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A dynamic prediction method for the outlet fluid temperature of the large-scale borehole thermal energy storage system based on the multi-channel parallel neural network model

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ABSTRACT

Borehole thermal energy storage (BTES) is a technology in which the thermal energy generated during non-heating seasons may be collected and stored in the soil for extraction in the heating season. However, the average soil temperature of BTES continues to decay with the heat extraction process, resulting in a serious mismatch between the heat extraction and the actual heat load. The variable flow operation of the BTES system allows for flexible adjustment of the heat extraction, increasing the heat flexibility of the BTES system. However, traditional heat transfer models of the BTES cannot quickly and accurately predict the outlet fluid temperature dynamically, making it difficult to match real-time heat load requirements through online regulation of the BTES system. The paper proposes a dynamic prediction method for outlet fluid temperature of the BTES system based on the multi-channel parallel neural network model. To train the neural network model, fluid temperature, flow rate, and multiple sets of soil temperature monitoring results from a large BTES project in Chifeng lasting 11,947 hours were used as the dataset. Randomly divide the dataset into 60% as the training dataset, 20% as the validation dataset, and 20% as the test dataset. The input layer of the basic model contains inlet fluid temperature, flow rate, and multiple sets of soil temperature; the outlet water temperature of the BTES is the output layer. The input features of the advanced model also include the inlet temperature, outlet temperature, and flow rate of the previous moment (hour). After training, the variance of the prediction error for the outlet temperature of the basic model and the advanced model is 0.93 (℃)2 and 0.27 (℃)2, respectively. The advanced model can rapidly and accurately predict the outlet temperature of the BTES, which implies that by continuously iterating with the model, the optimal flow rate can be found to match heat extraction with the real-time heat load.

The influence of changing the heat extraction flow rate of the BTES was also evaluated. The heat extraction of the BTES system increases rapidly with the heat extraction flow rate and then levels off, which emphasizes the importance of variable flow operation for the flexible operation of BTES systems.

Keywords: borehole thermal energy storage, multi-channel parallel neural network model, outlet fluid temperature, heat extraction, dynamic heat load matching

NONMENCLATURE

Abbreviations

BTES	Borehole thermal energy storage
TMB	temperature measuring borehole

Symbols

1. INTRODUCTION

With the increased attention to energy security and environmental issues, the application of sustainable energy sources, represented by solar energy and thermal energy from industrial waste, in the heating sector has been increasing. Sustainable energy sources are usually intermittent and unstable [1]. The sustainable energy

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generated in summer is wasted due to seasonal mismatches with heating demand. Perera et al. showed that long-term storage, which can utilize renewable energy surpluses in summer to meet winter heating needs, plays a crucial role in the energy transition and can increase flexibility in response to climate change [2].

The application of borehole thermal energy storage(BTES) allows thermal energy generated during the non-heating season to be captured and stored in the soil and extracted for heating during the heating season [3]. However. the average soil temperature of a BTES system under design conditions continues to decrease with the heat extraction process, resulting in a decreasing amount of heat extraction [4]. This means that there is a serious mismatch between the amount of heat extracted and the actual heat demand. The variable flow rate operation of the BTES system can flexibly regulate the heat extraction power, thus increasing the flexibility of the BTES system for heat supply. Current research on BTES systems is mainly based on the physical model, which simulates and calculates the BTES thermal response based on physical and thermodynamic principles. Software such as TRNSYS embedded with duct ground heat storage model [5], COMSOL [6], and FEFLOW [7] have been used to simulate BTES systems, which are mostly used to guide the design of BTES systems or for long-period simulations under design conditions [8] However, due to the large amount of parameter identification and the difficulty to accurately give the real-time soil temperature distribution after a long period of operation, it is difficult to meet the need for online flexible control caused by real-time thermal load fluctuations.

The heat extraction of the BTES system is calculated by multiplying the temperature difference between the inlet and outlet of the fluid by the flow rate. To meet the needs of the actual operation of large-scale BTES systems, it is necessary to develop a fast and accurate real-time prediction model of the outlet temperature of the BTES system. In recent years, with the arrival of the big data era, energy monitoring platforms have gradually been popularized and improved, resulting in a large amount of data in the field of heating, which lays the data foundation for the realization of the optimal operation and control of the system. Benzaama et al. predicted the evolution of the temperatures of the underground storage tanks and the earth-air heat exchanger based on the experimental data using the long and short-term memory network algorithm, and the results verified the accuracy of the neural network models [9]. Liu et al. constructed a database by using collaborative modeling with MATLAB and COMSOL and used artificial neural networks to learn from the database and perform long-term performance prediction of ground source heat pumps[10]. However, real-time outlet temperature prediction of the BTES system based on long-term experimental data has not yet been seen in the literature.

This paper proposes a dynamic prediction method for the outlet temperature of the BTES system based on multi-channel parallel neural network model, which combines the requirement of matching real-time heat load for heat extraction in the actual operation of the BTES system. To train the neural network model, 11947 hours of operating data from the 518,918 m^3 BTES project in Chifeng, China is used as the dataset. Using the neural network model, the thermal response problem of BTES can be simplified into a machine learning predictive control problem, which can satisfy the demand for real-time online optimal control and improve the safety, energy efficiency, and flexibility of the BTES-based heating system.

2. METHODOLOGY

2.1 Multi-channel parallel neural network

The multi-channel parallel neural network structure is a type of neural network that is divided into multiple channels or sub-networks. Multi-channel parallelism increases the capacity of the model, and each channel can specialize in learning different features or patterns thus reducing the likelihood of overfitting in each channel. And because each channel can learn different features, it makes the model more adaptable to improve the robustness of the model. Finally, the results of different channel-specific predictions can be merged in different ways to generate the final prediction. This structure is commonly used to improve the performance and robustness of deep learning models.

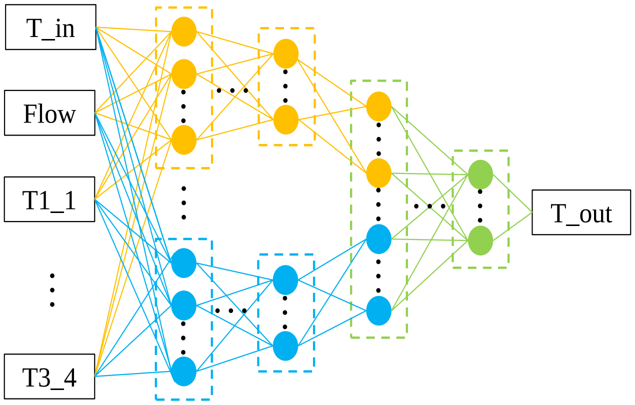


Fig. 1 Schematic diagram of multi-channel parallel neural network architecture

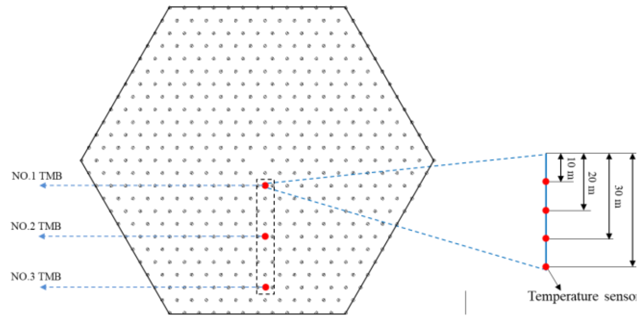
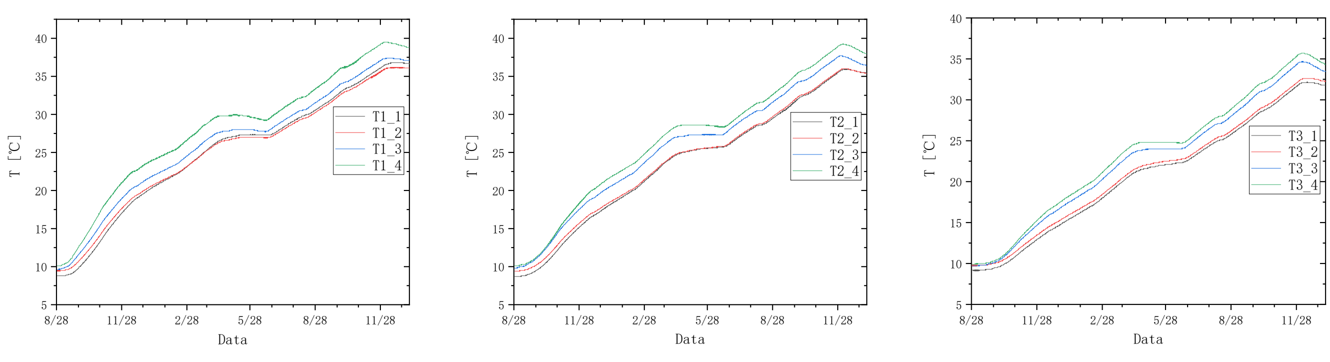


Fig. 2 Borehole layout and distribution of three temperature measuring boreholes (TMB) in one subzone of a borehole thermal energy storage system. Note: the four temperature sensors are at different depths in each TMB

As shown in Figure 1, the multi-channel parallel neural network used in this paper is mainly composed of several fully connected layers. The input features of the basic model include BTES inlet temperature, flow rate, and multiple groups of soil temperatures, totaling 14 input features, and the output is the outlet temperature. However, due to uneven soil temperature distribution, slow heat transfer rate inside the BTES, and small short-term changes in soil temperature away from the BTES U-tube heat exchanger, there may be errors in the prediction of the basic model when the inlet temperature fluctuates significantly. Arranging the temperature sensors at the soil adjacent to the U-tube heat exchanger of BTES can help solve this problem, but the construction difficulty is high. In this paper, another advanced model is proposed to add the inlet temperature, flow rate, and outlet temperature of the previous moment (hour) as input features on top of the original 14 input features, totaling 17 input features, to enable the algorithmic model to make more full use of the existing information and predict the outlet temperature at the current moment through data mining, which can help to improve the response accuracy.

2.2 Description of the system studied

The BTES system investigated was a 518, 918 m^3 system located in Chifeng, China (42.28°N, 118.87°E) [11]. Figure 2 shows the layout of the BTES; it consists of 468 boreholes spaced at 4 intervals, and each borehole is 80 m deep. Three temperature measurement boreholes are arranged from the inside to the outside, and a temperature measurement cable with four



(a) (b) (c)

Fig. 4 Long-term monitoring of soil temperature at different depths in various temperature measuring boreholes of a borehole thermal energy storage system: (a) No. 1 temperature measuring borehole; (b) No. 2 temperature measuring borehole; and (c) No. 3 temperature measuring borehole.

temperature sensors is arranged in each of the temperature measurement boreholes.

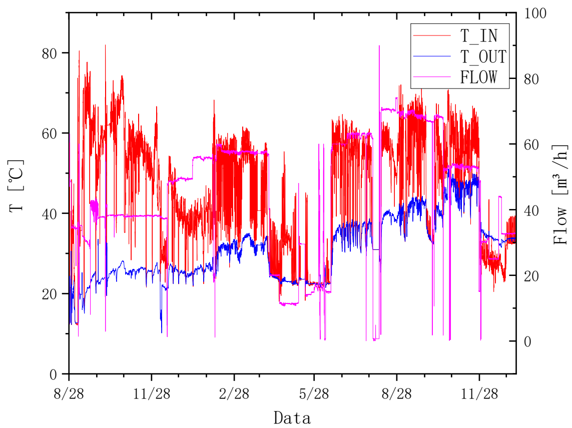


Fig. 3 Long-term monitoring data of inlet and outlet temperatures and flow rate of the BTES system

The BTES system had been in operation since August 28, 2016, and has recorded 11,947 hours of data [12]. The system utilizes industrial waste heat recovered from a local copper plant and a solar hot water system as the heat source for seasonal thermal energy storage. The actual operational data is shown in Figure 3. The BTES inlet temperature fluctuates significantly due to the high instability of the solar and industrial waste heat sources. The monitored soil temperature is shown in Figure 4. After data cleaning the valid data was 11766 sets, which is 98.5%. Randomly divide the dataset into 60% as the training dataset, 20% as the validation dataset, and 20% as the test dataset.

3. RESULTS

After many optimizations, the final multi-channel parallel neural network adopted in this paper uses four parallel channels, each channel consists of six fully connected layers (the number of neural network nodes is 64, 64, 32, 32, 16, 16), and the last layer is directly connected to get 64 neural network nodes and the merged nodes are passed through seven fully connected layers (the number of neural networks nodes are 64, 64, 32, 32, 16, 16, 1) final to the prediction results.

Figure 5 shows the histogram of the error distribution ($T_{\text{fluid\_out\_mea}} - T_{\text{fluid\_out\_pre}}$) between the measured temperature of the outlet fluid of the BTES system and the predicted temperature of the basic model (14 input features). The average absolute value of the error is 0.6 ℃, and the variance was 0.93 (℃)^2. More than 83.4% of the outlet temperature prediction error is less than ±1℃.

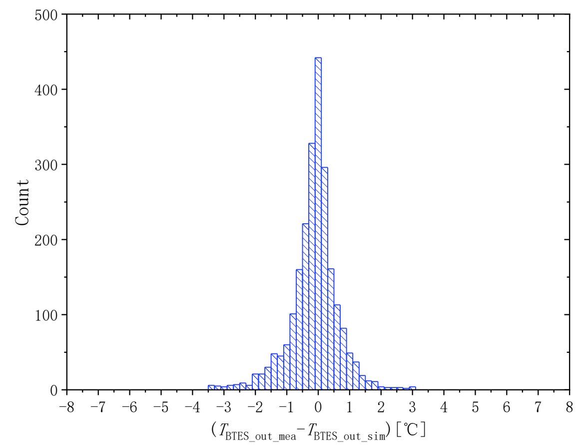


Fig. 5 Distribution of the error between the measured temperature of the outlet fluid of the BTES system and the predicted temperature of the basic model (14 input features)

Figure 6 shows the histogram of the error distribution between the measured outlet temperature and the predicted outlet temperature of the *advanced* model (17 input features). The average absolute value of the error is 0.27 ℃, and the variance was 0.27 (℃)^2. More than 97.4% of the outlet temperature prediction error is less than ±1℃.

The computational results indicate that both the basic model and the advanced model proposed in this paper, based on neural networks, can accurately predict the outlet fluid temperature of the BTES system. Furthermore, the advanced model exhibits higher prediction accuracy. The reason is that the limitations of experimental conditions result in the temperature measurement point being relatively far from the U-shaped heat exchanger of the BTES, resulting in low sensitivity of temperature data. The advanced model can rapidly and accurately predict the BTES outlet temperature, which implies that by continuously iterating with this model, the optimal flow rate can be found to match heat extraction with real-time heat loads.

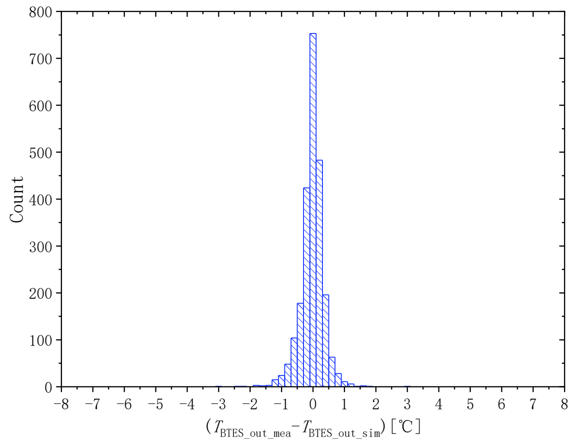


Fig. 6 Distribution of the error between the measured temperature of the outlet fluid of the BTES system and the predicted temperature of the advanced model *(17 input features)*

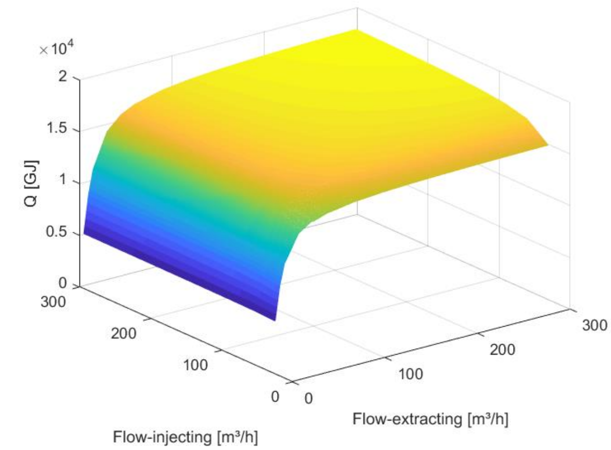


Fig. 7 Annual heat extraction under different combinations of heat injection/extraction flow rates

4. DISCUSSION

The above multi-channel parallel neural network model provides an accurate estimation of the outlet temperature of the BTES system. The BTES system has great flexibility in heating as it can adjust the heat extraction by adjusting the heat extraction flow rate. The objective of sensitivity analysis is to understand the trend of heat extraction of the BTES system concerning the heat extraction flow rate.

According to our previous research, the TRNSYS software embedded with the duct ground heat storage model can simulate the BTES system for long periods [13]. We take the actual parameters of the BTES system in Chifeng as the research object and simulate the heat storage flow range of 30 m^3/h -300 m^3/h and heat extraction flow range of 5 m^3/h -300 m^3/h, respectively. The long-period simulation of the system was carried out by using TRNSYS to invoke the duct ground heat storage model, and the annual heat extraction was calculated for different combinations of flow rates, as shown in Figure 7. The results indicate that the heat extraction of the BTES system increases rapidly with the heat extraction flow rate and then levels off.

Combining the calculation results with the actual heat demand, it is appropriate to moderately increase the heat storage flow rate during the heat storage period to extract more heat during the heat extraction period, and the heat extraction period should match the real-time heat load by adjusting the heat extraction rate, which can reduce the use of the peaking gas boiler. Based on the method proposed in this paper can quickly and accurately predict the outlet fluid temperature at different inlet flow rates, which means that the real-time optimal heat extraction flow rate can be quickly calculated. The method proposed in this paper can meet the demand for online optimal control and improve the safety and flexibility of the operation of BTES-based heating systems.

5. CONCLUSIONS

In this study, a dynamic prediction method for the outlet fluid temperature of the BTES based on the multi-channel parallel neural network model is proposed. Both the basic model and the advanced model used in the method have been validated based on long-term monitoring of a large BTES project in Chifeng. In the case study, the variance of outlet temperature prediction error is 0.93 (℃)^2 for the basic model with inlet temperature, flow rate, and multiple sets of soil temperatures as input features, and 0.27 (℃)^2 for the advanced model with the addition of new inlet temperatures, outlet temperatures, and flow rates from the previous moment (hour) as input features. In addition, the effect of the heat extraction flow rate on the heat extraction of the BTES system is discussed. We conclude that the heat extraction of the BTES system increases rapidly with the heat extraction flow rate and then levels off. The results of the study emphasize the importance of variable flow regulation for the flexible operation of BTES systems.

Based on the method proposed in this paper can quickly and accurately predict the outlet fluid temperature at different inlet flow rates and temperature, which means that by continuously iterating the model, the optimal flow rate that matches the real-time heat load can be found. The method proposed in this paper can meet the demand for online optimal control and improve the safety and flexibility of the operation of BTES-based heating systems.

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DECLARATION OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. All authors read and approved the final manuscript.

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