An integrated energy system load prediction study based on deep belief networks and multitasking learning

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Abstract. Load forecasting is an important research content in the field of integrated energy systems, improving the accuracy of load forecast results, and helping to improve the economics of the planning and operation of integrated energy systems. This paper puts forward a comprehensive energy system load prediction method based on deep belief network and multi-task learning, first of all, based on the comprehensive energy system general planning model, using Pearson coefficient quantitative calculation of the correlation between multiple loads, analysis of the common influencing factors in the load prediction process; The results show that the pre-test model presented in this paper has good prediction accuracy by validating the prediction method by study.

1. Introduction
The introduction of the dual carbon target will promote the whole society to speed up the adjustment and optimization of industrial structure and energy structure. Integrated energy system can realize the coupling and complementarity of different energy sources in a certain region, make use of the complementarity and substitution between energy sources, increase the efficiency of energy utilization, reduce the cost of energy use of the system, and have broad prospects for development [1]. Improving the accuracy of load prediction is the key foundation and important premise of integrated energy system planning, which can arrange energy supply plan economically and rationally, guarantee the normal production and life of society, effectively reduce the cost of energy use, and improve economic and social benefits.

There are many common load prediction methods, such as regression analysis, exponential smoothing, time series, Kalman filtering [2]. In load prediction, the use of intelligent algorithms has a good advantage [3]. The accuracy of prediction is improved by applying fuzzy theory to neural networks, the complexity of the original prediction model is reduced by combining the empirical mode decomposition with the deep learning theory [4], and the speed of algorithm load prediction is accelerated By using the traversal and uncertainty of chaos, the prediction model is constructed to reflect the load change of the user [5], the factors affecting the load change are taken into account in the load forecast, and the literature introduces machine learning into the field of load prediction, which brings new ideas to load prediction [6]. A new method based on similar day and radial base function networks is proposed [7]. The method has good stability and precision; A short-term load prediction method of
power system based on the theory of support vector machine (SVM) is proposed, which has better
generalization performance and accuracy [8]. The paper puts forward the selection method of model
learning parameters [9], and gives the optimization algorithm of Gauss nuclear function parameters
based on optimal direction search, which is convenient for the selection of model learning parameters
[10].

The above method is basically to make predictions on the original intelligent algorithm, the
improvement and optimization of the original algorithm is relatively small, the prediction accuracy
needs to be further improved. In this paper, the deep belief network and multitasking learning are used
in the process of load prediction, which has the advantages of simple operation, robustness and good
search, and improves the disadvantages of the traditional prediction methods which are easy to fall into
local minimum, slow learning convergence speed, hidden layer number and hidden layer node number.

2. Analysis of the influencing factors of load forecasting in integrated energy systems

The structure of the integrated energy system is generally composed of three parts: the incoming side,
the transmission side and the load side. The structure of a typical integrated energy system is shown in
Figure 1. Among them, the input side section is mainly powered by electricity, renewable energy and
natural gas; the middle side enables the generation, conversion, storage and transmission of a variety of
energy through various equipment; and finally, it is transferred to the load side of the integrated energy
system to meet the needs of the regional cold, hot and electrical loads. In the multi-load prediction, we
need to fully consider the relationship between many variables in the cold, hot and electric load, so as
to effectively improve the accuracy of load prediction.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure1.png}
\caption{Typical integrated energy system framework}
\end{figure}

2.1. Multi-load correlation analysis

The calculation of the Pearson correlation coefficient

In order to further quantitatively analyze the correlation between the cold, hot and electric loads of
the integrated energy system, Pearson correlation coefficient is used as an index to describe the
correlation.

Pearson correlation coefficient can excellently measure the correlation between two variables, the
size of which can better reflect the strength of the linear correlation between the two variables.

For \( C = [c_1, c_2, \ldots, c_n] \) variables and \( D = [d_1, d_2, \ldots, d_n] \), its Pearson correlation coefficient is calculated as

\[
r = \frac{n \sum (c_i - \bar{c})(d_j - \bar{d})}{\sqrt{\sum (c_i - \bar{c})^2 \sum (d_j - \bar{d})^2}}
\] (1)

Medium: \( \bar{c} \) and \( \bar{d} \) are the average of \( n \) sample data. The value range of the correlation coefficient \( r \) is \([-1, 1]\). The value of correlation coefficient \( r \) is defined as follows: the closer the \( |r| \) correlation
coefficient is to 1, the higher the correlation between \( x \) and \( y \), and the closer the correlation coefficient
is \( |r| \) to 0, the lower the correlation between \( c \) and \( d \).
2.2. Analysis of the correlation between load and influencing factors

In the actual forecasting process, the loads of cold, hot and electricity in the integrated energy system are not only related to other kinds of loads, but also the forecast results are influenced by economic conditions, social factors, climatic environment and other factors, but the more factors that are not considered in the forecast model, the better. The main reason is that these related factors need to be predicted in the forecasting process, and the prediction of the relevant factors is bound to be uncertain, and the uncertainty of these factors will increase the uncertainty of the forecast results. In response to such problems, this paper based on the Pearson coefficient correlation quantitative analysis, select the correlation of strong influencers for load prediction.

By effectively applying the correlation between cold, hot and electric loads and the correlation between load and related influencing factors, the influencer's prediction uncertainty can be reduced, and the prediction accuracy of the model can be improved.

3. Deep belief networks and multitasking use predictive methods

The basic feature of the deep neural network approach is an attempt to mimic the pattern of transmitting and processing information between neurons in the human brain. A series of methods of deep learning have solved the defect that traditional neural networks are prone to local minimum values. Integrated learning is a multi-algorithmically integrated machine learning method based on statistical learning theory that integrates information from multiple predictive models to generate new models, thereby improving the accuracy of their predictions.

In this paper, a DBN model based on restricted Boltzmann machine is used to extract unsuperfected learning characteristics of data samples using DBMs at the bottom of the model, and the top layer uses supervised BP neural network regression fitting to produce predictive results.

The RBM model is a thermodynamic-based energy model that defines its energy function \( E(v, h) \) for a given set of states \( \{v, h\} \), and the combined probability distribution of the hidden and visible layers is expressed as \( p(v, h) \) the energy function for the RBM of one of the layers as follows:

\[
E(v, h) = -\sum_{i=1}^{n_v} \sum_{j=1}^{n_h} w_{ij} v_i h_j - \sum_{i=1}^{n_v} a_i v_i - \sum_{j=1}^{n_h} b_j h_j
\]

(2)

Using the defined energy function, the combined probability density \( p(v, h) \) is expressed as:

\[
P(v, h) = \frac{1}{Z} e^{-E(v, h)}
\]

(3)

\[
Z = \sum_{v} \sum_{h} e^{-E(v, h)}
\]

(4)

In the formula, \( w_{ij} \) is the connection weight between the \( i \)th neuron in the hidden layer and the \( j \)th neuron in the visible layer, \( a_i \) is the bias of the \( i \)th neuron in the visible layer, and \( b_j \) is the bias of the \( j \)th neuron in the hidden layer. \( n_v \) and \( n_h \) respectively represent the number of visible layers and hidden layers. \( Z \) is a normalized molecule. Due to the special structure of RBM (that is, there are connections between layers and no connections within layers), it can be known that when the state of a visible unit is given, the activation state of each hidden unit is conditionally independent.

Finally, with the training sample \( v_0 \) as the initial state, after RBM to carry out a Gibbs sampling to get the difference between \( v_1 \) and the original data \( v_0 \), error is the reconstruction error, the reconstruction error as the RBM training evaluation index.

\[
error = \| v_1 - v_0 \|
\]

(5)

At this point, the multi-layer RBM is encapsulated in the DBN and a depth architecture with automatic extraction characteristics is formed. The top layer uses the feed-forward neural network in the supervised learning method to predict the fitting of the output power. On the one hand, the advanced abstract features of the extraction of the underlying DBN model are used as input to the top BP neural
4. Study validation

In order to verify the effectiveness of the planning scheme of the power load prediction model based on deep belief network and multi-task learning, this paper selects the actual energy data of a certain place in China, uses the exponential smoothing method in the traditional load prediction method and the prediction method proposed in this paper to make predictions respectively, and compares the prediction data of the two with the actual energy results.

Because it is necessary to compare the prediction results of different prediction models, in order to evaluate the prediction accuracy of the model as a whole, this paper uses the average absolute percentage error and the mean square root error to measure the overall degree of error and the degree of deviation between the prediction value and the real value, and the maximum relative error \( \varepsilon_{MAPE} \), \( \varepsilon_{RMSE} \), \( \varepsilon_{M} \) to reflect the degree of local prediction error. The three indicators are as follows:

\[
\varepsilon_{MAPE} = \frac{100}{n} \sum_{i=1}^{n} \left| \frac{l_i - \hat{l}_i}{\hat{l}_i} \right| \%
\]

\[
\varepsilon_{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (l_i - \hat{l}_i)^2}
\]

\[
\varepsilon_{M} = \max_{i=1}^{n} \left| \frac{l_i - \hat{l}_i}{\hat{l}_i} \right| \%
\]

Where: \( l_i \) is the actual load value, \( \hat{l}_i \) is the predicted load value, \( n \) is the total forecast load.

There are many factors that affect the load, such as weather, quarterly, electricity prices, politics, the geographic location of the user, etc. In different regions, the factors that need to be considered for load impact vary widely. This article uses load data from July 1, 2020 to August 20, 2020 (30 days per month) in a region of Sichuan, China, as training data, sampled once a day for a total of 50 load data points, and 40 points as test data from August 21, 2020 to September 30, 2020. The simulation effect diagram is shown in the figure below.
Table 1. Errors for different prediction methods

| Model                                              | Error | Electrical load | Cold load | Hot load |
|----------------------------------------------------|-------|-----------------|-----------|----------|
| Exponential smoothing                              | $\epsilon_{MAPE}$: 3.09% | 9.53%   | 6.12%    |
|                                                   | $\epsilon_{RMSE}$: 122.32 | 327.78  | 22.29    |
|                                                   | $\epsilon_{M}$: 8.33%    | 20.29%  | 18.18%   |
| Based on deep belief network and multitasking learning, predictable methods are used | $\epsilon_{MAPE}$: 0.84%   | 3.53%   | 2.06%    |
|                                                   | $\epsilon_{RMSE}$: 1.45    | 42.58   | 2.72     |
|                                                   | $\epsilon_{M}$: 1.39%    | 10.88%  | 3.58%    |

As can be seen from the figure above and Table 1, the planning scheme prediction effect of the load prediction model based on deep belief network and multitasking is significantly better than that of the exponential smoothing method, and the gap between the actual load curve is smaller. The load prediction method proposed in this paper is more accurate.

5. Conclusion
In this paper, a comprehensive energy system load prediction method based on deep belief network and multi-tasking is proposed, in view of the current situation of large-scale deployment of energy network sensors, the breakthrough point of technology is focused on the research of deep belief network and multi-task learning prediction method combined with big data technology, which can obtain more accurate prediction results with less computational overhead, and use better pre-processed sample data and related factors to invest in forecasting. The analysis results of the actual study show that the research method proposed in this paper has higher prediction accuracy and has some practical significance to the multi-load prediction of the integrated energy system.

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