model structures and lookback hours. The best performance model adopts a two-layer unidirectional LSTM structure to extract the temporal features of historical time series, and introduces an attention mechanism after the second-layer LSTM to adaptively learn the importance weights of different historical moments for the current prediction. Specifically, the model input is the feature data of the past 24 hours. After being processed by two layers of LSTM (64 units in each layer), the information of all time steps is weighted and fused through the attention layer, and then nonlinear transformation is carried out through a fully connected layer (32 neurons). Finally, output the predicted room temperature value. The model training adopts the Adam optimizer and is combined with learning rate preheating, dynamic learning rate adjustment, and early stop strategy to prevent overfitting. This model demonstrated a better fitting effect, with the training set

MAE=0.08℃ and the test set MAE=0.24℃. Figure7 and Figure 8 show the prediction accuracy MAE of the model for the training and testing set respectively.

In practical applications, the rolling prediction capability of the model is required. As shown in Figure 9, the indoor temperature for the next 24 hours is predicted by using the data of the past period, including the supply temperature of the secondary network, return temperature, flow rate, outdoor temperature, wind speed, wind direction angle, and weather conditions. The predicted average deviation MAE is 0.06℃.

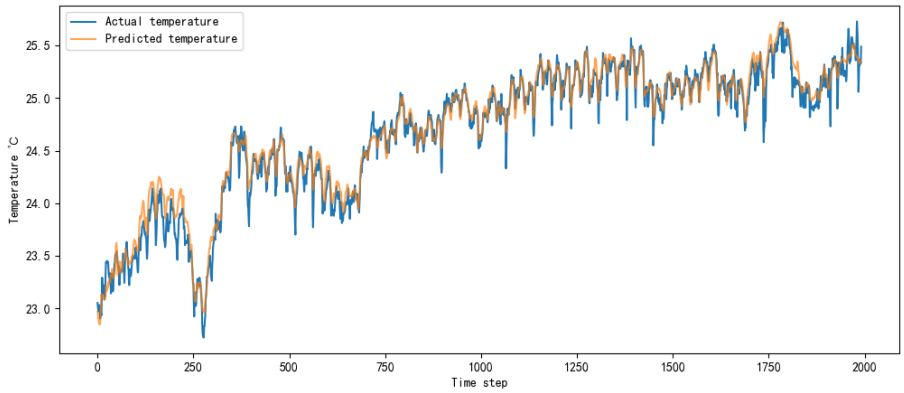


Figure7 The comparison between the predicted data and the actual data in the training set, MAE = 0.08 ℃

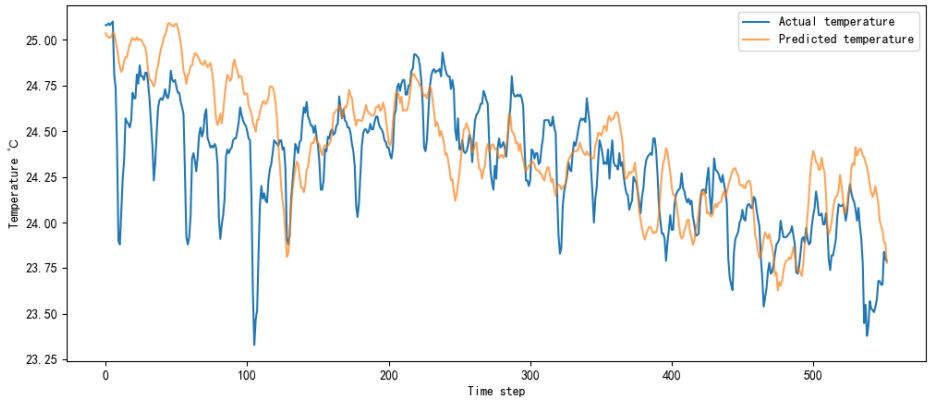


Figure 8 The comparison between the predicted data and the actual data in the test set, MAE = 0.24 ℃

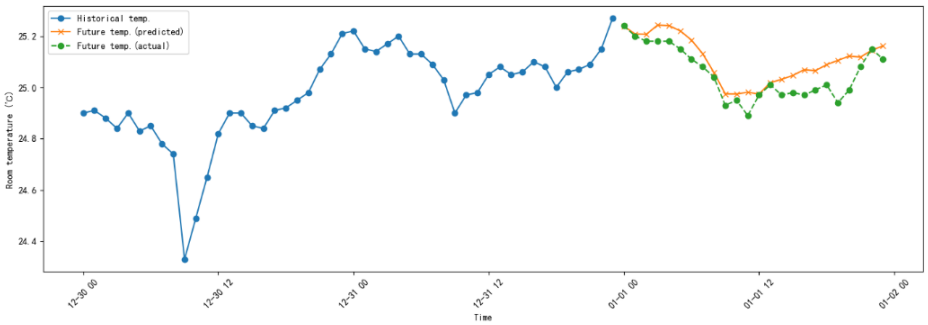


Figure 9 The example of the model rolling prediction, MAE = 0.06 ℃

The model interface is shown in the Figure 10. The basic information of the geothermal heat central are the inputs, including the geothermal production temperature, reinjection temperature, geothermal flow rate, heating area, heat index, system form. The weather forecast data is automatically captured from weather websites. After calculation, the hourly geothermal water flowrate, supply water temperature or heat pump set temperature, as well as heat supply and energy consumption are obtained.

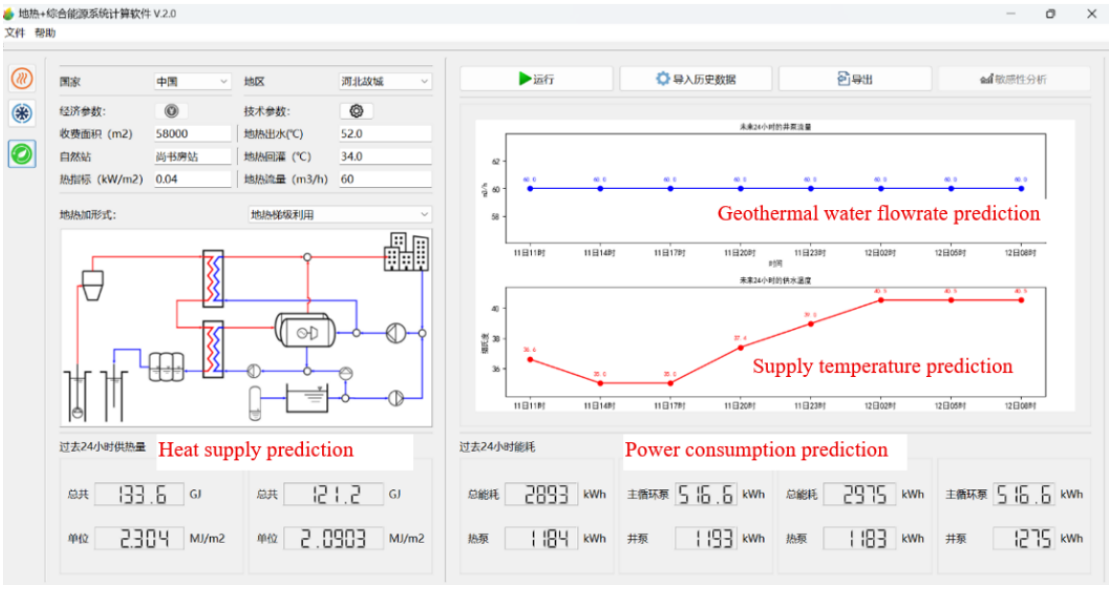


Figure 10 Model interface

Figure 11 compares the actual energy consumption with the optimized energy consumption. The actual energy consumption per unit area of heat central J was 6.3 kWh/m2, while the energy consumption per unit area after model optimization was 4.6 kWh/m2, a reduction of 27%. Meanwhile, the actual energy consumption and the optimized energy consumption of 15 geothermal heat centrals (A-O) were comprehensively compared. Different heat centrals have varied geothermal resource conditions and system designs, and the potential for energy consumption reduction can be as high as 71%.

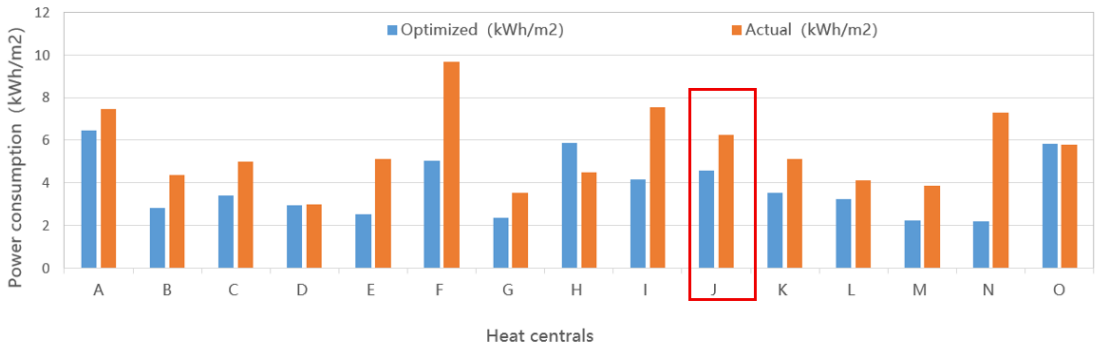


Figure 11 Power consumption optimization potentials

4 RESULT CONCLUSION

Geothermal energy heating provides a technically stable and economically feasible solution for energy conservation and carbon reduction in cities. The geothermal heating system is a complex nonlinear system, and its operation is influenced by multiple factors such as weather changes, system design, user behavior, building type and heat loss. Based on the traditional control strategy of geothermal heating systems, this paper introduces a neural network model. By establishing the functional relationship between operation data, meteorological data, building data and indoor temperature, the heat load and supply water temperature of the system are optimized to reduce system energy consumption. The main process involves training an artificial intelligence model based on the SCADA system data. The functional relationship established by the model reflects the response time of the mutual influence among the geothermal system, buildings, and the environment. The trained artificial intelligence model is integrated into the SCADA system to promote the automated and intelligent operation of the geothermal heating system.

This article analyzes the operation data of 15 heat centrals during the 2024-2025 heating season, taking heat central J as an example for illustration. Heat central J is a typical geothermal cascade utilization heating system. The indoor temperature distribution range for the households it supplies is from 18.3℃ to 30.5℃, indicating that the median heating room temperature exceeds the recommended range (18-24 ℃). Moreover, there are

problems of hydraulic balance and heating in the secondary network, and its energy consumption level is also relatively high.

This paper proposes a long short-term memory (LSTM) neural network model based on the attention mechanism for room temperature prediction in geothermal heating systems. The basic structure of the model is that the data passes through two layers of LSTM (64 units in each layer), the information of all time steps is weighted and fused by the attention layer, and then nonlinear transformation is carried out through a fully connected layer (32 neurons), and finally the room temperature prediction value is output. The model demonstrated a fitting effect with the training set MAE=0.08℃ and the testing set MAE=0.24℃.

The monitoring of 15 typical stations (A-O) during the 2024-2025 heating season shows that the actual energy consumption per unit area is 6.3 kWh/m2, and the energy consumption per unit area after optimization is 4.6 kWh/m2, with an energy-saving potential of 27%. Meanwhile, the actual energy consumption and the optimized energy consumption of 15 geothermal heat centrals (A-O) were comprehensively compared. Different heat centrals have different geothermal resource conditions and system designs, and the potential for energy consumption reduction can be as high as 71%.

This project promotes the intelligent transformation of geothermal heating systems, enhances energy utilization efficiency, and reduces manual intervention. While ensuring the quality of heating, reduce carbon emissions and contribute to the green and low-carbon development of cities. The relevant achievements have a promising prospect for promotion and have a demonstration significance for promoting the intelligent upgrade of the clean heating industry.

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