Short-term load prediction of integrated energy system based on neural network

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Abstract—Considering the correlation and nonlinear characteristics of multiple types of loads in the integrated energy system, grey relation analysis (GRA) and long short term Memory (LSTM) neural network are selected to establish the short-term load prediction model of the integrated energy system. The model uses GRA method to analyze the coupling between multiple types of loads and the meteorological factors, and then obtains the load forecast results through the LSTM prediction model. Finally, a practical example is given to verify the validity of the model.

1. Introduction

Integrated energy system is an energy system that can meet various loads needed by people at the same time. Its small capacity, decentralized and modular characteristics realize energy cascade utilization. It is the core of future energy technology development, and has been widely used in office and commercial buildings.

The integrated energy system has multiple types of loads, including cold load, thermal load and electric load. Accurate short-term prediction of multi-type load is the key to the operation and scheduling of integrated energy system. Recently, the effectiveness of neural network-based processing of nonlinear maps has been prominent, which is gradually used in the field of load prediction, such as wavelet analysis and Elman dynamic neural network[⁵], wavelet support vector machine[⁶], back propagation, radial basis and wavelet neural network[⁷]. Among them, LSTM network is more suitable to fit complex data and analyze data temporal correlations. Cold load, thermal load and electric load have strong time change and coupling, and many related influencing factors, so LSTM network is more suitable for load prediction of multiple types. IKHCMAC neural network was selected to predict cold and heat loads, and improved entropy weight method and empirical wavelet transform were selected to predict cold, heat and electrical loads.

In conclusion, due to the characteristics of time-varying, coupling and pluralism of cold, heat and electrical load prediction, based on the analysis of the correlation between multiple types of loads and meteorological factors, this paper establishes a short-term forecasting model of multiple types of loads in integrated energy system by using grey relation analysis and long short term memory neural network.

2. Correlation analysis of multitype load and influencing factors

The cold load, thermal load and electric load of the integrated energy system have strong randomness...
and coupling[4], therefore, before the short-term prediction of cold, heat and electricity load, the correlation between loads and the influence of various factors on loads should be analyzed[5]. This paper, the meteorological factors with the greatest impact on the load prediction are selected as the influencing factors, and GRA is selected to quantitatively analyze the correlation between the influencing factors and different types of loads.

2.1 GRA method
Grey relation analysis (GRA) is a multi-factor statistical Analysis method. Through the sample data of each factor, GRA is used to describe the strength, size and order of the relationship among factors. GRA method has a simple principle and is suitable for analyzing the nonlinear relationship among multiple factors such as multiple types of loads and meteorological influencing factors[6].

2.2 Related analysis of multiple type load and meteorological influence factors based on GRA method
In GRA method, calculating the correlation coefficient and correlation degree are the key problems, and the calculation formula is as follows:

$$\xi_i = \frac{\min_{k} \min_{j} |x_{i_0}(k) - x_j(k)| + \rho \max_{k} \max_{j} |x_{i_0}(k) - x_j(k)|}{\max_{k} \max_{j} |x_{i_0}(k) - x_j(k)|}$$  (1)

$$\gamma_i = \frac{1}{n} \sum_{k=1}^{n} \xi_i(k)$$  (2)

where $x_{i_0}(k)$ is normalized meteorological factor sequence; $x_j(k)$ is normalized load sequence; $\rho$ is the resolution coefficient, usually 0.5; $n$ is the number of elements.

This paper simulates the cold load, thermal load and electric load in the integrated energy system through DeST-C software. Summer (June to August) is mainly the cooling season, and both the correlation between the cooling load, electrical load of the integrated energy system and the multi-type load with various meteorological factors are analyzed. Winter (December - February of the next year) is the main heating season, and both the correlation between the thermal load, electrical load of the integrated energy system and the multi-type load with various meteorological factors are analyzed.

In summer, the data sequence matrix of cold load, electric load and various meteorological influence factors:

$$X_s = \begin{bmatrix} x_c & x_e & x_R & x_T & x_M \\ x_c(1) & x_e(1) & x_R(1) & x_T(1) & x_M(1) \\ x_c(2) & x_e(2) & x_R(2) & x_T(2) & x_M(2) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_c(n) & x_e(n) & x_R(n) & x_T(n) & x_M(n) \end{bmatrix}$$  (3)

where $x_c$ is the cold load; $x_e$ is the electric load; $x_R$ is the solar radiation; $x_T$ is the temperature; $x_M$ is the air humidity.

In winter, the data sequence matrix of thermal load, electric load and various meteorological influence factors:

$$X_w = \begin{bmatrix} x_h & x_e & x_R & x_T & x_M \\ x_h(1) & x_e(1) & x_R(1) & x_T(1) & x_M(1) \\ x_h(2) & x_e(2) & x_R(2) & x_T(2) & x_M(2) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_h(n) & x_e(n) & x_R(n) & x_T(n) & x_M(n) \end{bmatrix}$$  (4)

where $x_h$ is the thermal load.
After setting the data sequence matrix, the correlation coefficient and correlation degree are calculated according to equations (1) and (2) for correlation analysis. The correlation analysis results are shown in Tab.1 and Tab.2. E represents electrical load; C stands for cooling load; T is temperature; R stands for solar radiation; M stands for air humidity; H stands for heat load.

| Tab.1 Correlation analysis results of multi-type loads and influencing factors in summer |
|-------------------------------------|-----|-----|-----|-----|-----|
| E        | C    | T    | R    | M    |
| E        | 1    | 0.87 | 0.80 | 0.61 | 0.20 |
| C        | 0.87 | 1    | 0.81 | 0.66 | 0.24 |

| Tab.2 Correlation analysis results of multi-type loads and influencing factors in winter |
|-------------------------------------|-----|-----|-----|-----|-----|
| E        | H    | T    | R    | M    |
| E        | 1    | 0.65 | 0.81 | 0.64 | 0.23 |
| H        | 0.65 | 1    | 0.79 | 0.68 | 0.22 |

Considering the coupling between electric load, cold load and heat load, and the correlation analysis results among them, so as to improve the accuracy of load prediction of integrated energy system. On the other hand, due to the coupling characteristics between cold, heat and electrical loads and various meteorological factors, the load prediction results will be greatly affected, so the weather factors are taken as the theoretical basis for constructing the forecast data set[7]. In conclusion, each meteorological factor is set as the influence factor, and which is formed together with multiple types of historical load data as the input data set of this forecast model.

3. Short-term load forecasting model of integrated energy system based on neural network

3.1 LSTM neural network prediction model

Long short term memory (LSTM) neural networks are a modified variant of recurrent neural networks (RNN), retain the advantages of RNN network to process time load data, and effectively solve the problems of gradient disappearance and gradient explosion in RNN networks, improve the ability to process interval or delay longer samples in time data series[8]. In this paper, the load prediction of integrated energy system is nonlinear time series prediction, with more load types and dimensions, larger than simple electric load data, so LSTM network is selected as the prediction model theory.

The value passed in from the hidden layer of the last moment \((h_{t-1})\) and the input value of the current moment \((x_t)\) pass through the forgetting gate \((f_t)\) and selectively discard the information of the last stage through calculation, and the formula is as follows:

\[
f_t = \sigma \left( w_f \cdot [h_{t-1}, x_t] + b_f \right)
\]  (5)

where \(w\) is the weight matrix, \(b\) is the bias vector respectively, \(\sigma\) is the activation function (using sigmoid function).

The new information is then passed through the sigmoid function to obtain the data input into the memory unit, and a new candidate state is created through the tanh layer \((c_t)\), and the formula is as follows:

\[
i_t = \sigma \left( w_i \cdot [h_{t-1}, x_t] + b_i \right)
\]  (6)

\[
c_t = \tanh \left( w_c \cdot [h_{t-1}, x_t] + b_c \right)
\]  (7)

The result calculated by the input gate \((i_t)\) is multiplied with the new unit state value \((c_t)\) and added with the result obtained by the forgetting gate \((f_t)\) to obtain the unit state value at the current time, and the formula is as follows:
\[ c_t = f_t \cdot c_{t-1} + i_t \cdot k_t \]  \tag{8}

Note that the hidden layer data value passed to the next moment \( f_t \) is obtained using the new unit state processed by the tanh function \( c_t \) and the data classified by the sigmoid function \( o_t \), and the formula is as follows:

\[ o_t = \sigma \left( w_o \cdot \left[ h_{t-1}, x_t \right] + b_o \right) \]  \tag{9}

\[ h_t = o_t \cdot \tanh(c_t) \]  \tag{10}

3.2 Short-term load forecasting process of integrated energy system based on LSTM neural network

First, the eigenvector is selected from the analysis results obtained by GRA method and obtain the eigenvector matrix, and the data are normalized to form the input sample data set, then the input sample data sets \( D = \{ d_1, d_2, \ldots, d_n \} \) are divided into training sets \( t_{tr} = \{ d_1, d_2, \ldots, d_m \} \) and test sets \( t_{te} = \{ d_{m+1}, d_{m+2}, \ldots, d_n \} \) and sent to the LSTM layer for training, so the gate value and memory unit and implicit state are calculated. Finally, the LSTM prediction model is built to predict the load, and the prediction results are output at last. The prediction process is shown in Fig.1.

4. Calculation example analysis

The actual climate influence factors in northern China are simulated by DeST-C software. Cold load, heat load, electrical load data and meteorological impact factors are recorded at 24 points per day, namely one point per hour; meteorological factors include temperature, solar radiation, and air humidity. According to the results of correlation analysis, the data of cold load, heat load and electrical load, temperature, solar radiation and air humidity were taken as the input sample set of the prediction model.

The typical summer working day of this office is selected as August 2; January 26 is selected as the typical winter holiday day of this office building. Model 1 uses LSTM neural network to independently predict load. Model 2 uses LSTM neural network for comprehensive prediction. model 3 adopts short-
term load prediction model based on Elman neural network. The forecast value and actual value curve of the above 3 forecast models are shown in Fig.2 and Fig.3 (the working days of cooling load in summer and the rest days of electricity load in winter are selected respectively).

According to the Fig.3, Fig.4 and the summary of Tab.3, model 2 has the best prediction effect. The average absolute percentage error of cooling load on working days in summer is 1.72%, and that of electrical load on working days in winter is 1.52%, while the average absolute percentage error of Model 1 is [2%, 4%]. This indicates that model 2, which considers the coupling between cold, heat and electrical loads, has a better prediction effect. Compared with models 1 and 2, the true value and the curve of predicted value of model 3 are not well fitted, and the average absolute error of Model 3 is [5%, 8%].
So the short-term load prediction model of integrated energy system based on GRA-LSTM neural network has good multivariate prediction performance and high prediction accuracy.

5. Conclusion
GAR method is used to analyze the coupling between multitype load and prove the inseparable ability in load prediction. Considering the nonlinearity and observation time limit, cold load and thermal load are trained as the input sample set input model using LSTM network. According to the analysis of the prediction effect, the proposed model established has high prediction accuracy and excellent relative error, which is of some practical significance for the economic and stable operation of the integrated energy system.

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