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Two-Layer Control Strategy of the PCM-Based Electric Heating Optimal Control System Using LSTM Algorithm

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Abstract. Phase change material (PCM) can utilize different thermal storage modes to improve the efficiency of electric heating loads. Traditionally, PCM-based electric heating equipment is controlled by users respectively. There is a lack of interaction between the PCM-based electric heating equipment and the power dispatch company. The hierarchical optimal control strategy for electric heating load is proposed in this paper to deal with the problem. Firstly, based on the LSTM algorithm, the energy consumption characteristics of PCM-based electric heating are analyzed, and the load power of PCM-based electric heating is predicted, then the two-layer optimal electric heating loads control model is investigated with phase change thermal storage modes. The upper layer model is developed to minimize the cost of a comprehensive load dispatching scheme, and the lower layer model is aimed at minimizing the cost during peak and valley periods. Under different types of electric heating response, thermal storage response is designed to examine the electric heating load optimal control strategy. Finally, a typical example is used to verify the application of the two-layer optimal control strategy of the PCM-based electric heating loads. The technical method can effectively improve the thermal and electric conversion efficiency.

Keywords. LSTM, electric heating, phase change thermal storage, two-layer optimal control

1. Introduction

Promoting the energy consumption revolution and strengthening energy conservation can solve the problem of high energy consumption and high pollution caused by the extensive utilization of energy [1]. As a safe, clean, and comfortable heating method, electric heating plays a significant role in controlling air pollution and improving the quality of life of residents.

The research on electric heating load scheduling mainly focuses on load forecasting, load zoning scheduling, and so on. In Reference [2], a DR model is proposed to achieve multi-objective optimization. Considering the fluctuation of electric heating load, a power supply capacity evaluation method is presented based on attribute theory, and a robust optimization based on scenario analysis is established [3]. To reduce residual energy and thereby increase self-consumption of local renewable energy, two coordinated decentralized optimization methods are developed in Reference [4].

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Considering the thermal storage characteristics, a multi-objective optimization model is established based on the wind power and electric boiler with thermal storage (EBTS) system. The goals are designed to maximize wind power accommodation and minimize the operating costs of the EBTS system. An improved multi-objective particle swarm optimization algorithm is used to solve these functions, and an optimal compromise solution from the generated Pareto solution set is filtered using the fuzzy membership method [5].

Phase change energy storage is a kind of thermal energy storage that uses the thermal storage characteristics of PCMs to store or release the heat, to adjust and control the temperature of the surrounding environment. Traditionally, electric heating equipment with thermal storage is controlled by users respectively. Few have studied the interaction between the PCM-based electric heating equipment and the power dispatch company. Therefore, this paper designs a two-layer optimal dispatching model that takes into account the relationship between the power grid and the users, to achieve the dynamic change of the power grid dispatching, and facilitate the electric heating requirements [6].

2. PCM-Based Electric Heating Model

2.1. PCM-Based Electric Heating Introduction

PCMs can utilize different thermal storage modes to improve the efficiency of electric heating loads. Therefore, the combination of phase change thermal storage technology and electric heating is a more energy-saving form of heating. It can assist in the realization of grid peak shaving and valley filling, reducing the cost of electric heating for residents [7].

The thermal storage of the *m*-th PCM-based electric heaters Q_m is expressed as:

$$Q_m = M_m \cdot L_m + M_m \cdot C_{m,p}(T_{m,in} - T_{m,out}) \tag{1}$$

where M_m is the mass of the phase-change heat-storage material of the *m*-th phase-change heat-storage electric heating, kg; L_m is the latent heat of phase transition, kJ/kg; $C_{m,p}$ is the constant pressure specific heat, kJ/(kg · °C); $T_{m,in}$ is the inlet water temperature of the heat storage device,°C; $T_{m,out}$ is the outlet water temperature of the heat storage device, °C.

2.2. Analysis and Calculation of the Data Required for the Modeling of Phase-Change Regenerative Electric Heating Based on LSTM Algorithm

The data structure framework required for the PCM-based electric heating model is shown in Figure 1. Through the statistical analysis of various parameters of the PCM-based electric heating and the characteristic parameters of the user, the key parameters for the construction of the PCM-based electric heating model are obtained.

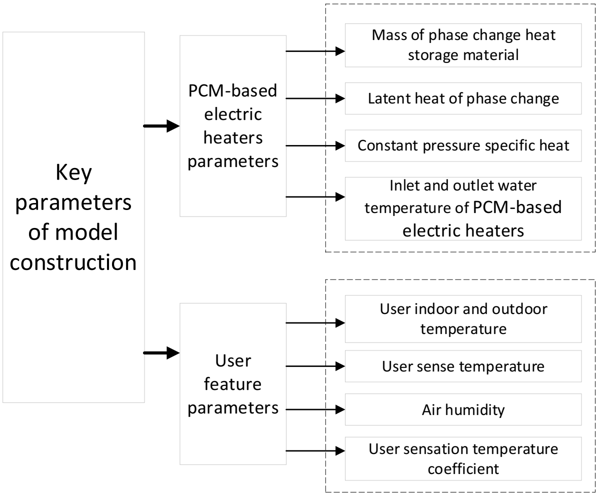

Figure 1. Data structure required for the PCM-based electric heating model.

Datasets are needed to be standardized in model training and prediction to adapt to the input requirements of the LSTM algorithm. The detailed steps of the data processing are as follows:

Step 1. The load power of the i_th PCM-based electric heaters $P_i(t)$, load power extreme value $P_{i,min}$, $P_{i,max}$, the trend of lad changes $T_i(t)$, load fluctuation information $F_i(t)$, and other factors are put. The datasets are arranged by matrix and performed by smoothing processing in the M-order window. Then, the output load data is $P_i{}^w = \{P_{i,1}^w, P_{i,2}^w, \ldots, P_{i,m}^w\}$.

Step 2. Using Python software, the load data is zoomed in [-1, 1] using the MinMaxScaler module conversion to meet the input requirements of the LSTM. The converted historical data collection is set as $X_i = \{X_{i,1}, X_{i,2}, \ldots, X_{i,k}, X_{i,n}\}$. The output data set is the load change trend prediction information.

Step 3. The data set is reconstructed in a sliding window segmentation. If the LSTM input time step is l_1, output data prediction steps are l_2, then the sliding window length is set to $l_1 + l_2$. When the window slides a unit each time, $(n - m - l_1 + l_2 + 1)$ sequences are generated which have the length $l_1 + l_2$. In each sequence, the first l_1 data is taken to build the input sequence $\mathrm{X_{i,in}}=\{\mathrm{X_{i,1}}, \mathrm{X_{i,2}}, \ldots, \mathrm{X_{i,j}}, \ldots, \mathrm{X_{i,n\text{-}m\text{-}l_1-l_2+1}}\}$, where $X_{i,j}=\{x_{i,j}, x_{i,j+1}, x_{i,j+2}, \ldots, x_{i,j+l_1-1}\}$, and the next l_2 data is taken to build the output sequence $Y_{i,j}$. The output data set can be expressed as $Y_{i,out}=\{Y_{i,1}, Y_{i,2}, Y_{i,j}, \ldots, Y_{i,n-m-l_1-l_2+1}\}$, where $Y_{i,j}=\{x_{i,j+l_1}, x_{i,j+l_1+1}, \ldots, x_{i,j+l_1+l_2-1}\}$.

The processed data is marked as $D_i=\{X_{i,in}, Y_{i,out}\}$, which is divided into the training set and test set according to a certain proportion ε, where the training set $D_{i\_tr}=\{X_{i\_tr}, Y_{i\_tr}\}$, the test set $D_{i\_ts}=\{X_{i\_ts}, Y_{i\_ts}\}$.

Step 4. The current time step and the previous time step hike state are sent to the door of the long-short memory network as the input data. They are processed by three full-connection layers with Sigmoid activation functions to calculate the value of the input gate, the forget gate, and the output gate. Therefore, the values of the three gates are in the range (0, 1). In LSTM structure, an H hidden unit is set, the input sequence is X_{i_tr}, and the intermediate output is $H_{t-1} \in R^{n*h}$. Accordingly, the door of the time step

t is defined as follows: Define the input gate $I_t \in R^{n*h}$, the forgotten gate $F_t \in R^{n*h}$, the output gate $O_t \in R^{n*h}$. The gate control in LSTM is shown as

$$H_t = O_t \odot tanh\ (C_t) \tag{2}$$

where C_t is a memory unit, H_t is the hidden state, and O_t is used to control how much information is required to be transmitted to the hidden state. $\odot$ means an exclusive-NOR multiplication.

The calculations are described as

$$I_t = \sigma(X_{i_{tr},t}W_{xi} + H_{t-1}W_{hi} + b_i) \tag{3}$$

$$F_t = \sigma(X_{i_{tr},t}W_{xf} + H_{t-1}W_{hf} + b_f) \tag{4}$$

$$O_t = \sigma(X_{i_{tr},t}W_{xo} + H_{t-1}W_{ho} + b_o) \tag{5}$$

where $W_{xi}, W_{xf}, W_{xo} \in R^{d*h}$ and $W_{hi}, W_{hf}, W_{ho} \in R^{h*h}$ are weight matrixes, $b_i, b_f, b_o \in R^{1*h}$ are the bias vectors.

Thus, when the number of the input sequences is selected, the LSTM model is continuously trained, and the training process can be expressed as

$$Y_{i\_tr} = F(W, b)(X_{i\_tr}) \tag{6}$$

The purpose of LSTM training is to look for the relationship between historical load data X_{i_tr} and load data prediction Y_{i_tr}, where $Y_{i\_tr}=\{Y'_{i,1}, Y'_{i,2}, \ldots, Y'_{i,j}, \ldots, Y'_{i,n-m-l_1-l_2+1}\}$. The difference between the model actual output $Y'_{i,j}$ and the theoretical output $Y_{i,j}$ can be expressed as the loss function $L_{i,j} = l(Y_{i,j}, Y'_{i,j})$. The loss function is used to measure the difference between the predicted value and the real value. In the LSTM training process, the weights W and b are updated in the neural layer gradually, and the training is stopped when the specified error level or the number of iterations is satisfied.

Step 5. When the model training is completed, the corresponding predicted value Y_{i_pre} is obtained.

$$Y_{i\_pre} = \{Y'_{i,1}, Y'_{i,2}, \ldots, Y'_{i,j}, \ldots, Y'_{i,n-m-l_1-l_2+1}\} \tag{7}$$

The load prediction value Y_{i_pre} can be obtained by inverse scaling and refractive amplification.

MAPE (mean absolute percentage error) and RMSE (root mean square error) are used as an evaluation index to evaluate the prediction effect of the LSTM algorithm.

$$MPAE = \frac{1}{n}\sum_{i=1}^{n}\frac{|p_i^{pre} - p_i^{test}| \times 100\%}{p_i^{test}} \tag{8}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(p_i^{test} - p_i^{pre})^2} \tag{9}$$

where p_i^{test} is the actual value of the load in the test set ; p_i^{pre} is the load prediction value in the test set.

3. Two-Layer Optimal Control Strategy of the PCM-Based Electric Heating Loads

With the advancement of the coal-to-electricity project, the proportion of electric heating in the heating load in the Northern region is significantly increasing in winter. Because electric heating devices are decentralized demand response resources, this paper proposes a two-layer optimal control strategy including power companies, load aggregators, and the PCM-based electric heating loads.

In the upper-layer, the power dispatching system collects real-time operation data, sends the optimized adjustment plan to the load aggregator; in the lower layer, the load aggregator optimizes the dispatched task to the user according to the dispatch amount issued by the upper layer, taking into account the economic benefits and comfort of the user, and feeds back the load value to the power dispatching system [8, 9].

3.1. The Upper-Layer of Power Grid Dispatch Strategy

Aiming at the daily operation economy of the entire distribution network, an optimization model of the dispatch plan of the thermal storage electric heating system is established, and the objective function is to take the minimum overall cost as the objective function:

$$min\, C_z = C_b + C_m - C_s - C_d \tag{10}$$

where C_z is the comprehensive total cost, C_b is the electricity purchase cost of the thermal storage electric heating system, C_m is the operation and maintenance cost, C_s is the clean energy heating subsidy, and C_d is the income from the peak-shaving auxiliary service.

The constraints on the value of the electric power dispatch plan for the *i*-th load aggregator in the period *t* are expressed as

$$P_{s,i}(t) = \alpha_i \times p_i^{pre} \tag{11}$$

where α_i is the electric power dispatch coefficient of the *i*-th load aggregator.

The electricity purchase cost of the thermal storage electric heating system C_b can be expressed as:

$$C_b = \sum_{i=1}^{I} \sum_{t=1}^{T} c_b^t \times P_{s,i}(t) \tag{12}$$

where c_b^t is the electricity price of decentralized electric heating, ¥/kW.

The calculation of the operation and maintenance cost C_m of the load aggregator is shown as follows:

$$C_m = \sum_{i=1}^{I} \sum_{t=1}^{24} c_{i,mstor} \times H_{i,in}(t) + c_{i,mstor} \times H_{i,out}(t) + c_{i,mgrid} \times P_{s,i}(t) \quad (13)$$

where $c_{i,mstor}$ is the unit power operation and maintenance cost of the energy storage part of the i-th load aggregator, ¥/kW; $c_{i,mgrid}$ is the unit power operation and maintenance cost of the electric-heat conversion part of the i-th load aggregator, ¥/kW; $H_{i,in}(t)$, $H_{i,out}(t)$are the energy storage charging and discharging power of the i-th load aggregator respectively, kW.

The clean energy heating subsidy for the thermal storage electric heating system C_s can be expressed as:

$$C_s = \sum_{i=1}^{I} \sum_{t=1}^{T} k_i \times c_{cl,i} \times f_n(P_{s,i}(t)) \quad (14)$$

where k_i is the subsidy price coefficient of the i-th load aggregator, kW^{-1}; $c_{cl,i}$ is the subsidized price for the i-th load aggregator, ¥/kW; $f_n(P_{s,i}(t))$ is the quadratic subsidy function of the electric power dispatch plan value of the i-th load aggregator in the period t.

The income C_d from the peak-shaving auxiliary service of the thermal storage electric heating system can be expressed as:

$$C_d = \sum_{i=1}^{I} \sum_{t=1}^{T} c_{peak,i}(t) \times P_{s,i}(t) \quad (15)$$

where $c_{peak,i}(t)$ is the hourly auxiliary peak-shaving subsidy price for the i-th load aggregator, ¥/kW.

To ensure the safe operation of the power grid, the constraints include that the load aggregator capacity do not exceed the limit; the electric heating user load meets the needs of electricity balance constraints; the electric-heat conversion equipment satisfies the maximum operating power constraints.

3.2. The Lower-Layer of the PCM-Based Electric Heating Loads Control Strategy

The upper-layer of the power dispatching system issues the target task to the lower-level according to the obtained dispatch plan value $P_{s,i}(t)$ of the i-th load aggregator in the period t. The load aggregator has the control right of the PCM-based electric heating equipment [10, 11].

In the lower-layer, a comprehensive control strategy is considered to minimize the electricity price cost and maximize its benefits in the i-th load aggregator. Suppose that the i-th load aggregator has some direct electric heating devices and the PCM-based electric heating devices. According to device response characteristics and forecast data, $P_{i,j}(t)$ is the power that the j-th electric heating equipment can provide in the t period. The electricity of the electric heating loads $S_i(t)$ in period t is:

$$S_i(t) = \sum_{j=1}^{n} \mu_j(t) P_{i,j}(t) \quad (16)$$

where $\mu_j(t)$ is the switching state of the electric heating device in the *t* period. If $\mu_j(t)$=1, it means that the electric heating device is turned on to participate in the system response, else $\mu_j(t)$=0 means that the electric heating device is turned off.

The deviation $E_i(t)$ between $S_i(t)$ and the dispatch plan $P_{s,i}(t)$ of the *i*-th load aggregator is shown as:

$$E_i(t) = S_i(t) - P_{s,i}(t) \tag{17}$$

The power company settles the load scheduling according to the implementation of the PCM-based electric heating system. Therefore, the benefit $F_i(t)$ of the *i*-th load aggregator in the *t* period is:

$$F_i(t) = \delta(t)S_i(t)\Delta t, E_i(t) \geq 0 \tag{18}$$

where $\delta(t)$ is the settlement price of the PCM-based electric heating system by the dispatching department in the *t* period.

When the electricity price is at the valley value, the price cost $J_{g,i}(t)$ of the *i*-th load aggregator is:

$$J_{g,i}(t) = \sum_{j=1}^{N_z} P_{z,j}\mu_{i,j}(t)c_g(t) + \sum_{j=1}^{N_x} P_{xc,j}\mu_{i,j}(t)c_g(t) \tag{19}$$

where N_z, N_x are the number of direct electric heating devices and the PCM-based electric heating devices in the *i*-th load aggregator respectively; $P_{z,j}$, $P_{xc,j}$ are the rated power of the direct electric heating devices and the PCM-based electric heating devices respectively; $c_g(t)$ is the electricity price in the valley period.

When the electricity price is at the peak value, the price cost $J_{f,i}(t)$ of the *i*-th load aggregator is

$$J_{f,i}(t) = \sum_{j=1}^{N_x} P_{xF,j}\mu_{i,j}(t)c_f(t) \tag{20}$$

where $P_{xc,j}$ are the rated power of the PCM-based electric heating devices in heat releasing mode respectively; $c_f(t)$ is the electricity price in the peak period.

The *i*-th load aggregator implements the load control decision-making objective to maximize the benefits and minimize the total price cost:

$$maxF_i(t) - J_{g,i}(t) - J_{f,i}(t) \tag{21}$$

The constraints are required to meet the load demand, the upper and lower electric power limits of the direct heating equipment, and the upper and lower electric power limits of the PCM-based electric heating equipment.

The above model is a nonlinear multi-objective optimization problem, and MATLAB optimal algorithm is used to solve it.

4. Simulations

To highlight the load aggregation characteristics, the peak and valley electricity price is set in two stages. the rated power of the direct electric heating devices and the PCM-based electric heating devices are 6 kW and 6.7 kW respectively. The energy efficiency ratio is set to 3. As the energy consumption of the heat releasing process is much smaller than that of the heating process, so the rated power of the PCM-based electric heating devices in heat releasing mode is 1 kW.

In scenario 1, the thermal storage capacity is set to be 200 kWh. The load prediction value is shown in Figure 2. According to the two-layer optimal control strategy of the electric heating system, the actual power grid dispatch curve of the upper-layer can be obtained in Figure 2.

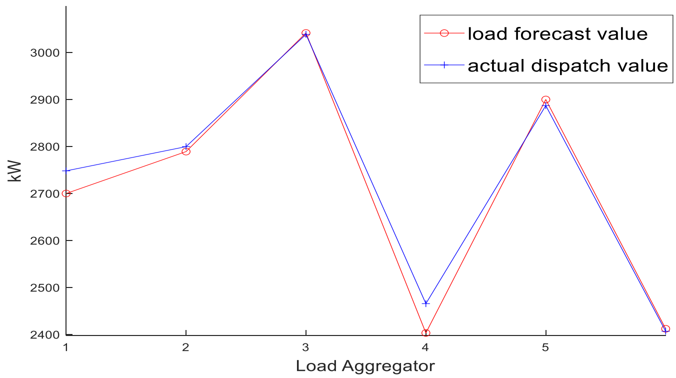

Figure 2. Actual scheduling curve.

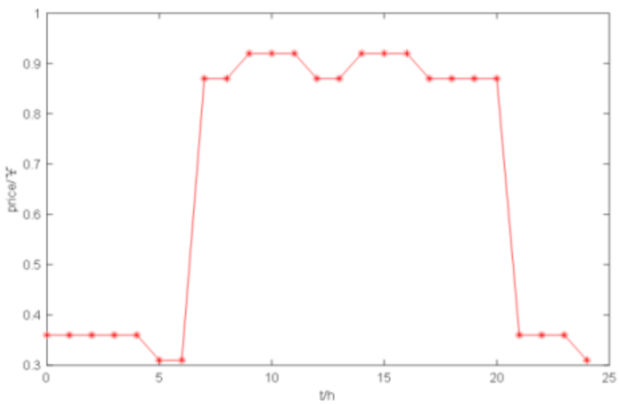

Figure 3. Typical peak and valley electricity price curve.

The peak-to-valley electricity price curve for load aggregators is shown in Figure 3.

Assuming that the optimal comfortable temperature of users is 22°C, the parameter information is put in and constraint conditions are met. Therefore, the heat of electric heating equipment can be obtained, as shown in Figure 4.

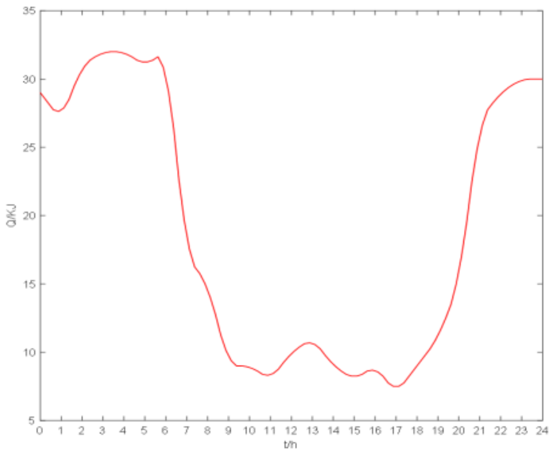

Figure 4. The heat of electric heating equipment in scenario 1.

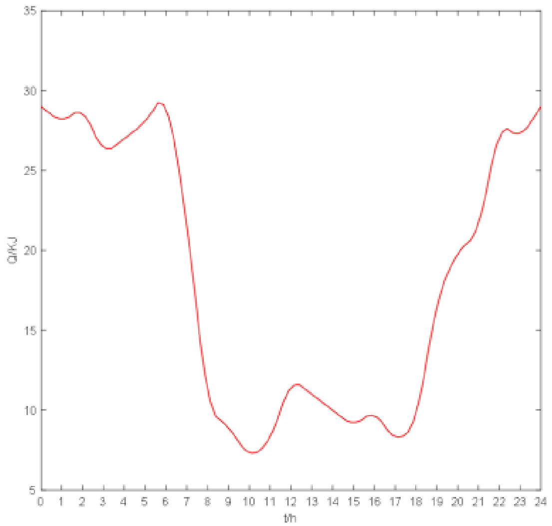

Figure 5. The heat of electric heating equipment in scenario 2.

In scenario 2, the thermal storage capacity is set to be 120 kWh, and the comfortable temperature range of the human body is set as 18°C-25°C. The full thermal storage plan is unable to meet the peak electricity of heat load demand. At the time of peak electricity, the thermal storage heat is released completely, and the direct heating heat equipment is opened in an optimized operation manner. Therefore, the heat of electric heating equipment can be obtained, as shown in Figure 5.

It can be seen that the user load characteristics are all high at both ends and low in the middle. To achieve the lowest electricity price cost, the equipment is worked when the electricity price is in the valley. The load characteristics of direct electric heating devices reflect the load demand. However, The PCM-based electric heating devices can transfer the electricity from the peak to the valley of electricity price. For the PCM-based electric heating devices, the electricity consumption in the heat releasing process is smaller than that of electric heating process. The optimizing process can ensure the minimum total price cost and maximum benefit greatly.

5. Conclusion

The two-layer optimized strategy designed in this paper can be used for electric heating load scheduling, which can ensure the user income under the condition of minimizing the heating costs. It can provide suggestions for the design of PCM-based electric heating load scheduling system.

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