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• **Supplementary File** •

A hybrid teaching-learning artificial neural network for city level electrical load prediction

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Appendix A TLBO and iTLBO algorithms

In this section, we concretely introduce the implementation process of TLBO (shown in Figure S1) and iTLBO(shown in Figure S2). Meanwhile, the flow chart for the main construction steps of iTLBO-ANN model is also given in Figure S3.

Appendix B Performance tests using benchmark functions

To verify the performance of iTLBO, 10 benchmark functions are selected,which include 7 unimodal functions and 3 multimodal functions. The detailed descriptions of these functions are provided in Table S1. The two TLBO algorithms, i.e., TLBO, iTLBO, use the same parameters to compare the fitting accuracy. The parameters of the two algorithms are set as: the problem dimension D = 30, the maximum number of iterations of the function FES = 10000D, the population size NP = 50. To avoid the random error of the test results, each benchmark function runs 50 times respectively. The results show that iTLBO get significant improvements compared with basic TLBO on each benchmark function. Convergence graphs are presented in Figure S4.

Appendix C Data pre-processing

In this section, the original data of YiZheng city's electrical energy data and daily weather data contain strong noise and significant singular values. We use DWT to denoise and smooth the original data. In the phase of wavelet reconstruction, we use db3 wavelet to decompose the original signal into six layers of wavelet, and get the approximate coefficient and the details coefficient. Specifically, we keep all the wavelet coefficients that are greater than the specified threshold. The wavelet coefficients that less than the specified thresholds are set to zeros. The DWT decomposition diagram is described in Figure S5, and the electrical load data before / after DWT is shown in Figure S6.

For city energy prediction, redundant or inappropriate input variables may probably lead to convergence and low accuracy problems. For this reason, the relevant input variables are selected using principal component analysis (PCA) in this study. Specifically, we used PCA to reduce the dimension of the five original input variables. The obtained principal component diagram is shown in Figure S7.

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Appendix D Results analysis

To assess the accuracy of the proposed model, two kinds of error index, i.e. CV (Coefficient of Variation of the Root Mean Square Deviation) and MAPE (Mean Absolute Percentage Error) are used, which are formulated below:

$$CV = \frac{\sqrt{\sum_{j=1}^{N}(y_{pred,j} - y_{data,j})^2/N}}{\overline{y}_{data}}, \tag{1}$$

$$MAPE = \frac{1}{N} \times \sum_{j=1}^{N}(\frac{|y_{pred,j} - y_{data,j}|}{y_{data,j}}). \tag{2}$$

where $y_{pred,j}$ denotes the predicted value, $y_{data,j}$ represents the real data, and $\overline{y}_{data}$ is the average of real data.

Five predictive models, including ANN, TLBO-ANN, iTLBO-ANN, DWT-PCA-TLBO-ANN and DWT-PCA-iTLBO-ANN, are all investigated for performance comparison. The results are recorded in Table S2. From the results, it is found that:

(1) The prediction accuracy of iTLBO-ANN model (CV_{ave}=0.0618) is better than that of TLBO-ANN model (CV_{ave}=0.0671), and the ANN model (CV_{ave}=0.0818).

(2) By employing the DWT-PCA preprocessing, the hybrid models' accuracies are further improved. For example, the CV_{ave} of DWT-PCA-iTLBO-ANN model is 0.0470, which is 24% better than that of iTLBO-ANN model (CV_{ave}=0.0618). Similarly, the CV_{ave} of DWT-PCA-TLBO-ANN model is 0.0544, which is 19% better than that of TLBO-ANN model (CV_{ave}= 0.0671).

Table S1 Ten benchmark functions

Benchmark function	Dimension	Domain	Optimum
$f_1 = \sum_{i=1}^{D} x_i^2$	30	$[-100, 100]^D$	0
$f_2 = \sum_{i=1}^{D} \lvert x_i \rvert + \prod_{i=1}^{D} \lvert x_i \rvert$	30	$[-10, 10]^D$	0
$f_3 = \sum_{i=1}^{D} (\sum_{j=1}^{i} x_j)^2$	30	$[-100, 100]^D$	0
$f_4 = max_{i=1}^{n} \{\lvert x_i \rvert\}$	30	$[-100, 100]^D$	0
$f_5 = \sum_{i=1}^{D-1} [100(x_{i+1} - x_i^2)^2 + (1 - x_i^2)]$	30	$[-30, 30]^D$	0
$f_6 = \sum_{i=1}^{D} [\lvert x_i + 0.5 \rvert]^2$	30	$[-100, 100]^D$	0
$f_7 = \sum_{i=1}^{D} i x_i^4 + random(0, 1)$	30	$[-1.28, 1.28]^D$	0
$f_8 = -\sum_{i=1}^{D} (x_i^2 - 10\cos(2\pi x_i) + 10)$	30	$[-5.12, 5.12]^D$	0
$f_9 = -20\exp(-0.2 \times \sqrt{\sum_{i=1}^{n} x_i^2/n}) - \exp(\sum_{i=1}^{n} \cos(2\pi x_i/n)) + 20 + e$	30	$[-32, 32]^D$	0
$f_{10} = \frac{1}{4000} \sum_{i=1}^{n} {x_i}^2 - \prod_{i=1}^{n} \cos(\frac{x_i}{\sqrt{i}}) + 1$	30	$[-600, 600]^D$	0

Table S2 Performances of five selected models for daily city electrical load prediction

Prediction Model	Evaluation indices	1	2	3	4	5	Average
DWT-PCA-iTLBO-ANN	CV	0.0510	0.0456	0.0458	0.0498	0.0429	0.0470
	MAPE	0.0400	0.0355	0.0360	0.0408	0.0336	0.0372
	Time(s)	1.4	1.2	1.3	1.1	1.2	1.2
DWT-PCA-TLBO-ANN	CV	0.0524	0.0537	0.0528	0.0615	0.0514	0.0544
	MAPE	0.0428	0.0396	0.0422	0.0446	0.0427	0.0424
	Time(s)	1.2	1.7	1.4	1.1	1.5	1.3
iTLBO-ANN	CV	0.0625	0.0680	0.0614	0.0541	0.0630	0.0618
	MAPE	0.0456	0.0495	0.0457	0.0404	0.0463	0.0455
	Time(s)	1.5	1.0	1.3	1.4	1.6	1.4
TLBO-ANN	CV	0.0643	0.0731	0.0707	0.0689	0.0583	0.0671
	MAPE	0.0459	0.0538	0.0556	0.0521	0.0466	0.0508
	Time(s)	1.2	1.1	1.0	1.5	1.1	1.2
ANN	CV	0.0916	0.0738	0.1157	0.0670	0.0611	0.0818
	MAPE	0.0578	0.0529	0.0652	0.0481	0.0451	0.0538
	Time(s)	4.3	3.4	3.8	4.7	4.2	4.1

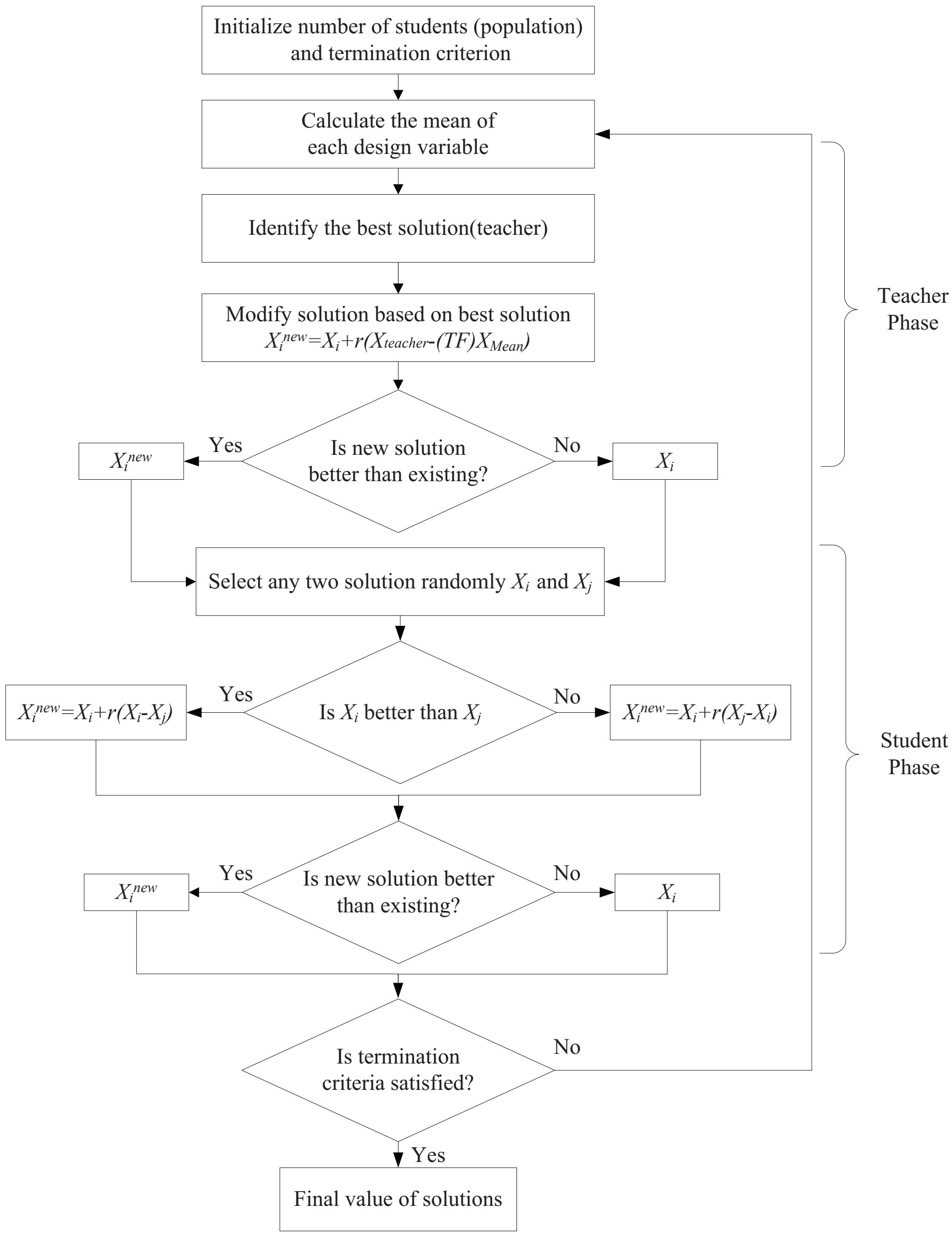

Figure S1 Flow chart of TLBO algorithm

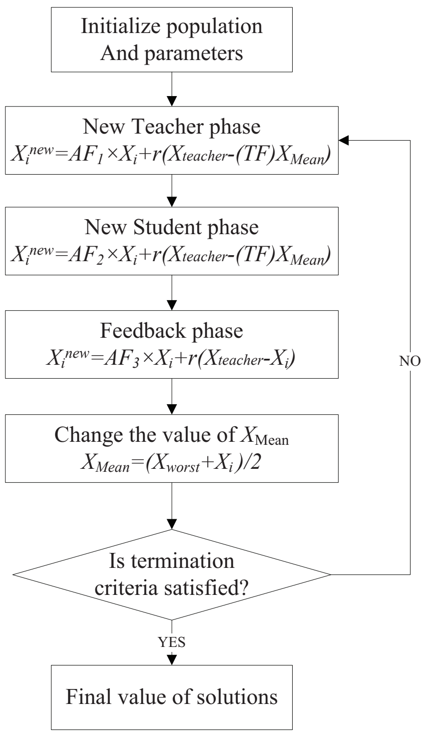

Figure S2 Flow chart of iTLBO algorithm

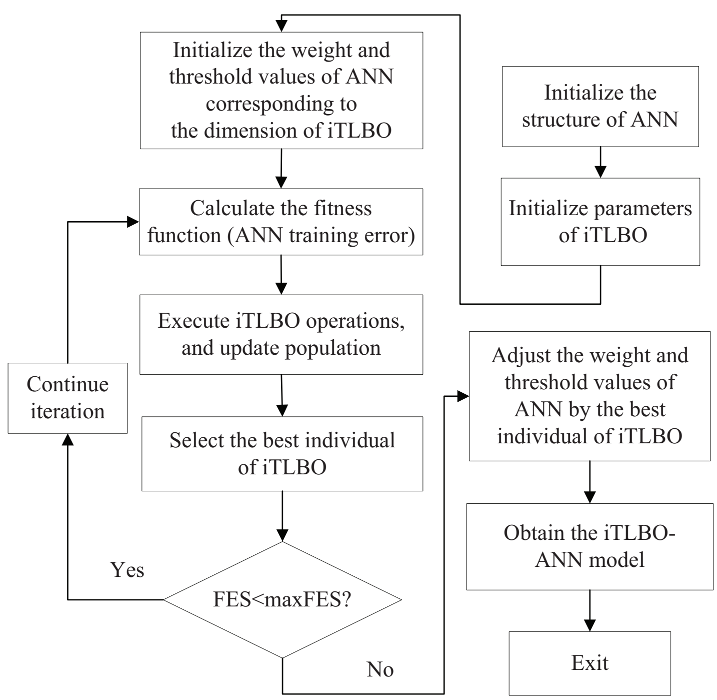

Figure S3 Flow chart of iTLBO-ANN model

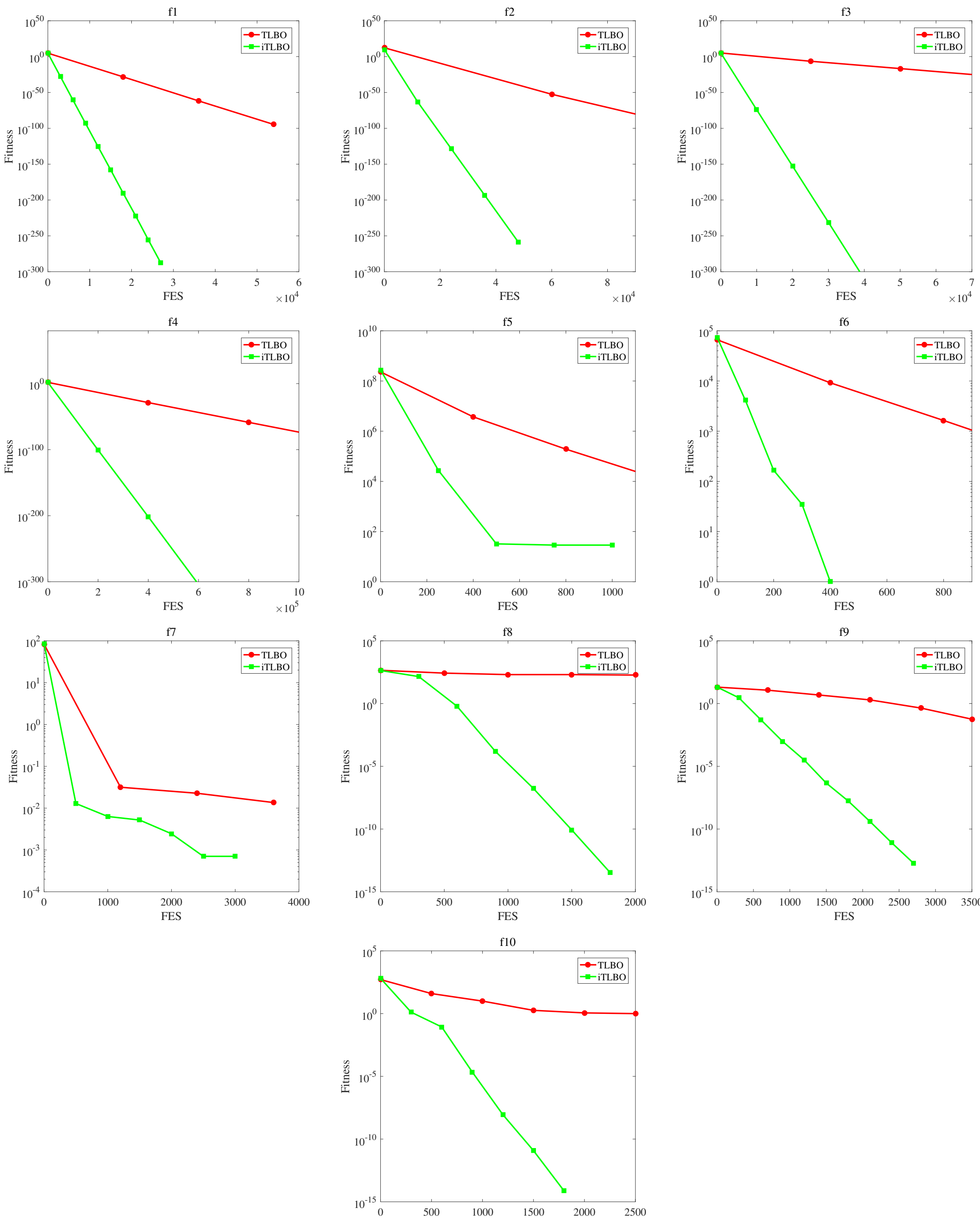

Figure S4   Convergence graphs of ten benchmark functions

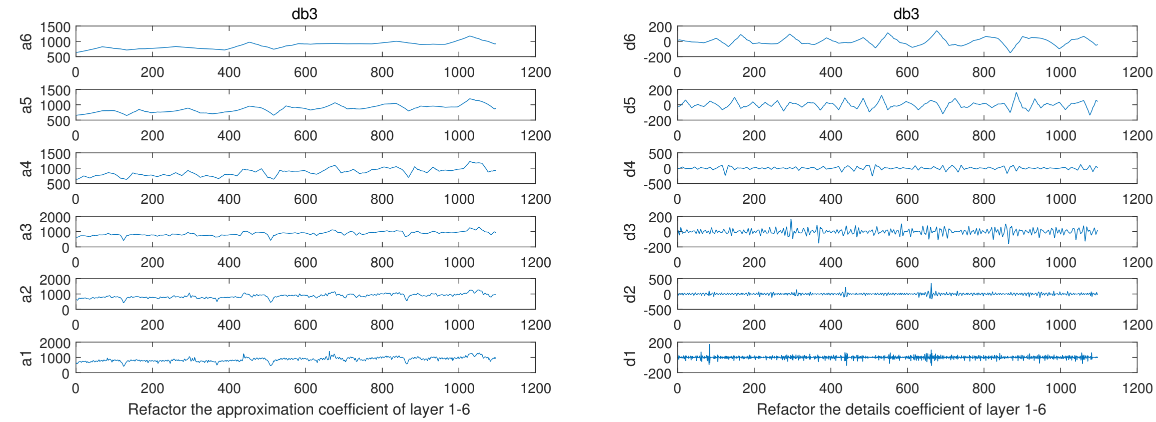

Figure S5 The details of DWT pre-processing

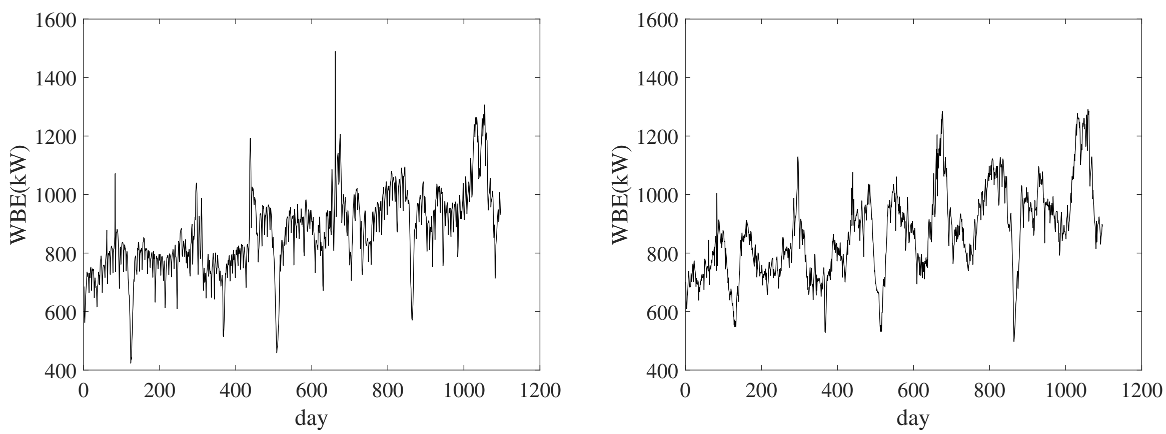

Figure S6 The electrical load data before / after DWT

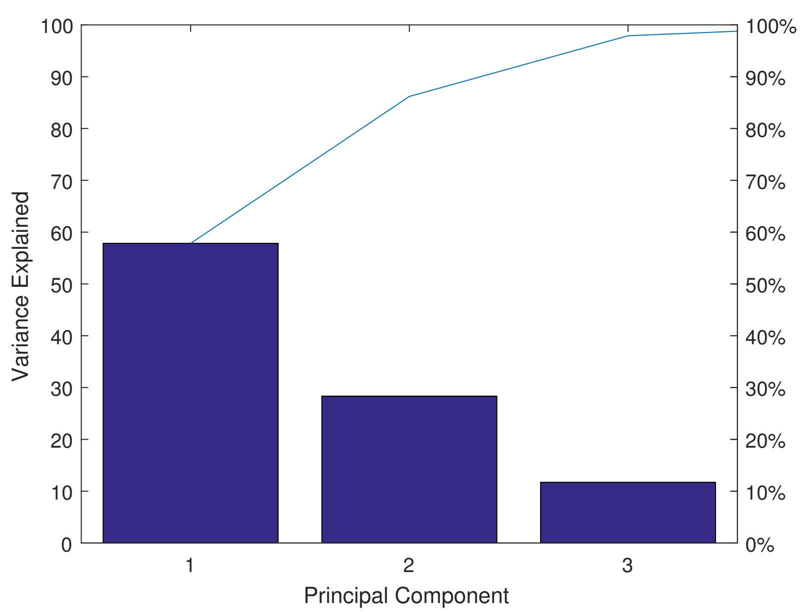

Figure S7 The contribution rate and cumulative contribution rate of principal components