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Forecasting Building Energy Consumption Based on Hybrid PSO-ANN Prediction Model

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Abstract: As a popular data driven method, Artificial Neural Networks (ANNs) are widely applied in building energy prediction field. In this paper, a hybrid prediction approach that combines Particle Swarm Optimization (PSO) and ANN is presented. Before the prediction model applied, the principal component analysis (PCA) is used for the selection of the input variables, which helps to reduce the input dimension and simplify the model structure. To improve the prediction accuracy, PSO is used to adjust the ANN model's weight and threshold values. The performance of the proposed hybrid model is investigated using the data set of the Energy Prediction Shootout I contest, and the results indicate that PSO-ANN have better performance than regular ANN in term of prediction accuracy. In addition, another kind of hybrid prediction model which combines Genetic Algorithm (GA) and ANN is also proposed. Performance comparison shows that PSO-ANN has the same accuracy level with GA-ANN, and has simpler structure which is more suitable for online prediction tasks.

Key Words: Particle Swarm Optimization, Artificial Neural Networks, Principal Component Analysis, Genetic Algorithm, Building Energy Prediction

1 Introduction

Nowadays, building energy consumption accounts for an important proportion of the whole energy consumption and carbon emissions worldwide. To achieve a suitable energy demand management in an efficient way , it is necessary to estimate a reliable and an accurate prediction of the energy consumption load curve [1], which makes prediction of building energy consumption has become a crucial topic [2].

In present, it is difficult to predict the building energy consumption precisely, since there are many factors influencing the energy usage, such as weather conditions, building structure and characters, geographic location, occupancy [3] and operation of appliances [4]. There are various forecasting techniques that have been applied to the building energy consumption, such as Engineering method [5], statistical method [6], Artificial Neural Networks (ANNs) [7,8], support vector machines (SVMs) [9], fuzzy logic and gray models techniques [10], etc.. During the past two decades, the most applied techniques are ANNs and their developments. A variety of papers discussed energy prediction based on ANNs, where input variables selection, network structure construction and training algorithm improvements are three vital issues [11,12]. For input variables selection, Karatasou [13] utilized a systematic approach based on least squares estimation (LSE) and statistical tests in building energy modeling and got a simple ANN model. Besides, principal component analysis (PCA) [14] was used to analyze the pre-input variables.

In the last ten years, various kinds of intelligent optimization algorithms have been developed dramatically and applied widely, such as: Genetic algorithm (GA), ant colony algorithm, particle swarm optimization (PSO) algorithm, tabu search algorithm, etc.. Li and Hao developed a PSO modified ANN prediction model to forecast chaotic time series and the results proved that the PSO-ANN has better nonlinear fitting ability and higher prediction accuracy than ANN itself [15]. In the field of building energy forecasting, intelligent optimization methods are also widely used. The method, hybrid GA-Adaptive Network-based Fuzzy Inference System (GA-ANFIS), was studied by Li in 2011[16]. The authors used two different data sets from the Great building Energy Predictor Shootout and a library building to train and test the proposed model. The best prediction accuracy was improved 19.5% compared with ANN method, which fully indicated the great global searching ability of the hybrid method.

In this paper, a different hybrid building energy consumption prediction method is proposed, and the focus of this method is on the optimization of ANN structure based on PSO approach. Concretely, the weight and threshold values of ANN model is trained and adjusted by PSO method. Before the prediction model applied, the PCA is used to reduce the input dimension and simplify the model structure. The performance of the proposed hybrid model is investigated using the data set of the Energy Prediction Shootout I. Results show that PSO-ANN has better prediction accuracy than regular ANN. In addition, another kind of hybrid prediction model which combines GA and ANN is also proposed. Performance comparison shows that PSO-ANN has the same accuracy level with GA-ANN, and has simpler structure which is more suitable for online prediction tasks.

2 Modeling

2.1 ANN

ANNs, inspired by the thinking mechanism of human brain, are parallel nonlinear adaptive systems composed of a large number of simple processing units. In recent years,

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ANNs have been widely applied to the modeling of complex nonlinear system. The topology structure of the ANN is illustrated in Fig. 1, and the mapping function from input layer to output layer takes the following form [17,18]:

$$Y = f(b_0 + \sum_{j=1}^{k} h(\psi_j + \sum_{i=1}^{m} p_i w_{ij}) b_j) \tag{1}$$

where the network outputs are the predicted values Y, denoted by nonlinear transfer function $f(\cdot)$ of the inputs p_i, b_0 is the output bias, b_j is the weight values from hidden layer to output layer, ψ_j is the hidden layer biases, w_{ij} is the weight from input layer to hidden layer and $h(\cdot)$ is hidden layer activation function.

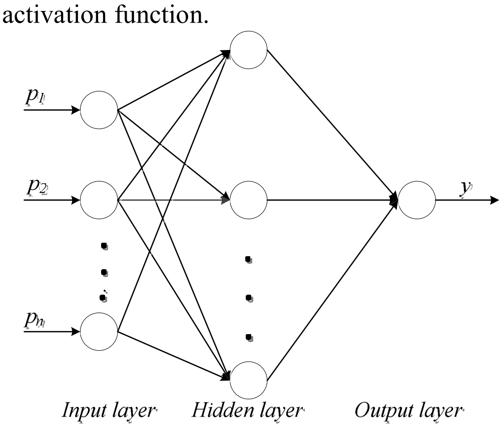

Fig. 1 Structure of ANN

2.2 Hybrid PSO-ANN

The PSO algorithm has a strong ability for global optimal solution searching [19,20]. Nevertheless, it has a disadvantage that the search around global optimum is very slow. On the contrary, the back-propagation (BP) algorithm has a strong ability to search local optimal solution, but its capability of finding the global optimal solution is quite weak for complex models. In this paper, a hybrid prediction model is proposed which combines BP algorithm with PSO, and the PSO usage is to train the weight and threshold values of ANN. The weight and threshold values in ANN are equal to the particles' position of PSO algorithm. The update method of PSO' velocity and position is formulated by [21]:

$$\begin{cases} v_j(n+1) = wv_j(n) + c1r1(p_j(n) - x_j(n)) + c2r2(p_g(n) - x_j(n)) \\ x_j(n+1) = v_j(n+1) + x_j(n) \end{cases} \tag{2}$$

where $v_j(n)$ is the speed of the jth particle in the nth generation. $r1$ and $r2$ are random numbers obeying uniform distribution in the range of [0, 1]. $c1$ and $c2$ are constants named acceleration coefficients. $x_j(n)$ is the position of the jth particle in the nth generation. $p_j(n)$ is the best previous position yielding the best fitness value for the jth particle. $p_g(n)$ is the best position discovered by whole particles. w is the inertia weight used to balance between the global and local search abilities. The adjustment strategy of inertia weight is as follows:

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \times k \tag{3}$$

where w_{max} is the initial weight value; w_{min} is the final weight value; k is the current iteration number; $iter_{max}$ is the maximum number of iteration.

The flow diagram of this hybrid prediction model is illustrated in Fig. 2 and the detailed procedure can be conducted as follows:

Step 1: collect and pre-process the data set;

Step 2: confirm the topology structure of ANN according to the input data set, and randomly initialize the positions and velocities of all particles in the N-dimensional problem space;

Step 3: determine the fitness function and calculate each initialized particle's fitness value, and update individual and group history optimal position;

Step 4: update all particles' position and velocity according to Eq. (2), and ensure new particles' position and velocity within the boundary;

Step 5: if the maximal iterative generations of PSO are arrived, output the optimal solution, else, return to step 3;

Step 6: use the optimal solution got from PSO to assign weight and threshold values of ANN;

Step 7: train and test PSO-ANN prediction model, if stopping criteria are satisfied, forecast the building energy consumption and analysis the simulation results.

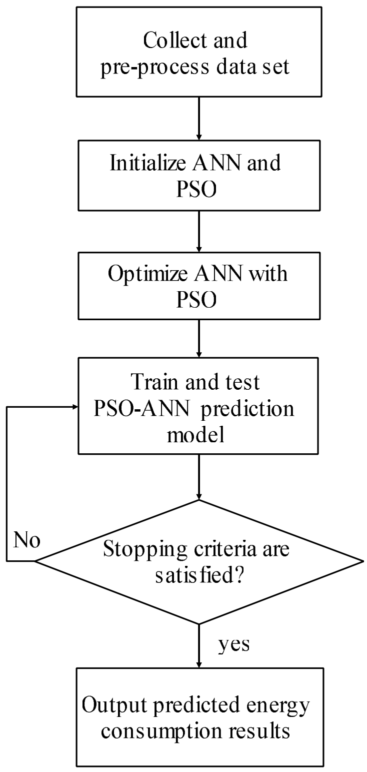

Fig. 2: The flow chart of hybrid prediction model

3 Data set

3.1 Data set Description

The building energy consumption's data set comes from the Great Building Energy Predictor Shootout I, organized by American society of heating, refrigeration and air conditioning engineers (ASHRAE). It consists of the following variables: outdoor dry bulb temperature, solar radiation, humidity ratio and wind speed [22,23]. The contest required the prediction of building energy use (electricity, hot and cold water) of a large building without any other details (like type of use and occupancy). For the input variables, data were available at hourly intervals for the period from September 1989 to February 1990, whereas energy consumption data were available only for September to December 1989 [13,16].

3.2 Data Pre-processing

In order to reduce the dimensionality of the data set which may include a large number of irrelevant variables, the PCA is conducted. Analysis results are listed in Table 1, which indicated that the first two principal components can explained 82.389% of the total variance. Through refining the principal components, the new variables, named $PC1$ and $PC2$, are less dimensional, mutually independent, and represent most information provided by the original building energy consumption data.

Table 1: PCA Result

Component	Eigen Values	Contribution Rate (%)	Cumulative (%)
PC1	2.620	43.436	43.436
PC2	2.349	38.953	82.389
PC3	0.685	11.357	93.746
PC4	0.377	6.254	100.00

In addition, the occupancy of the building has a strong effect on the energy use. Thus, days were classified and encoded as 1 (weekday) and 0 (weekend or holiday).

The hour of the day is coded by its sine and cosine values which denoted by Eq. (4) and Eq. (5).

$$sh = \sin \frac{2\pi h(t)}{24} \tag{4}$$

$$ch = \cos \frac{2\pi h(t)}{24} \tag{5}$$

All inputs and outputs are normalized to the interval [-1, 1] and represented by the following formula:

$$y = 2 \times \frac{x - x_{min}}{x_{max} - x_{min}} - 1 \tag{6}$$

where x is input data, x_{min} is the minimum value within the entire data of x, x_{max} is the maximum value within the entire data of x, and y is the normalized value.

4 Results

4.1 PSO-ANN Results

The first model is PSO-ANN with a single hidden layer of *tansig* neurons and the task is to predict the whole building electric power consumption (WBE). The input set (S1) includes: $PC1$ and $PC2$, session flag s, sine of the hour of the day sh, cosine of the hour of the day ch. The number of concealed level is calculated by the Eq. (7)

$$k = \sqrt{m + n} + l \tag{7}$$

where m is output number, n is input number, k is concealed number, and l is an integer between 1~10.

The data set contains 4208 groups of data, [1, 3208] are available for training, and [3209, 4208] for testing which are not used during the training phase. To assess the obtained results, the coefficient of variation (CV) and mean absolute percentage error (MAPE) are used. They are given as the following:

$$CV = \frac{\sqrt{\sum_{i=1}^{N} (y_{pred,i} - y_{data,i})^2 / N}}{\bar{y}_{data}} \tag{8}$$

$$MAPE = \frac{1}{N} \times \sum_{i=1}^{N} \left(\frac{\left| y_{pred,i} - y_{data,i} \right|}{y_{data,i}} \right) \tag{9}$$

where $y_{pred,i}$ is predicated energy consumption value, $y_{data,i}$ is real energy consumption value, $\bar{y}_{data}$ is the average value of real energy consumption value, N is the number of testing data set.

In order to explore the influence of short past values of energy consumption, the input set (S2) adds previous energy consumption values $y(t-1)$ and $y(t-2)$. The results are recorded in Table 2, which indicated that short past consumption values can dramatically improve the prediction accuracy. The comparison between prediction value and real energy consumption are shown in Fig. 3 and Fig. 4.

Table 2: Accuracy of PSO-ANN

No.	CV(S1)	MAPE(S1)	CV(S2)	MAPE(S2)
1	0.0744	0.0619	0.0265	0.0171
2	0.0734	0.0625	0.0263	0.0176
3	0.0726	0.0606	0.0259	0.0169
4	0.0759	0.0627	0.0262	0.0174
5	0.0714	0.0607	0.0268	0.0177
Average	0.0735	0.0617	0.0263	0.0173
Best	0.0714	0.0606	0.0259	0.0169

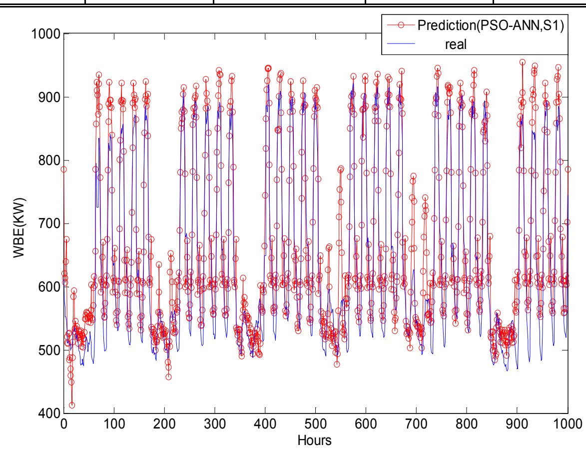

Fig. 3: Predicted building electricity loads using PSO-ANN, S1

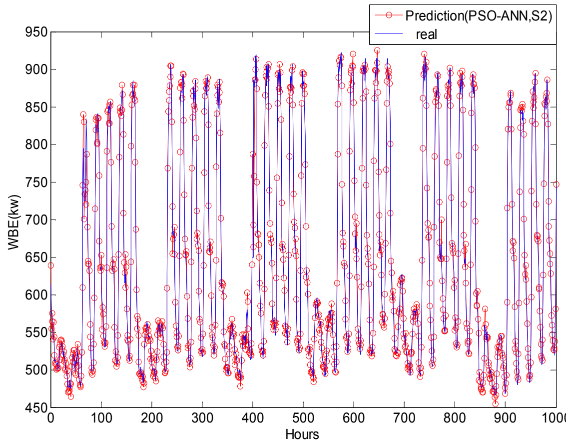

Fig. 4: Predicted building electricity loads using PSO-ANN, S2

4.2 ANN Results

To compare the prediction performance of the hybrid PSO-ANN model, the same data set are used in the ANN model. The best five results of the two prediction models are shown in Table 3, which also manifests the average and best results.

Table 3: Accuracy of ANN

No.	CV(S1)	MAPE(S1)	CV(S2)	MAPE(S2)
1	0.0835	0.0712	0.0303	0.0200
2	0.0830	0.0708	0.0338	0.0266
3	0.0845	0.0722	0.0304	0.0182
4	0.0839	0.0706	0.0305	0.0222
5	0.0899	0.0733	0.0307	0.0196
Average	0.0850	0.0716	0.0311	0.0213
Best	0.0830	0.0706	0.0303	0.0182

As shown in Fig. 5 and Fig. 6, the graphical comparison between the prediction value and the real energy consumption of ANN model is given.

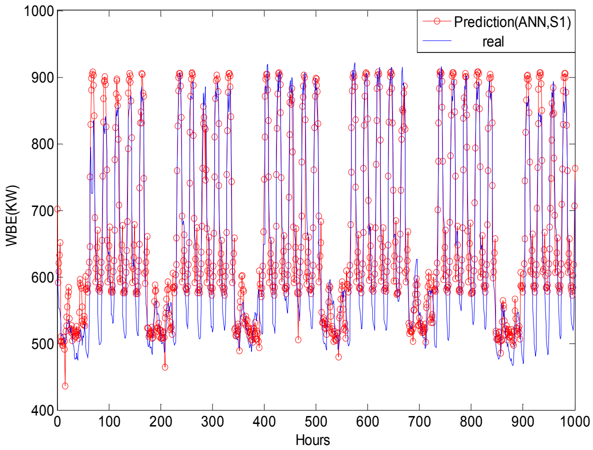

Fig. 5: Predicted building electricity loads using ANN, S1

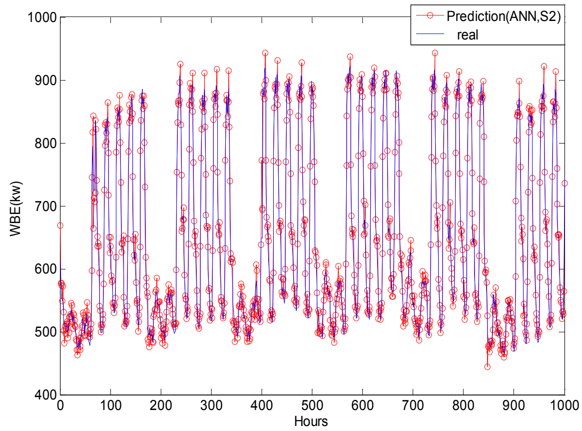

Fig. 6: Predicted building electricity loads using ANN, S2

4.3 GA-ANN Results

Because GA has strong global search ability and good scalability, it has a broad application in optimization issues, especially in complex optimization problems where the number of parameters is large [24]. Similar to the PSO-ANN, another hybrid prediction model is proposed which combines GA and ANN to forecast the building energy consumption. GA is used to train the weight and threshold values of ANN. This hybrid method is investigated by using the same data set and the same precision evaluation standards. CV and MAPE values are shown in Table 4, and the graphical comparison between the prediction value and the real energy consumption is shown in Fig. 7 and Fig. 8.

Table 4: Accuracy of GA-ANN

No.	CV(S1)	MAPE(S1)	CV(S2)	MAPE(S2)
1	0.0758	0.0644	0.0291	0.0193
2	0.0764	0.0634	0.0296	0.0202
3	0.0759	0.0633	0.0274	0.0189
4	0.0776	0.0661	0.0298	0.0200
5	0.0767	0.0649	0.0291	0.0199
Average	0.0765	0.0644	0.0290	0.0197
Best	0.0758	0.0633	0.0274	0.0189

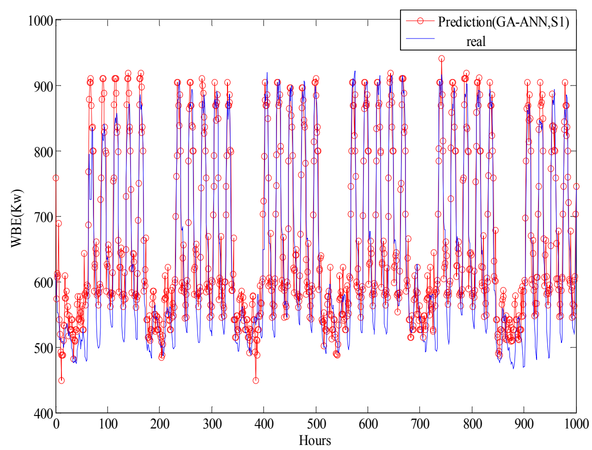

Fig. 7: Predicted building electricity loads using GA-ANN, S1

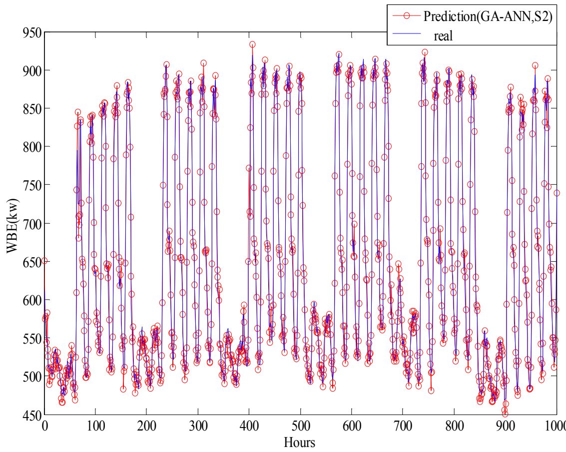

Fig. 8: Predicted building electricity loads using GA-ANN, S2

4.4 Discussion of the results

It can be seen from the simulation results that the hybrid PSO-ANN model achieved smaller CVs and MAPEs when compared with ANN model using the same data sets. When PSO joins to optimize the parameters of ANN, the model structure obtains distinctly improvement, which is probably unavailable merely by gradient descent algorithm. Additionally, GA can also improve the structure of ANN. The performance comparison shows that PSO-ANN has the same accuracy level with GA-ANN, but PSO-ANN has simpler structure than GA-ANN, which makes the proposed method more suitable for online prediction tasks.

5 Conclusion

In order to overcome the defects of trapping into local minimal easily and slow convergence of ANN, we used PSO and GA algorithm to optimize the weight and threshold values of ANN in this paper. The hybrid models are applied to predict building energy consumption, and the performance comparison is conducted.

In the application of Great Building Energy Predictor Shootout I, the PCA is utilized to reduce the dimension of input variables. The simulation results illustrate that both PSO-ANN and GA-ANN method are both effective and practical for building energy forecasting and have better prediction accuracy than traditional ANN method. What's more, PSO-ANN has simpler structure than GA-ANN, which makes it more suitable for online prediction tasks.

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