SCIENCE CHINA
Information Sciences

• LETTER •

May 2020, Vol. 63 159204:1–159204:3
https://doi.org/10.1007/s11432-018-9594-9

Hybrid teaching–learning artificial neural network for city-level electrical load prediction

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Received 24 May 2018/Revised 27 June 2018/Accepted 11 August 2018/Published online 9 October 2019

Citation Li K J, Xie X M, Xue W P, et al. Hybrid teaching–learning artificial neural network for city-level electrical load prediction. Sci China Inf Sci, 2020, 63(5): 159204, https://doi.org/10.1007/s11432-018-9594-9

Dear editor,
Rapid economic growth, accompanied by structural changes, strongly affects the global trend of electrical energy consumption. Short-term electrical load forecasting plays a significant role in efficient energy management, fault diagnosis, and power system optimization. For large-scale energy prediction, it is difficult to determine future energy usage as many noisy, incomplete, and multi-sourced factors influence the energy consumption behaviors. Owing to the ease of use and adaptability of optimal solution seeking, in recent years, data-driven predictive models have been demonstrated to be efficient tools for energy forecasting [1].

To improve prediction accuracy and robustness, this study proposes a hybrid predictive model that combines an evolutionary algorithm, i.e., teaching-learning-based optimization (TLBO), with artificial neural networks (ANNs). To enhance the convergence speed and precision, the basic TLBO is further improved through several measures.

City-level electrical data and weather information are collected using data mining technology. Before conducting an energy prediction test, data cleaning and dimension reduction are performed using discrete wavelet transform (DWT) and principal component analysis (PCA), respectively. The performance of the hybrid model is investigated using real city energy data of Jiangsu Province, China. The results will validate the effectiveness and efficiency of the proposed method.

iTLBO-ANN model. ANN methods are popular for energy load forecasting, and they are capable of providing reliable results with good accuracy [2]. However, they also have some disadvantages, such as the ease of falling into the local optimum, conflict of modeling accuracy and generalization, and prolonged training for convergence. Compared to the genetic algorithm, particle swarm optimization or other global optimization techniques, such as TLBO proposed by Rao et al. [3] in 2011, have the advantages of a simple structure, high precision, and fast convergence. These advantages have been demonstrated in various engineering applications [4].

The basic idea of TLBO is to simulate the teaching and learning process between teacher and learners. In the teaching phase, the best individual is selected as the teacher and the rest are selected as students. The basic formula is as follows:

$$X_i^{\text{new}} = X_i + r \times (X_{\text{teacher}} - \text{TF} \times X_{\text{mean}}), \quad (1)$$

where X_i^{new} is a new individual produced by X_i, X_{mean} is the mean position of the current class, r is a random value, TF represents the teaching factor, and X_{teacher} represents the best value for the current individual.

In the learning phase, learners improve their abilities by communicating with each other. If one student has more knowledge, the other students will learn from him according to the following for-

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mula [3]:

$$X_i^{\text{new}} = \begin{cases} X_i + r \times (X_i - X_j), & \text{if } f(X_i) < f(X_j). \\ X_i + r \times (X_j - X_i), & \text{otherwise}, \end{cases} \quad (2)$$

where X_i and X_j are selected randomly according to the value of the fitness function. X_i^{new} is the new position according to X_i. The detailed flowchart of the basic TLBO algorithm is shown in Appendix A (Figure S1).

Based on the regular TLBO, three improvements are proposed in this study to enhance the optimization accuracy and convergence speed. (1) Add a feedback stage. This is used to enhance the ability of students under the guidance of the teacher directly, i.e., $X_i^{\text{new}} = X_i + r \times (X_{\text{teacher}} - X_i)$. (2) Add accuracy factors. These are introduced to evaluate the accuracy of knowledge acquired by learners in all three stages: AF_1 for the teaching stage, AF_2 for the learning stage, and AF_3 for the feedback stage. This measure can increase the diversity of the population. (3) Change the value of X_{mean}. The formula $X_{\text{mean}} = (X_{\text{worst}} + X_i)/2$ is used to replace the average value of the grades of all students. The purpose is to enhance the diversity of the population and avoid premature convergence (the flowchart of the improved TLBO (iTLBO) algorithm is shown in Appendix A (Figure S2)). Before applying the iTLBO algorithm to energy prediction, ten benchmark functions are selected to verify its performance. Further details can be found in Appendix B (Table S1 and Figure S4).

The obtained iTLBO is used to adjust the weights and threshold values of the ANN model in this study. The hybrid iTLBO-ANN model integrates the advantages of both the ANN and iTLBO and is helpful for overcoming the defects of the ANN model. The main construction steps of the iTLBO-ANN are described as follows (also see the flowchart in Appendix A (Figure S3)).

Step 1. Construct a three-layer back propagation neural network. The parameters of the ANN and iTLBO are initialized.

Step 2. All the weights and threshold values of the ANN are considered as the grades of students in the iTLBO algorithm.

Step 3. At each iteration of iTLBO, the grades of all learners are updated using iTLBO operations. The fitness function is calculated by minimizing the training error of the ANN model.

Step 4. The searching loop continues until the optimal parameters of the ANN are obtained.

Data pre-processing. The electrical data of this study are collected from a small city, Yizheng, Jiangsu province, which has a population of 567.8 thousand with a total area of 859.19 km^2. A total of 1090 daily electrical energy data sets are obtained for the period from September 2013 to September 2016. The local weather data (temperature, humidity, wind speed, etc.) are obtained using web crawler technology. According to previous literature, the following five energy-related variables form the inputs of the predictive model: short-term history energy data $y(t-1)$ and $y(t-2)$, history energy data of the last week $y(t-7)$, daily high bulb temperature $T(t)$, and holiday flag s.

High-quality prediction can be achieved through high-quality data. As the obtained real data are noisy, incomplete, and multi-sourced, data preprocessing is required in this study. DWT and PCA are used for data cleaning and dimension reduction in this study, respectively.

(1) Discrete wavelet transform. DWT is a type of linear signal processing technique with multiscale analysis ability. The main formulas are described as follows:

$$\text{DWT}(m,n) = \frac{1}{\sqrt{m}} \sum_{t=0}^{T-1} f(t)\psi\left(\frac{t-n}{m}\right), \quad (3)$$

where m and n are the scale parameter and time-shift parameter, respectively. T is the length of the signal $f(t)$.

Owing to the probable inaccurate or abnormal samples obtained from meters or the internet, the original data inevitably contain noise and singular values. DWT is used to reduce noise and smooth the data [5]. In the phase of wavelet reconstruction, we use the db3 wavelet function and retain all the wavelet coefficients greater than the specified threshold.

(2) Principal component analysis. It is known that redundant or inappropriate input variables may lead to slow convergence and low accuracy issues. Therefore, the relevant inputs are refined using the PCA method. The main formulas of the PCA procedure are described as follows:

$$R = (S_{ij})_{m\times m}, \quad (4)$$

$$S_{ij} = \frac{1}{n-1}\sum_{k=1}^{n}(x_{ki} - \overline{x_i})(x_{kj} - \overline{x_j}), \quad (5)$$

$$|\lambda E - R| = 0, \quad (6)$$

where R is a covariance matrix, S_{ij} is the covariance of the original variables x_i and x_j, and λ is the eigenvalue vector of R. Further details of the DWT and PCA procedure are provided in Appendix C.

Results and discussion. As discussed above, the original data are denoised and smoothed first using DWT. Subsequently, using PCA, the three most relevant variable sets are refined and normalized for energy forecasting based on the proposed hybrid iTLBO-ANN model. Figure 1(a)

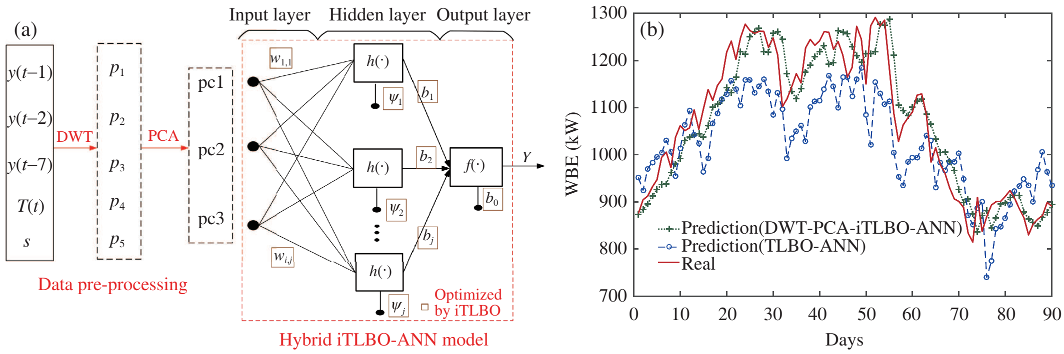

Figure 1 (Color online) (a) Flowchart for predicting city-level energy consumption and (b) predicted daily city electrical loads using iTLBO-ANN model with/without data pre-processing.

shows the basic flowchart of the proposed DWT-PCA-iTLBO-ANN modeling procedure. A total of 1090 sets of city-scale electrical energy data are collected. The first 1000 sets are employed for model training, and the remaining data of three months (90 sets) are used for testing. To assess the accuracy of the proposed model, two types of error indices, i.e., (CV) and (MAPE), are used (see Appendix D for details). To investigate the performance of the proposed model in a large-scale energy prediction case, the basic TLBO-ANN model is also employed for comparison. Under the same parameter setting, the predictive results are presented in Figure 1(b). It can be observed that both hybrid models fit the real energy load curve well, and the proposed DWT-PCA-iTLBO-ANN model has better fitting ability than the basic TLBO-ANN model.

Furthermore, five predictive models, i.e., the ANN, TLBO-ANN, iTLBO-ANN, DWT-PCA-TLBO-ANN, and DWT-PCA-iTLBO-ANN models, are investigated for performance comparison in this study. The results are presented in Table S2, which indicates the superior performance of the proposed hybrid model in terms of prediction accuracy (see Appendix D for details). In addition, as the proposed iTLBO algorithm has a simpler structure than other evolutionary algorithms, it has a shorter modeling time ($\mathrm{Time}_{\mathrm{ave}} = 1.2$ s) than other hybrid models. Thus, it has significant potential for short-term electrical load prediction at different scales in the future.

Conclusion. This study proposed a new hybridized method called iTLBO-ANN for city-level electrical load forecasting. To improve the accuracy and robustness of the regular ANN model, iTLBO was utilized to optimize the parameters of the ANN in the global scope. At the data pre-processing stage, DWT was used to eliminate the noise and singular values of the original data. PCA was applied to refine the most relevant input variables. The proposed hybrid predictive model was used for one-day-ahead electrical load forecasting at the city level. A case study revealed that the proposed iTLBO-ANN model shows good performance in terms of prediction accuracy. Furthermore, its simple structure makes it suitable for online energy prediction and analysis at different scales in the future.

Acknowledgements This work was supported by National Natural Science Foundation of China (Grant Nos. 61873114, 51705206), China Postdoctoral Science Foundation (Grant Nos. 2018T110457, 2016M601741), and Project Foundation for Priority Academic Program Development of Jiangsu Higher Education Institutions.

Supporting information Appendixes A–D. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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