Research Article

An Optimal Dispatch Framework of Electric and Heating Networks Based on Controllable Electric and Thermostatically Controlled Loads

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With the increasing capacity of wind power generators (WTGs), the volatility of wind power could significantly challenge the stability and economy of electric and heating networks. To tackle this challenge, this paper proposes an optimal dispatch framework based on controllable load (including controllable electric load and controllable thermostatically load) to reduce wind power curtailment. A forecasting model is developed for the controllable load, which comprehensively considers autocorrelation, weather factor, and consumers' behavior characteristics. With adjusting controllable load, an optimal dispatch model of power system is then established and resolved by Sequential Least Squares Programming (SLSQP) method. Our method is verified through numerous simulations. The results show that, compared with the state-of-the-art techniques of support vector machine and recurrent neural networks, the root mean square error with the proposed long short-term memory can be reduced by 0.069 and 0.044, respectively. Compared with conventional method, the peak wind power curtailment with dispatching controllable load is reduced by nearly 10% and 5% in two cases, respectively.

1. Introduction

With the increasing renewable energy integration, the adjustment capability of power network is decreased. To tackle this challenge, flexible adjustment resource (AR) has been widely recognized as an effective approach to enhance the adjustment capability. However, insufficient flexible AR capacity and its inaccurate prediction have an influence on the power adjustment and optimization of the power network. For instance, the curtailment of wind power in Northern China becomes more severe in heating period due to the significant thermal requirements supplied by combined heat and power (CHP) units [1–4]. Therefore, it is urgent to tackle the problems of wind power curtailment and optimization of electric and heating networks.

The flexible ARs can contribute to the stable operation and optimization of electric and heating networks by shifting

their consumptions. The popular ARs mainly includes (a) electric energy storage (EES). EES is helpful to the power balance. However, the costs and geographical characteristics (e.g., battery-based storage and pumped storage) are still their main limitations [5]; (b) thermal energy storage (TES). The thermoelectric coupling characteristics of CHP units can be reduced if TES is deployed [6]; (c) controllable electric load (CEL). These consumers are mainly scheduled based on electricity price mechanism and incentives [7]; (d) thermostatically controlled load (TCL). Thanks to their thermal inertia and heating storage, TCL can contribute to regulate power balance within a certain period [8]. These two controllable loads (CL) also need to meet the consumers' requirements.

The above ARs have been widely studied. For EES, with the rapid development of the battery-based EES, its technology has shown the characteristics and trends for large-

scale integration and distributed applications with multi-objective collaboration [9]. A multienergy storage system architectural model and its coordination operational strategy with the same flexibility as in the pumped storage power station and battery-based EES are studied [10]. Heat transfer constraint of TES is considered in a detailed model of district heating network [11]. Reference [12] proposes a stochastic day-ahead scheduling model of integrated energy system (IES) considering multitype energy storages (including electric storage, heat storage, and gas storage) to accommodate wind power. Reference [13] proposes a novel scheduling strategy to dispatch CELs with nonlinear power-efficiency characteristics, such as desalination devices. An optimal bidding model of controllable loads is proposed to minimize the worst-case conditional expectation of electricity purchase cost, which is suitable for CEL and TCL [7]. Reference [14] presents a mathematical formulation of the problem and develops a coordination framework of TCLs using the mechanism design approach. Furthermore, a learning scheme is presented to account for the unknown TCL model parameters and evaluate the proposed framework through realistic simulations [15]. To further promote the accommodation of wind power and enhance the flexibility of the electric and heating networks, reference [16] presents a method of heat and power load dispatching by exploring the energy storage ability of electric heating boilers and district heating systems. However, controllable power industry load, as a CEL, occupies a certain proportion of power load, and it is rarely studied and applied to system dispatch. Therefore, this paper explores the coordination dispatch method of CEL and TCL to enhance the regulation capability of the electric and heating networks.

In the methods of controllable power industry load prediction, commonly, the probability distribution functions (e.g., Gaussian or Beta) are used to characterize the load forecast deviation by some random variables [17]. This approach can be used to validate the robust performance of the dispatch method, but it cannot reduce the economic cost loss caused by the prediction error. Commonly, regression analysis and time series methods are applied to make a short-time load prediction based on the historical power data [18]. However, short-term load prediction, especially for the controllable power industry load, mainly depends on customer behaviors, events, and environmental factors, which may increase the consumption uncertainty.

Deep learning has been recently developed, which is a promising technique to extract comprehensive information from historical data, such as multilayer neural network, recurrent neural network (RNN), and support vector machine (SVM) [19]. Among them, long short-term memory (LSTM) is considered as an effective method to tackle the time series forecasting challenges owing to its efficient performance for accurate modeling [20–22]. There are a few interesting works that have developed LSTM-based techniques for modeling residential load in power system. Reference [23] explores an LSTM recurrent neural network to identify active power fluctuations. An LSTM recurrent neural network-based framework is developed to forecast aggregated residential load [24]. To recognize industrial

equipment in manufacturing systems, an LSTM is adopted to analyze their behavior features [25]. In particular, weather data (such as temperature, wind speed, and cloud cover) are considered to enhance the accuracy of LSTM-based power load prediction [26]. However, few deep learning methods are deployed to predict controllable power industry load.

Therefore, this paper develops a deep learning-based method to predict controllable power industry load. Thereafter, an optimal dispatch framework is established to enhance the flexibility of the electric and heating networks by CEL and TLC. Our contributions are as follows.

- (i) An optimal dispatch framework based on the coordination of CEL and TLC is developed to reduce the wind power curtailment of electric and heating networks
- (ii) A LSTM-based prediction model of TLC, considering behavior characteristics integrating sequence characteristic and external factors, is proposed to enhance prediction precision
- (iii) Compared with conventional method, the peak wind power curtailment with dispatching CEL and TCL is reduced by nearly 10% and 5% in the two cases, respectively

2. Preliminaries

2.1. Overall Structure. The overall schematic diagram of the electric and heating networks is shown in Figure 1. The electric network consists of CHP with TES, thermal power plant (TPP), wind power plant (WPP), EES, UL, and CL. The CL includes controllable thermostatically load (TCL) (e.g., distributed electric heating storage) and controllable electric load (CEL) (e.g., commercial buildings). The CHP units with TES deliver thermal power to the district heat load for the heating network, limiting their electric power outputs. The TCL consumes electric power and supplies the heat requirement of distributed heat load. As a result, the electric and heating networks are inextricably linked. CLs are utilized in this research to optimize the operation of electric and heating networks.

2.2. Operation Constraints and Costs

2.2.1. CHP with TES

(1) Operation Characteristics Analysis. During the heating season, CHP units are the primary source for meeting consumers' electrical and thermal needs, which is an important coupling device for connecting power system and thermal system. Considering the operating characteristics of CHP with TES, its Thermal-electricity relationship is shown in Figure 2. The operation region of the CHP is within the area of A-B-C-D. $P_{\text{CHP,min}}^E$ and $P_{\text{CHP,max}}^E$ are the minimum and maximum electric power of the CHP without thermal power production, and $P_{\text{CHP,max}}^T$ is the maximum thermal power of the CHP. Line segments AB and DC, respectively, represent the operating conditions of the maximum and minimum output power of CHP. Line segment AD

FIGURE 1: Schematic diagram of electric and heating networks.

FIGURE 2: Thermal-electricity relationship of the CHP with TES.

represents that the given steam intake of CHP is all used for power generation, and the thermal power is zero. Line segment BC represents that the given steam intake of CHP is almost all used for steam extraction heating, and the output electric power of CHP is the minimum output to meet the heat load. The thermal production of CHP needs to generate corresponding electric power. As can be seen in Figure 2, the

coupling characteristics of CHP limit its range of power regulation, resulting in the instability of electric grids with CHP. As grid wind penetration and heat demand increase, the abandonment of wind power is likely to increase. Therefore, the heat output capacity of CHP with TES can be extended to A-E-F-G-H-J region under the action of TES and according to the modeling of CHP operation in [27]. $P_{TES,max}^T$ is the maximum thermal power of the TES. The following models and equations can be found in [27].

(2) *Constraints of CHP with TES.* According to the operation characteristics of CHP, the constraints of electric power $P_{CHPi,t}^E$ and thermal power $P_{CHPi,t}^T$ for CHP i ($i = 1, \dots, I$, and I is the total number of CHP) at time t ($t = 1, \dots, T$, and T is the total time points) are given by

$$\begin{cases} (P_{CHPi,min}^E - c_v P_{CHPi,t}^T) \leq P_{CHPi,t}^E \leq (P_{CHPi,max}^E - c_v P_{CHPi,t}^T), \\ R_{CHPi,min}^E \leq P_{CHPi,t}^E - P_{CHPi,t-1}^E \leq R_{CHPi,max}^E, \\ P_{CHPi,min}^T \leq P_{CHPi,t}^T \leq P_{CHPi,max}^T, \end{cases} \quad (1)$$

where c_v is the conversion coefficient from thermal power to electric power, and $R_{CHPi,min}^E$ and $R_{CHPi,max}^E$ are the lower and upper ramp rate limits of CHP i .

The constraints of thermal power $P_{TESj,t}^T$ and capacity $S_{TESj,t}^T$ for TES j ($j = 1, \dots, J$, and J is the total number of TES) are expressed by

$$\begin{cases} P_{TESj,min}^T \leq P_{TESj,t}^T \leq P_{TESj,max}^T, \\ S_{TESj,min}^T \leq (S_{TESj,t}^T = S_{TESj,t-1}^T + P_{TESj,t}^T) \leq S_{TESj,max}^T, \end{cases} \quad (2)$$

where $P_{TESj,min}^T$ and $P_{TESj,max}^T$ are the minimum and maximum thermal power of TES j , and $S_{TESj,min}^T$ and $S_{TESj,max}^T$ are the lower and upper capacity limits.

(3) *Cost of CHP with TES.* The operation cost of CHP with TES C_{CT} is described in

$$\begin{cases} C_{CT} = \sum_{i=1}^I C_{CHPi} + \sum_{j=1}^J C_{TESj}, \\ C_{CHPi} = \sum_{t=1}^T \{a_i [P_{CHPi,t}^E + c_v P_{CHPi,t}^T]^2 + b_i [P_{CHPi,t}^E + c_v P_{CHPi,t}^T] + c_i\}, \\ C_{TESj} = \sum_{t=1}^T (c_{o1} P_{TESj,t}^T), \end{cases} \quad (3)$$

where C_{CHPi} is the fuel cost of CHP i , C_{TESj} is the operation and maintenance cost of TES j , a_i , b_i and c_i are the fuel cost coefficients, and c_{o1} is the operation cost coefficient.

2.2.2. *Thermal Power Plant.* TPP can regulate the power balance of the power system. The interested reader can refer to [26] for more details about constraints and additional

formulations, which represent minimum up/downtimes or startup and shutdown trajectories for the TPP. The TPP output is limited by the minimum load, maximum capacity, and ramp rates. The operation constraints of electric power $P_{TPPd,t}$ for TPP d ($d = 1, \dots, D$, and D is the total number of TPP) at time t are described in

$$\begin{cases} P_{TPPd,min} \leq P_{TPPd,t} \leq P_{TPPd,max} \\ R_{TPPd,min} \leq P_{TPPd,t} - P_{TPPd,t-1} \leq R_{TPPd,max} \end{cases} \quad (4)$$

where $P_{TPPd,min}$ and $P_{TPPd,max}$ are the minimum and maximum electric power, and $R_{TPPd,min}$ and $R_{TPPd,max}$ are the lower and upper ramp rate limits. The fuel cost C_{TPP} is obtained by

$$C_{TPP} = \sum_{d=1}^D \sum_{t=1}^T (a_d P_{TPPd,t}^2 + b_d P_{TPPd,t} + c_d), \quad (5)$$

where a_d , b_d , and c_d are the fuel cost coefficients of TPP k .

2.2.3. Wind Power Plant. To simplify the analysis, we generally assume that the wind power generation equals the actual value plus a random forecast error that follows normal distribution. The model of wind power plant output at time t is shown in

$$\begin{aligned} \hat{P}_{WPPw,t} &= P_{WPPw,t} + \sum_{n=t}^t \varepsilon_n, \quad t = r, r+1, \dots, N, \\ \begin{cases} \varepsilon_n = 0, & n = r, \\ \varepsilon_n \sim N(0, \sigma_n^2), & n > r, \end{cases} \end{aligned} \quad (6)$$

where $\hat{P}_{WPPw,t}$ represents the wind power estimation made of WPP w ($w = 1, \dots, W$, and W is the total number of WPP) at time t , $P_{WPPw,t}$ is the actual value, and ε_n is the forecast error. Note that the deviation of the estimation $\hat{P}_{WPPw,t}$ from the actual value $P_{WPPw,t}$ increases with the prediction window length ($t-r$). Specifically, for generating the day-ahead estimation of $\hat{P}_{WPPw,t}$, we could just let r be 1 in (6). The standard deviation σ_n of ε_n is assumed to be 20%.

The cost of wind power curtailment C_W is calculated by

$$C_W = c_Q \sum_{w=1}^W \sum_{t=1}^T \Delta P_{WPPw,t}, \quad (7)$$

where c_Q is the cost coefficient of wind power curtailment. $\Delta P_{WPPw,t}$ is wind power curtailment of WPP w .

2.2.4. Electric Energy Storage. EES is charged during load valley periods and discharged during load peak periods. In this way, EES can effectively reduce the different values between peak and valley. However, EES with large capacity will increase the economic cost of power system. To balance the above contradictions, the optimal output strategy of EES is scheduled, and the constraints of EES are established. The constraints of electric power $P_{EESg,t}$ and capacity $S_{EESg,t}$ for EES g ($g = 1, \dots, G$, and G is the number of EES) are expressed by

$$\begin{cases} P_{EESg,max}^c \leq P_{EESg,t} \leq P_{EESg,max}^d \\ S_{EESg,t} = S_{EESg,t-1} + P_{EESg,t} (1 + \rho_{EESg}^c), \text{ when charge,} \\ S_{EESg,t} = S_{EESg,t-1} + P_{EESg,t} (1 + \rho_{EESg}^d), \text{ when discharge,} \\ S_{EESg,min} \leq S_{EESg,t} \leq S_{EESg,max} \end{cases} \quad (8)$$

where $P_{EESg,max}^c$ and $P_{EESg,max}^d$ are the maximum charge and discharge power, and ρ_{EESg}^c and ρ_{EESg}^d are charge and discharge losses of EES g , respectively. The operation cost of EES C_{EES} is calculated by

$$C_{EES} = \sum_{g=1}^G \sum_{t=1}^T (c_{o2} P_{EESg,t}), \quad (9)$$

where c_{o2} is the operation cost coefficient of EES.

3. Operation Characteristic of CL

3.1. Operation Characteristic. The role of CEL can be summarized as follows: to consume electricity, CEL (such as commercial buildings, electric vehicles, and interruptible loads) can make the dispatching system increase its reference value when the power generation is greater than the power load consumption, especially when the wind power is surplus. When the power generation is less than the consumption of the power load, the dispatching system will reduce the reference quantity to achieve the power balance of the grid. In this paper, to solve the problem of imbalance between power and heating networks, CL (including CEL and TCL) is adopted to participate in scheduling. Because of the flexibility of CL, resources in the network can be managed through energy transfer, thus maximizing the economic benefits of the network. Generally, the CELs are scheduled through an economic way, which is compensated by the electric network. Thus, the cost of adjusting FELs C_{CEL} is described by

$$C_{CEL} = \sum_{h=1}^H \sum_{t=1}^T (c_{o3} \Delta P_{CELh,t}^E), \quad (10)$$

where the subscript h denotes the h th CEL, H denotes the total number of CEL, c_{o3} is the adjustment cost coefficient of CEL, and $\Delta P_{CELh,t}^E$ is the power adjustment of CEL h at time t .

While ensuring the lowest economic cost, it also needs to meet consumers' demand for electricity throughout the day. The constraints of the CEL are expressed by

$$\begin{cases} P_{CELh,min}^E \leq P_{CELh,t}^E \leq P_{CELh,max}^E \\ \Delta P_{CELh,min}^E \leq \Delta P_{CELh,t}^E \leq \Delta P_{CELh,max}^E \\ \sum_{t=1}^T \Delta P_{CELh,t}^E = 0, \end{cases} \quad (11)$$

where $P_{CELh,min}^E$ and $P_{CELh,max}^E$ are the minimum and maximum power of CEL h , $P_{CELh,t}^E$ is the consumption power of CEL h at time t , and $\Delta P_{CELh,min}^E$ and $\Delta P_{CELh,max}^E$ are the minimum and maximum power adjustment of CEL h .

For TCLs, such as distributed electric heating storage (DEHS), heat pumps, and electric water heaters, because of its storage capacity and thermal inertia, its working periods can be flexibly adjusted according to the needs of the grid. Take DEHS as an example; it generally operates at rated power. The basic operation principle of DEHS is shown in Figure 3. Taking economic costs into account, DEHS can operate based on fluctuations in electricity prices, heating and storing in the valley-time price region and cutting off electric power in the peak-time price region. It quits operation when the temperature of DEHS is approaching to the limitation and starts again to compensate heat energy before the end of valley time.

As with CEL, DEHS also needs to meet the thermal requirements of consumers throughout the day. The constraints of the TCL are expressed by

$$\begin{cases} P_{TCLm,min}^E \leq P_{TCLm,t}^E \leq P_{TCLm,max}^E, \\ \Delta P_{TCLm,min}^E \leq \Delta P_{TCLm,t}^E \leq \Delta P_{TCLm,max}^E, \\ \sum_{t=1}^T \Delta P_{TCLm,t}^E = 0, \\ S_{TCLm,min}^T \leq S_{TCLm,t}^T \leq S_{TCLm,max}^T, \\ \varsigma_{min} P_{TCLRm,t}^T \leq P_{TCLm,t}^T \leq \varsigma_{max} P_{TCLRm,t}^T, \end{cases} \quad (12)$$

where $P_{TCLm,t}^E$ is the electric consumption power of TCL m at time t , $P_{TCLm,min}^E$ and $P_{TCLm,max}^E$ are the minimum and maximum electric power of TCL m , $\Delta P_{TCLm,t}^E$ is the power adjustment of TCL m , $\Delta P_{TCLm,min}^E$ and $\Delta P_{TCLm,max}^E$ are the minimum and maximum power adjustment of TCL m , $S_{TCLm,t}^T$ is the thermal storage capacity of TCL m , $S_{TCLm,min}^T$ and $S_{TCLm,max}^T$ are the lower and upper limits of its capacity, $P_{TCLm,t}^T$ is the output thermal power of TCL m to meet the heat load demand $P_{TCLRm,t}^T$, and ς_{min} and ς_{max} are the lower and upper limited proportions of adjustment of TCL m .

The cost of adjusting controllable thermostatically loads C_{TCL} is calculated by

$$C_{TCL} = \sum_m \sum_{t=1}^T (c_{o4} \Delta P_{TCLm,t}^E), \quad (13)$$

where c_{o4} is the adjustment cost coefficient of TCL.

3.2. Autocorrelation Analysis. In terms of load prediction, in order to understand the situation and rule of load changes over time and make better prediction, this paper firstly conducts correlation analysis on TCL and CEL. The autocorrelation analysis and correlation analysis with other external factors of TCL can be found in [28]. The analysis of CEL is shown as follows. To analyze the sequence correlation, the autocorrelation coefficients between original data and different time series are calculated by the Pearson correlation coefficient method. Pearson correlation coefficient, also known as product difference correlation coefficient, is usually used to measure the closeness and correlation direction of the correlation between two variables with linear correlation, and its calculation formula is shown in

FIGURE 3: The operation principle diagram of DEHS.

$$\hat{\rho}_{U,V} = \frac{\sum_{l=1}^L (u_l - \bar{u})(v_l - \bar{v})}{\sqrt{\sum_{l=1}^L (u_l - \bar{u})^2 (v_l - \bar{v})^2}}, \quad (14)$$

where $\bar{u}$ and $\bar{v}$ are the empirical means of the samples $U = (u_1, \dots, u_L)$ and $V = (v_1, \dots, v_L)$. In this case, U and V represent original power data (U) and lag power data [$V = (u_{1+k}, \dots, u_{L+k})$, k is the lag time, $k = 1, 2, \dots$, i.e., $t-k$ denotes the lag data falls behind the original data by k data points], respectively.

The results of DEHS autocorrelation analysis are shown in Figure 4 and Table 1. Partial autocorrelogram is an important tool to determine the order of autoregressive models for time series. The partial autocorrelograms are utilized to help identify the lag time. According to the partial autocorrelogram, the lag time is selected as 5 [29].

In Figure 4, the correlation coefficients are relatively high, which denotes that the history data influence the current data or future data. In Table 1, the correlation coefficients would be decreased with the increasing lag time. The electric power data of DEHS have a sequence characteristic, which is suitable for LSTM model.

3.3. Correlation Analysis with External Factors. Generally, the available factors affecting the electric power consumption of CEL are weather and time-of-use price. Therefore, these factors are considered in the correlation analysis. The relationships of power with external factors (including temperature, pressure, humidity, wind speed, and time-of-use price) are shown by the scatter plot in Figure 5. The correlation of electric power with the external factors is calculated based on the Pearson correlation coefficient method in (14). In this case, U and V represent power data and external factors data, respectively. The calculation results are shown in Figure 6.

The closer the absolute value of the correlation coefficient is to 1, the stronger the linear correlation of the two variables is, and the sign of coefficients indicates that if the two variables increase or decrease in the same direction (positive) or opposite direction (negative), as can be seen from Figure 6, the temperature factor is strongly correlated with wind speed and electricity price, so this paper considers the temperature factor in the forecasting model.

FIGURE 4: Autocorrelation coefficients of the electric power data of DEHS.

TABLE 1: Autocorrelation coefficient analysis results.

Lag	Correlation	Lag	Correlation	Lag	Correlation
$t-1$	0.96	$t-2$	0.92	$t-3$	0.87
$t-4$	0.82	$t-5$	0.76	$t-6$	0.69
$t-7$	0.62	$t-8$	0.55	$t-9$	0.48
$t-10$	0.41	$t-11$	0.34	$t-12$	0.27
$t-13$	0.21	$t-14$	0.16	$t-15$	0.11

4. Optimal Dispatch Based on Forecast of DEHS

With the increasing penetration of wind power, the wind power curtailment may be induced by a couple of electric and thermal power in electric and heating networks. On the basis of the above, we discussed that the regulation capacity of the network can be strengthened through CL

participation in scheduling. Therefore, in this paper, LSTM is used to establish the prediction model of TCL and CEL. The prediction model of TCL can be found in [28], and the prediction model of CEL is constructed as follows. After making the prediction model and making the prediction, a dispatch model is constructed according to the prediction results. Finally, Sequential Least Squares Programming method is used to optimize the objective function.

4.1. Prediction Model Based on LSTM. According to the above analysis, we establish the prediction model for CEL. The essential of RNN is to utilize the sequence characteristics to establish a model, which is suitable for the prediction of DEHS. However, the memory ability of RNN is short-lived, where the context may be significant or useless. As a popular

FIGURE 5: Scatter plot of power data of DEHS and external factors data.

FIGURE 6: Correlation coefficients of DEHS with external factors.

extended RNN method, with three gates (input, forget, and output gates) in memory cells, LSTM network can remember, update, and focus on effective information, which is helpful in tracking information for a longer period. LSTM has the advantage of avoiding gradients vanishment and filtering effective information [21]. Each cell is updated based on the current input and the previous cell state. The product of the result obtained by the activation function and the input gate of the input vector represents the information retained after the input data is filtered. Previously reserved information plus current input meaningful information will be retained for the next LSTM cell. We then take the activation value of this updated memory as a possible output, usually the tanh activation function. The last thing left is the output gate, which determines which of the outputs activated by the current memory are useful. Let c_t be memory cell state at time step t and h_t be the output hidden state; then c_t and h_t are updated:

$$\begin{cases} i_t = \sigma(w_{xi}x_t + w_{hi}x_t + b_i), \\ f_t = \sigma(w_{xf}x_t + w_{hf}x_t + b_f), \\ o_t = \sigma(w_{xo}x_t + w_{ho}x_t + b_o), \\ c_t = f_t \odot c_{t-1} + i_t \odot f(w_{xc}x_t + w_{hc}x_t + b_c), \\ h_t = o_t f(c_t), \end{cases} \quad (15)$$

where $\sigma(x) = 1/(1 + e^{-x})$ is the sigmoid function, $f(\cdot)$ is activation function, i_t , f_t and o_t are input gate, forget gate,

and output gate vectors, w_{xi} , w_{xf} , w_{xo} , w_{hi} , w_{hf} and w_{ho} are the weights for linear combination, b_i , b_f and b_o are the relative bias, and $\odot$ is element-wise production.

In this paper, we consider the behavior characteristics integrating sequence characteristic and external factors (including weather factors and time-of-use price) in the prediction model framework. The block diagram of the electric power prediction of CEL with the LSTM is shown in Figure 7. This diagram illustrates the flow of a time series with some features of length S through two LSTM layers. After correlation analysis of power and temperature data, feature dimensions are obtained according to time series to predict CEL load state, and LSTM network is updated according to (13). However, the other impact factors can also be considered in this framework according to the requirement.

$$\begin{cases} [W_{ea,t}, P_t^n] = x_t^k, \\ c_t^n, h_t^n = \text{LSTM}^n([W_{ea,t}, P_t^n], c_{t-1}^n, h_{t-1}^n | W^n), \end{cases} \quad (16)$$

where $W_{ea,t}$ is the weather parameters, P_t is the power consumption of DEHS, $\text{LSTM}(\cdot)$ is the state updating of the LSTM cells (i.e., short for (12)), $[\cdot, \cdot]$ means concatenating several vectors into one vector, and W is the trainable weights of LSTM.

4.2. Objective Function. A day-ahead dispatch model of electricity and heat networks for reducing wind power curtailment is established. Factors such as the fuel cost of CHP with TES, TPP, average operation and maintenance cost of EES, the cost of wind power curtailment, and scheduling CL are considered. Summing up equations (3), (5), (7), (9), (10), and (13), the objective function of economic cost C_{EC} of day-ahead scheduling model is expressed in

$$\min C_{EC} = C_{CT} + C_{TPP} + C_W + C_{EES} + C_{CEL} + C_{TCL}. \quad (17)$$

4.3. Electric and Heating Networks Balance

4.3.1. Electric Network Balance. Total generations and electric loads must be balanced at each operation period as described in

FIGURE 7: Block diagram of electric power prediction of CEL with LSTM.

$$\begin{aligned} & \sum_{i=1}^I P_{CHP,i,t}^E + \sum_{d=1}^D P_{TPD,d,t} + \sum_{g=1}^G P_{EES,g,t} + \sum_{w=1}^W (P_{WPP,w,t} - \Delta P_{WPP,w,t}) = \\ & P_{L,t}^E + \sum_h^H (P_{CEL,h,t}^E + \Delta P_{CEL,h,t}^E) + \sum_m^M (P_{TCL,m,t}^E + \Delta P_{TCL,m,t}^E), \end{aligned} \quad (18)$$

where $P_{L,t}^E$ is load electric demand at time t .

4.3.2. District Heating Network Unbalance. Since the inertia of the heating network can maintain the temperatures, the unbalance between thermal power generation and demand can be within a limited range as shown in

$$\chi_{\min} P_{L,t}^T \leq \left(\sum_{i=1}^I P_{CHP,i,t}^T + \sum_{j=1}^J P_{TES,j,t}^T \right) \leq \chi_{\max} P_{L,t}^T, \quad (19)$$

where $P_{L,t}^T$ is the heat demand at time t . $\chi_{\min}$ and $\chi_{\max}$ are the lower and upper limited proportions of adjustment in the district heating network.

5. Case Study

Several cases are conducted with real data in the Liaoning provincial grid of China to verify the effectiveness of the proposed prediction method and the optimal dispatch solution. Although the data used to validate the effectiveness is only from one country, it should be noted that the proposed method and optimal dispatch solution can be used in any system globally. A nonlinear quadratic programming problem can be used to solve the optimal dispatch problem. The Sequential Least Squares Programming method is used as a resolving solution in Python.

5.1. Forecasting Method Validation. The proposed LSTM model is compared with two advanced methods: RNN and SVM. The LSTM model's fitness of train data and test data of CEL is obtained by mean absolute error (MAE) loss function as shown in Figure 8.

FIGURE 8: The fitness of the train data and test data of CEL.

In Figure 8, with the increasing epoch, the losses gradually approach 0.2. The training and testing sets are consistent, proving that LSTM has high accuracy and is suitable for forecasting CEL. The prediction results for each method are shown in Figure 9 and Table 2.

In Figure 9(a), with different methods, the overall prediction trends are consistent considering the weather. Figure 9(b) shows that the prediction result with LSTM is closest to the real data. In Table 2, it can be seen that MAPE and root mean square error (RMSE) with LSTM are the least, which shows the higher accuracy of the proposed model. Thus, the superiority of LSTM in CEL prediction is reflected.

5.2. Optimal Dispatch Validation. In this paper, the scheduling results with and without CL are compared to prove the effectiveness of CL for day-ahead optimization scheduling. The consumption curves of electric load and heat load are predicted. The wind power curve in recent two months is shown in Figure 10. Wind power data are measured on a time scale of 15 minutes, and two typical curves of this month are selected, namely, the curves of maximum output power and minimum output power. It can

FIGURE 9: Real data and prediction data of CEL. (a) The real data and prediction data for five days; (b) the real data and prediction data for the first day.

TABLE 2: The values of MAPE, RMSE, and NRMSE of the prediction results with different prediction methods.

Prediction methods	MAPE	RMSE
SVM	0.014	7.365
RNN	0.012	7.340
LSTM	0.011	7.296

TABLE 3: Simulation parameters.

Parameters	Values	Parameters	Values
c_v	0.15	c_{o1}	10 USD
a_i	0.0044 USD/MW ²	c_{o2}	26 USD/MW
b_i	13.29 USD/MW	c_{o3}	10 USD/MW
c_i	39 USD	$\chi_{\min}$	0.9
a_d	0.03 USD/MW ²	$\chi_{\max}$	1.1
b_d	23.66 USD/MW ²	$\varsigma_{\min}$	0.9
c_d	16.22 USD	$\varsigma_{\max}$	1.1
c_Q	30 USD/MW

FIGURE 10: Typical wind power curves.

prove that the proposed methods can cope with different operating conditions. In Case 1, the lower wind power curve is applied, and the upper wind power curve is used in Case 2. The electric power curve of CEL is predicted by LSTM model, and TCL power is selected in [28]. The simulation parameters are the same with the Liaoning provincial grid as shown in Table 3.

The optimization results of the two cases with different methods are shown in Figures 11 and 12. In Figure 11(a), the electric power of load (P_L^E) is supplied by power sources in the electric network. With the two methods, the electric power of CHP P_{CHP}^E and TPP P_{TPP} is generally consistent. Due to the small capacity of EES, it has a small space to

participate in power grid regulation, so it cannot eliminate all wind power curtailment only by EES. CL participation in grid dispatching can enhance the effect of wind power consumption together with EES. The results show that the output of wind power P_{WPP} with CL involved in scheduling is greater than that without CL involved in scheduling.

As shown in Figure 11(b), in the peak-time region of base load (from time points 30 to 60), due to weak wind power, it cannot meet the base load demand, and the output of CHP, TTP, and EES is high. It is almost up to the limit. At about time point 12, due to the reduction of the electric power of load, wind power not only meets the load demand, but also generates part of curtailment power. However, after CL participates in dispatching, it can effectively reduce wind abandoning by transferring CEL and TCL consumption, especially in peak wind power periods, realizing efficient utilization of renewable energy. The results show that the peak wind power curtailment is reduced by about 50 MW, accounting for about 10% of the total power generation. At the same time, EES life, because of the reduction of large charge and discharge times, has been improved.

Figures 11(c) and 11(d) show the thermal supply and consumption for the district heating networks and TCL, respectively. It can be seen that, in the district heating network, due to the help of TES, the requirement of thermal power with two methods can be met for the residents. For

FIGURE 11: The dispatch results in Case 1. (a) Electric power of load, CHP and WPP; (b) electric power of wind power curtailment, EES, CEL, and TCL; (c) thermal power in district heating network; (d) thermal power for TCL.

FIGURE 12: Continued.

FIGURE 12: The dispatch results in Case 2. (a) Electric power of load, CHP and WPP; (b) electric power of wind power curtailment, EES, CEL, and TCL; (c) thermal power in district heating network; (d) thermal power for TCL.

the TCL, the thermal requirement is met. The final economic costs of the dispatch model C_{EC} are 5,571,203 USD and 5,612,126 USD with CL and without CL, respectively. The results in Case 2 are shown in Figure 12.

In Figure 12(a), during the period of (points 80–96), with the reduction of base load demand, wind power output increases. CHP and TTP even reach the lower limit of output because they do not have to produce too much, and excessive wind power leads to the increase of wind power curtailment. As shown in Figure 12(b), with dispatching CL, wind power output is larger than that without CL. The results show that the peak wind power curtailment is reduced by about 25 MW (accounting for about 5% of the total power generation); thanks to the adjustment of the consumption of CEL and TCL of the peak wind power curtailment is reduced. It can be seen from Figures 12(c) and 12(d) that the thermal sources can meet the thermal requirement of the district heating network and TCL, respectively. The final economic costs C_{EC} are 5,668,098 USD and 5,738,626 USD with CL and without CL respectively, and the economic cost is reduced by 70,528 USD. Therefore, the proposed dispatch method can reduce wind power curtailment and economic costs.

6. Conclusion

This paper proposes a framework of optimal dispatch based on controllable load (including CEL and TCL). The prediction model of LSTM of distributed electric heat storage based on correlation is established. The prediction model, considering their autocorrelation, weather factor, and consumers' behavior characteristics, improves the prediction accuracy of distributed electric heating storage. The effectiveness of the proposed prediction model and the dispatch method are verified through simulations. Compared with the state-of-the-art techniques of support vector

machine and recurrent neural networks, the root mean square error with the proposed long short-term memory can be reduced by 0.069 and 0.044, respectively. Compared with conventional method, the peak wind power curtailment with dispatching CEL and TCL is reduced by nearly 10% and 5% in the two cases, respectively.

Data Availability

The raw data in our study are from Liaoning provincial grid of China.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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