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Heating Analysis and Prediction Based on GOOSE-BP Model Mathematical Modeling and Neural Networks

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Abstract: *The wide application of air source technology has imposed considerable pressure on the power grid system. By accurately predicting indoor temperatures and reducing unnecessary energy consumption, this will help alleviate the burden on the power system and bring about certain social and economic benefits. This article first provides the relevant background information and collects relevant data from two locations. Different identification parameters are set and combined with the thermodynamic differential equation model to solve the parameters for different locations. Secondly, GOOSE-BP and BP neural networks are used to predict different locations respectively, and their effects are also evaluated. Finally, based on the above two results, a constant temperature control strategy is established, and a dynamic programming model is established based on the electricity prices during peak and off-peak periods and constraints to calculate the optimized electricity costs for different locations. This article proposes different strategies for the two different locations to reduce the electricity burden of enterprises. Meanwhile, a feasible neural network model is proposed to optimize power distribution and reduce the burden on the power grid.*

Keywords: *Neural Network, Heating Analysis, Thermodynamic Differential Equation Model, Constant Temperature Control Strategy, Dynamic Programming Model*

1. Introduction

Air source heat pumps have gained increasing attention from people due to their environmental-friendly and clean features, and are being used in various fields [1]. According to a study, this method is widely applicable in most rural areas of Beijing and is highly suitable for buildings in medium-sized and small cities [2]. However, as its wide application progresses, related issues cannot be ignored either. For instance, when the heat pump is in a state of frosting and humidity, the heat resistance of the heat exchanger increases, resulting in a decrease in heat transfer efficiency [3]. A study from France indicates that as the global climate warms, the excess electricity demand during normal conditions during cold snaps will increase, and the heating demand will show a more frequent but shorter fragmented pattern, which may exacerbate the burden on the power grid [4]. At the same time, as the number of installations increases, the power consumption of the heat pump will also exert considerable pressure on the power grid. Therefore, by implementing optimization strategies to reduce the usage time of heat pumps and thereby minimize unnecessary power consumption, it plays a crucial role in reducing the burden on the power grid. At the same time, it can also create certain social value.

So far, there have been many studies on the optimization of heat pumps. Liang C et al. developed an all-year-round efficient ASHP system by adopting an independent and long-distance heat extraction method. They verified the deicing effectiveness and heating/cooling performance, and applied it to practical scenarios. In winter, it achieved a 43%-60% energy saving compared to traditional water chillers and boilers, and overall, it reached 51% [5]. Naghipour P et al. proposed a hybrid machine learning model combining extreme gradient boosting (XGB), histogram gradient boosting (HGB), and three advanced optimization algorithms (SBO, CMA-ES, TOA) to evaluate the model performance through K-fold cross-validation. The final results showed that it was significantly superior to the traditional model, providing a high-precision and reliable heating energy consumption prediction framework for sustainable energy management of regional residential buildings [6]. Zhou Y et al. believe that in the field of regional heating, machine learning has application value in demand prediction, energy

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scheduling, and alternative model development [7].

In this article, the data collected come from two locations that use air-source heat pumps. Based on the conditions of the two different locations, parameter identification is carried out, and neural networks are utilized for future predictions. At the same time, constraints, constant temperature control conditions, and dynamic programming models are introduced to optimize the electricity cost calculation for these two locations and provide relevant suggestions for the use of heat pumps in these locations. This helps enterprises reduce related operating costs while reducing the burden on the power grid.

2. Method

2.1 Data source and data preprocessing

In this article, our data are sourced from https://www.saikr.com/c/nd/31166. The data used in this study include historical heating data and indoor temperature measurement data from two locations. For the date of some categories in the dataset to be missing, therefore, in this study, the k-nearest neighbor algorithm (KNN) was employed to fill in the missing values.

2.2 Thermodynamic differential equation model

The construction of buildings mainly consists of two layers: the air layer and the structural layer. In real life, the air layer and the structural layer have different specific heat capacities and temperatures. Air-source heat pumps convert electrical energy into thermal energy mainly in the air layer, while the structural layer acts as a medium for heat exchange with the external environment, enabling the air layers inside and outside to undergo heat exchange reactions [8]. Therefore, the parameters that we need to identify are C_{qi}, C_{qiang}, R_1, R_2, η_0 and $\cos\phi$. They respectively represent the specific heat capacity of the air layer, the specific heat capacity of the structural layer, the thermal resistance between the air layer and the structural layer, the total thermal resistance of the environment, the initial thermal efficiency of the heat pump, and the power factor of the heat pump. The relevant formulas are as follows:

Optimization objective:

$$\min\sum_{i=1}^{N}(T_{qi}(t)-T_{qiang}(t))^2 \tag{1}$$

Air layer energy balance equation:

$$C_{qi}\frac{dT_{qi}}{dt}=\eta P_{real}+\frac{T_{struct}-T_{qi}}{R_1}-\frac{T_{qi}-T_{out}}{R_2}-Q_{water} \tag{2}$$

Structural layer energy balance equation:

$$C_{qiang}\frac{dT_{qiang}}{dt}=\frac{T_{qi}-T_{qiang}}{R_1} \tag{3}$$

Heat pump power:

$$P_{rebeng}=\sqrt{3}V_{avg}\times I_{avg}\times\cos\phi \tag{4}$$

Heat pump efficiency:

$$\eta=\eta_0(1-\alpha(T_{gong}-T_{hui}) \tag{5}$$

Water loss due to heat absorption:

$$Q_{sunshi}=m_{shui}\times c_{shui}\times\frac{T_{qi}-T_{out}}{3600} \tag{6}$$

Water system hot melt:

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$$C_{qi} = C_{qi\_base} + c_{shui} \times \rho_{shui} \times V_{total} \tag{7}$$

Among them $V_{avg} = \frac{1}{3}(V_1 + V_2 + V_3)$, $I_{avg} = \frac{1}{3}(I_1 + I_2 + I_3)$, T_{qi}, T_{qiang}, T_{out} V_{age}, I_{age} and m_{shui} respectively represent the temperature of the air layer, the temperature of the structural layer, the outdoor ambient temperature, the average value of the three-phase voltage, the average value of the three-phase current, and the flow rate of the supplementary water.

2.3 Goose algorithm

The GOOSE algorithm is inspired by the behavior of geese when they rest and forage [9], and it is divided into the exploration and exploitation stages. In the first iteration, it checks the values within the population to restore the values outside the boundaries. At the same time, it implements the objective function to determine the best score and the best position within the search boundaries. To control the development and exploration phases, a random variable rand that selects values randomly is used. If the value of rand is greater than or equal to 0.5, the exploration phase is activated.

2.4 Constant temperature control strategy

To ensure the comfort of indoor temperature, we have designed an indoor temperature control strategy.

(1) The above-mentioned thermodynamic model has been discretized [8]. Here, R_{qinei} represents the thermal resistance of the structural layer, and the calculation method is as follows:

$$T_{shinei}(t+1) = T_{shinei}(t) + \Delta t \times \frac{1}{C_{qi}}\left[\frac{T_0(t) - T_{shinei}(t)}{R_{qinei}} - \frac{T_{qinei}(t) - T_{shiwai}(t)}{R_{qiwai}}\right] \tag{8}$$

(2) A better-fitting neural network is used to predict the outdoor temperature $T_{wai}(t+k)$ for the next 4 hours, where k = 1, 2, 3, 4, among them, T_{shinei} is greater than or equal to 19 but less than or equal to 21. The optimization objective and related equations are as follows:

$$\min_{T_0(t+1:t+4)} \sum_{k=1}^{4} (\parallel T_{shinei}(t+k) - 20 \parallel^2 + \lambda P(t+k)^2) \tag{9}$$

$$P(t+k) = \eta \times (T_0(t) - T_{wai}(t+k)) \tag{10}$$

2.5 Dynamic programming model

From the given conditions, we know that the electricity prices at the low and peak periods are 0.6 yuan per kilowatt-hour and 1.2 yuan per kilowatt-hour respectively. Therefore, in order to ensure that enterprises can save more electricity costs, it is necessary to increase the temperature during the low-usage period to store heat and reduce the electricity consumption for heating during the peak period. Correspondingly, the corresponding equation is as follows:

$$\min \sum_{t=1}^{24} [\eta \times (T_0(t) - T_{wai}(t)) \times \Delta t \times C(t)] \tag{11}$$

At the same time, the indoor temperature at the next moment is calculated using the thermodynamic equation. The state transition equation is as follows:

$$T_{shinei}(t+1) = f_{relixue}(T_{shinei}(t)T_0(t), T_{wai}(t)) \tag{12}$$

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3. Results

3.1 The parameter results and analysis for location one and location two

Using the PSO algorithm, we obtained the optimal result graph as shown in Figure 1:

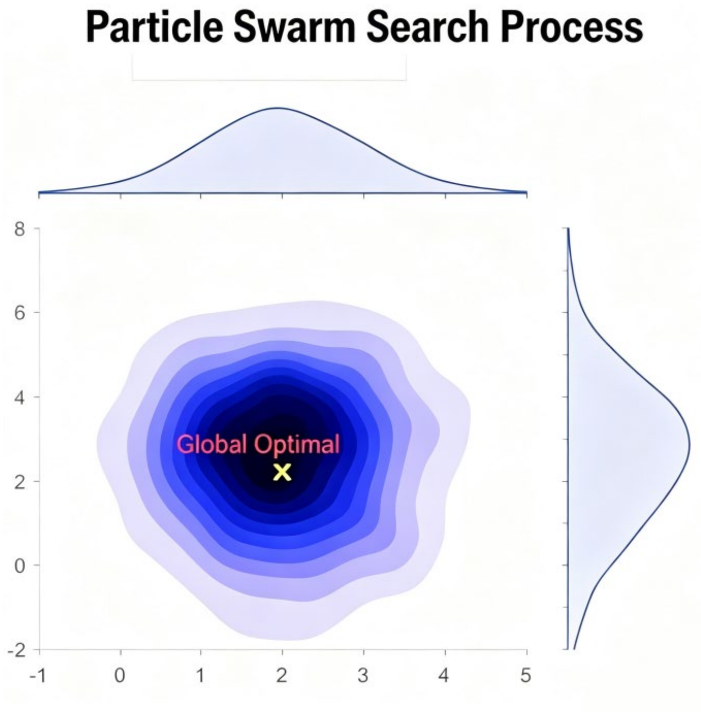

Figure 1. Global optimal node

After determining the optimal nodes, they were substituted into the thermodynamic differential equation to obtain the results for Location One and Location Two, as shown in Table 1: C_{qi}, C_{qiang}, R_1, R_2, η_0 and $\cos\phi$.

Table 1. The results of the identification parameters for Location One and Location Two

Identification parameters	Location 1	Location 2
C_{qi}	$140kj/℃$	$200kj/℃$
C_{qiang}	$600kj/℃$	$1000kj/℃$
R_1	$12℃/kw$	$8℃/kw$
R_2	$20℃/kw$	$14℃/kw$
η_0	0.85	0.78
$\cos\phi$	0.92	0.88

From this, it can be seen that the wall of location 1 has less energy loss and better insulation effect, stronger heat storage capacity, higher heat pump efficiency, greater energy saving and efficiency, and more stable heating effect; location 2 has slightly lower heat pump efficiency, requires frequent and continuous energy supplementation, has higher sensitivity requirements for the temperature response system, and is more dependent on external heating facilities.

3.2 Experimental results, comparison and analysis of GOOSE-BP and BP neural networks

After inputting the cleaned data into the model for training, the results are shown in Figure 2:

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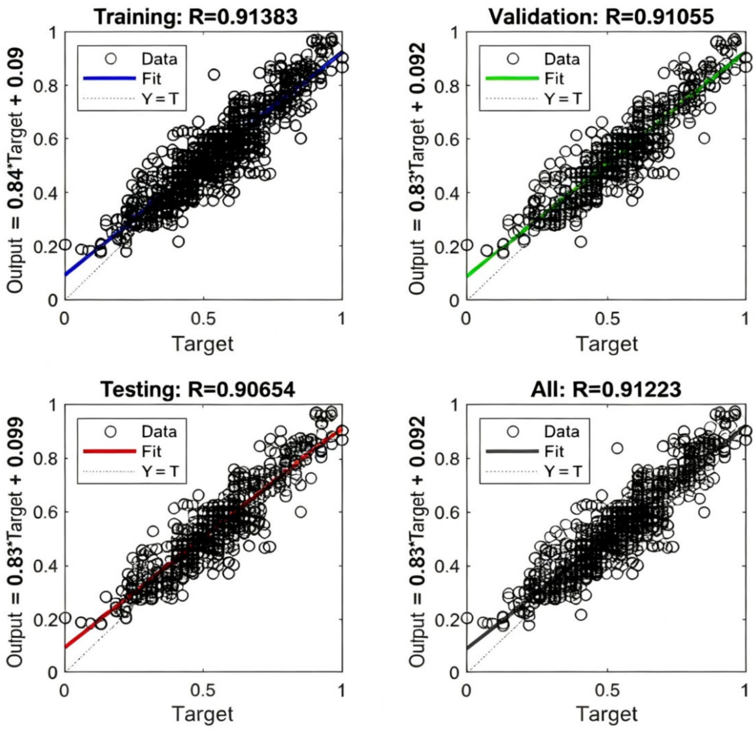

Figure 2. Regression plot

As shown in Figure 2, the overall goodness of fit R2 = 0.91223, indicating that the model has a good generalization ability. The prediction accuracy is high both on the training set and the test set. Meanwhile, the error indicators for Location One and Location Two are shown in Table 2:

Table 2. Location Error Index

Location name	Method	MAE	MSE	RMSE	MAPE
Location one	Traditional BP	0.25036	0.10574	0.30517	0.012332%
	GOOSE-BP	**0.21928**	**0.07872**	**0.28057**	**0.010825%**
Location two	Traditional BP	0.38649	0.25546	0.50543	0.019509%
	GOOSE-BP	**0.3054**	**0.15725**	**0.39654**	**0.015541%**

From the data in the table, it can be seen that the prediction effect of the GA algorithm optimized BP neural network is superior to that of the traditional BP neural network in both location 1 and location 2. At the same time, we have visualized the average absolute percentage error (MAPE) of each point on the test and training sets of location 1 and location 2. The specific results are shown in Figures 3 and 4:

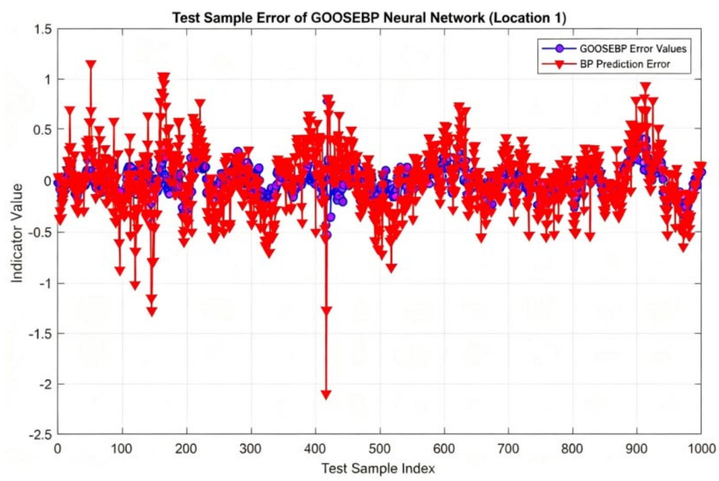

Figure 3. Location 1 - Error comparison chart on the test set

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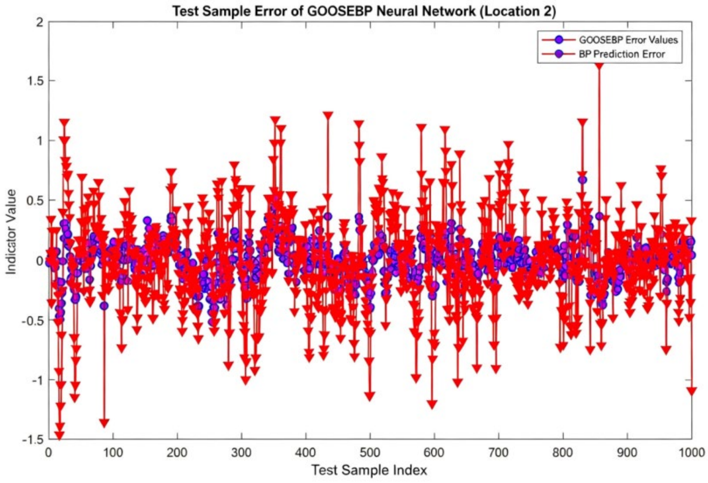

Figure 4. Location 2 - Error comparison chart on the test set

The temperature prediction errors of the algorithm-optimized BP neural network at locations 1 and 2 fluctuate around 0, and the fluctuation range is smaller than that of the traditional BP neural network. This further indicates that the BP neural network optimized by the goose algorithm has superior performance that cannot be matched by the traditional BP neural network. We still used the traditional BP and GOOSE-BP for prediction, and the results are shown in Figure 5 and Figure 6. Then, we conducted a 4-hour prediction using the thermodynamic equation and GOOSE-BP, and the results are presented in Figure 7 and Table 3:

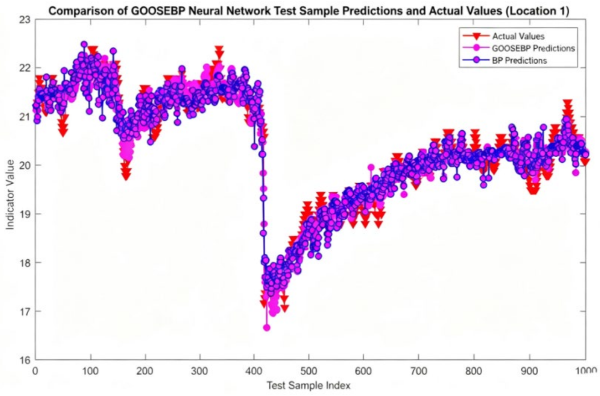

Figure 5. Comparison chart of GOOSE-BP neural network prediction values and actual values (Location 1)

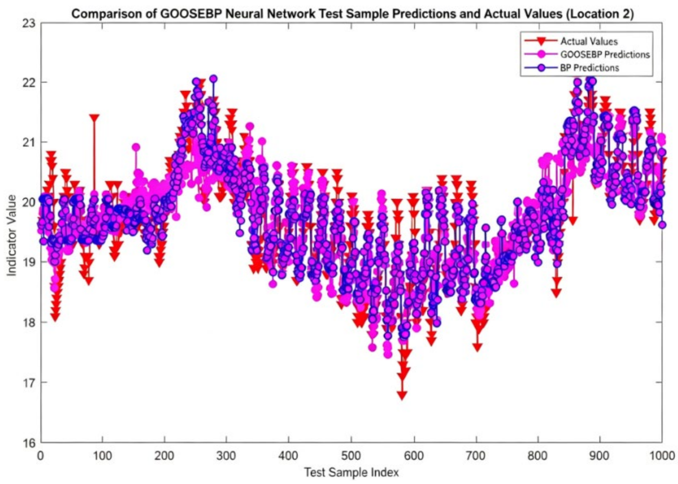

Figure 6. Comparison chart of GOOSE-BP neural network prediction values and actual values (Location 2)

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The predicted values of the model on the test set have a good degree of overlap with the actual values, which further demonstrates the accuracy of the model's predictions.

Table 3. The specific results of indoor temperature predictions for locations one and two during each period

Period	Location one	Thermodynamic model predicts temperature (°C)	GOOSE-BP Predicted Temperature (°C)	Location two	Thermodynamic model predicts temperature (°C)	GOOSE-BP Predicted Temperature (°C)
2025/3/16 0:00		19.373	19.704		16.819	16.012
2025/3/16 1:00		19.398	19.021		16.104	15.714
2025/3/16 2:00		19.405	19.429		16.103	16.616
2025/3/16 3:00		19.394	18.929		16.116	15.218

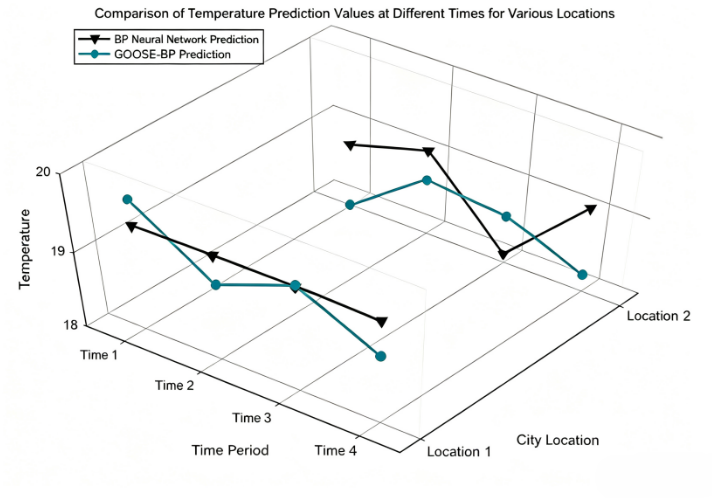

Figure 7. Comparison chart of temperature predictions at different times and locations

Both the graphs and the tables show that the predicted results of the two methods are quite similar, fluctuating around 0.5. The indoor temperature at location 1 is significantly higher than that at location 2. This further confirms the conclusion in question 2 that the wall energy loss is less and the insulation effect is better at location 1, demonstrating the accuracy of the model.

3.3 Comparison and analysis of the results of location one and location two under the constant temperature control strategy and the dynamic programming model

The relevant results are shown in Figure 8:

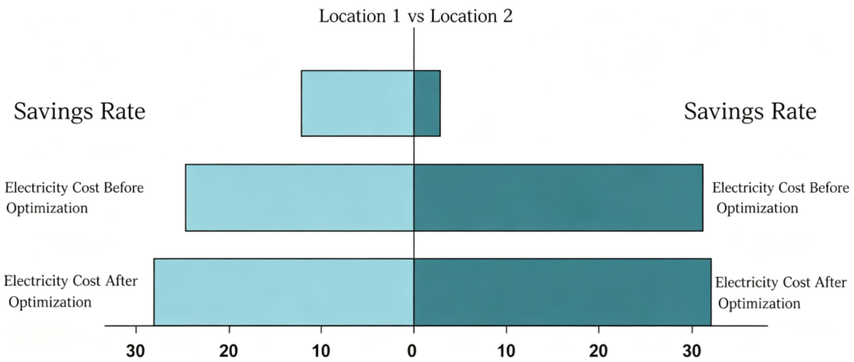

Figure 8. Comparison chart of temperature predictions at different times and locations

Table 4. Comparison of electricity costs before and after optimization at two locations in 2025/3/15

Location name	The electricity bill before optimization	Optimized electricity bil	Savings rate
Location one	28.17	24.77	12.1%
Location two	32.01	31.13	2.7%

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From the above table 4, it can be concluded that the houses in location 1 have better insulation performance, and the heat is preserved for a longer period during peak hours; while the insulation performance of the houses in location 2 is worse compared to location 1, and continuous heating is required for a long time to ensure the comfort of the house temperature.

4. Conclusions

In this article, by using an optimized BP neural network model combined with dynamic programming and thermodynamic models, and oriented towards the lowest electricity cost, it was successfully achieved that the electricity costs of the two buildings at Location 1 and 2 decreased to a certain extent.

Moreover, the experimental results show that compared with the BP neural network, GOOSE-BP has better capabilities in power prediction and fitting, and has certain practical application value. Moreover, machine learning algorithms are usually influenced by manual parameter tuning, which might affect or miss better results.

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