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A MULTI-STEP PREDICTION MODEL FOR HOUSEHOLD POWER CONSUMPTION USING PSO, HOLT-WINTER, AND EXTREME LEARNING MACHINE

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ABSTRACT

With the increase of residential energy consumption, its proportion in primary energy consumption is higher and higher. Accurate prediction of residential electricity consumption is the premise of rational residential energy management. In this paper, a novel multi-step prediction model using particle swarm optimization (PSO), Holt-Winter (HW) method, and extreme learning machine (ELM) network is proposed for forecasting household power consumption. The HW model optimized by PSO is the main predictor and used to deal with the periodicity and seasonality of household electricity load. ELM model is introduced as the correction predictor to predict the prediction error of HW, so as to improve the prediction accuracy. The experimental results show that the PSO-HW-ELM model has higher prediction accuracy and better stability compared with the single HW and ELM model.

Keywords: Holt-Winter method, particle swarm optimization, extreme learning machine, household power consumption prediction

1. INTRODUCTION

With social development, building energy consumption is getting higher and higher. According to statistics, building energy consumption in China currently accounts for 20.6% of the total national primary energy consumption, among which residential building energy consumption accounts for 61.5%, and the trend is still rising year by year[1]. Therefore, the ability to forecast household energy consumption is vital to implementing home energy management and efficiency initiatives required to curb emissions[2].

There have been many studies on forecasting household power consumption. Luo[3] employed an artificial neural network (ANN) based method for the day-ahead forecasting in the home energy management system that relies on three stochastic variables: solar radiation, ambient temperature, and must-run house load. Songpu[4] proposed an evolutionary ensemble neural network pool (EENNP) method to achieve a population of well-performing networks with proper combinations of configuration and initialization automatically. The experimental results illustrate that EENNP can effectively process the missing historical data, so as to achieve the prediction of household demand. Dong[5] developed an hybrid modeling approach for residential building energy consumption forecasting which integrates data-driven techniques with forward physics-based models, and applied it to single-family residential houses. The proposed modeling approach was validated through one month measured data from four residential buildings. Yumiko[6] used multiple linear regression (MLR) as the forecast method. Historical electricity load data, predicted external air temperature data, and day of the week were used as explanatory variables for the load forecast. Stepwise regression was used in the MLR procedure to choose the explanatory variables on each day. All the above methods have a good impact on improving the prediction accuracy of household electricity load, but they do not take into account the cyclical and seasonal trends of household electricity load itself. Besides, the accuracy of medium-term or long-term prediction is limited and cannot accurately describe the load characteristics.

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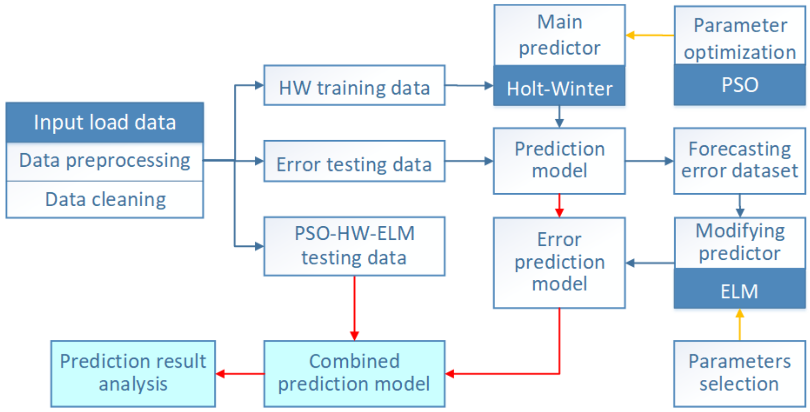


Fig 1 The whole process of the PSO-HW-ELM model

In this paper, particle swarm optimization (PSO), Holt-Winter (HW) method, and extreme learning machine (ELM) network are used to build a multi-step household power consumption prediction model. HW method is used as the main predictor to process periodic and seasonal time series data. The model parameters of HW are optimized by PSO. Then, ELM network is introduced to predict the prediction error of HW model to correct the prediction error. Finally, the performance indexes of several different correlation models are compared, and the performance of the proposed PSO-HW-ELM model is evaluated intuitively.

2. METHODOLOGY

2.1 The PSO-HW-ELM model

The construction procedure of the proposed power consumption prediction strategy in this paper is demonstrated in Fig. 1. The detailed descriptions are further explained as follow:

Step1: The power consumption of a family data are pre-processed and divided into HW training data, error testing data and HW-ELM testing data.

Step2: Considering the advantages of HW in dealing with periodic and seasonal time series, it is used as the main predictor. The HW prediction model with the optimized parameter by PSO is built based on HW training data. The forecasting error dataset is calculated by subtracting the PSO-HW forecasting dataset from the error testing dataset.

Step3: The ELM network is utilized as the modifying predictor. The ELM error prediction model is constructed based on forecasting error dataset to predict the forecasting error of the HW prediction model.

Step4: The PSO-HW model and the ELM model are combined to get the combined prediction model. Performances of models are evaluated using testing data.

The methods covered in the above steps such as PSO[7], HW[8] and ELM[9][9] have been used in many studies, and details can be found in these references.

2.2 Evaluation index

The evaluation indexes which are chosen to appraise models performance are root mean square (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and R^2 score respectively. The expressions are as shown follow:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Y_{pre}(t) - Y_{act}(t)| \tag{1}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_{act}(t) - Y_{pre}(t)}{Y_{act}(t)}\right| \times 100\% \tag{2}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_{pre}(t) - Y_{act}(t))^2} \tag{3}$$

$$R^2 = 1 - \frac{\sum(Y\_actual - Y\_predict)^2}{\sum(Y\_actual - Y\_mean)^2} \tag{4}$$

where Y_{pre} is the forecasting sequence, Y_{act} is the true sequence, *n* is the length of sequence.

In addition, A relative error reduction ratio is used to evaluate the performance of the target model. The expressions are as shown follow:

$$P_{MAE} = \frac{MAE_t - MAE_s}{MAE_t} \times 100\% \tag{5}$$

$$P_{MAPE} = \frac{MAPE_t - MAPE_s}{MAPE_t} \times 100\% \tag{6}$$

$$P_{RMSE} = \frac{RMSE_t - RMSE_s}{RMSE_t} \times 100\% \tag{7}$$

$$P_{R^2} = \frac{R_t^2 - R_s^2}{R_t^2} \times 100\% \tag{8}$$

Where t is the PSO-HW-ELM model, s is compared model.

3. CASE STUDY

3.1 Data description

The power consumption data of a family from 2015.7 to 2018.6 are taken as the original dataset, after data pre-processing, the 2015.7-2016.6 data are used as the HW training set, the 2016.7-2017.6 data are used as the error testing set and the 2017.7-2018.6 data are used as the HW-ELM testing set.

3.1.1 Stationarity

The stationarity of the original time series data is the premise of using the regression algorithm to predict, and the augmented Dickey Fuller (ADF test) test [10] is used to verify the stationarity of the time series data.

(1) Significance value is the most important parameter in the ADF test result, which is generally divided into (0.01, 0.025, 0.05, 0.1, 0.9, 0.95, 0.975, 0.99) for several grades, when significance value is close to zero, the time series stability is better and better.

(2) When the ADF test statistic is less than critical values (1%, 5%, 10%), the time series is stationary.

Table 1 shows the ADF test results of household electricity load data: the significance value is far less than 0.01, and the test statistic is less than the critical values (1%, 5%, 10%), so the original data is stable.

Table 1 Result of ADF test

Parameter	Value
significance value	3.15e-28
Test statistic	-15.41
Critical values(1%)	-3.43
Critical values(5%)	-2.86
Critical values(10%)	-2.57

3.1.2 Periodicity

On one hand load change has obvious randomness and volatility, on the other hand, the trend of family load change has an undulating trend with day cycle. The load mean value, peak value and variation trend of the adjacent cycles are different, but the difference is not significant. Fig. 2 shows the three-day load curve.

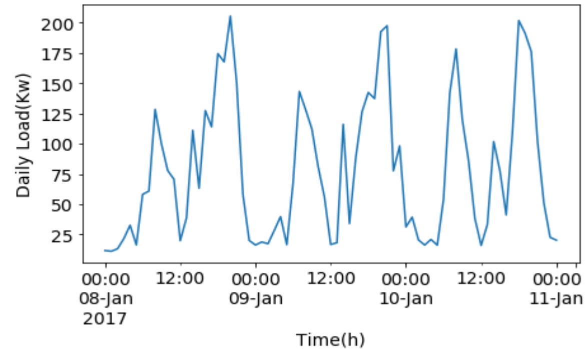
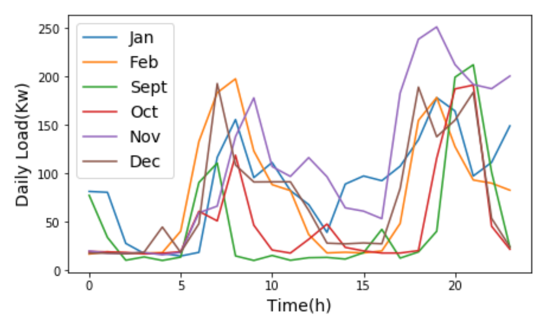


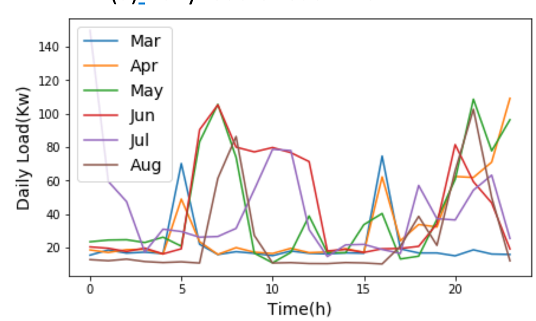
Fig 2 Three days' power load

3.1.3 Seasonal tendency

With the change of seasons, changes in temperature, sunshine duration and other factors will indirectly change users' electricity consumption habits, thus causing changes in load. Therefore, the load curve presents a strong seasonal trend. In order to verify the above inference, load curves on the 15th day of each month were selected for comparison, as shown in the Fig. 3.



(a) Daily load of each month#1



(b) Daily load of each month#2

Fig 3 Load curve on the 15th day of each month

The average daily power consumption from March to August is lower than that of the other six months. The slope of the load curve becomes smaller between 15:00 and 24:00 every day, the peak value becomes lower, and the time of wave peak is delayed. Therefore, different months and seasons affect the change of load.

3.2 Experiments

Parameter optimization of HW model [8] is to obtain the best prediction effect by changing the values of three damping coefficients (α, β, γ).PSO is a powerful optimization technique for finding the global optimum in a multi-dimensional searching space. In this paper, PSO is adopted to achieve HW parameter optimization: RMSE is taken as the optimization objective, and the iterations number of PSO is 300, particle swarm size is 50, velocity interval is [-1, 1], and location interval is (0, 1). The iterative process is shown in the Fig. 4.

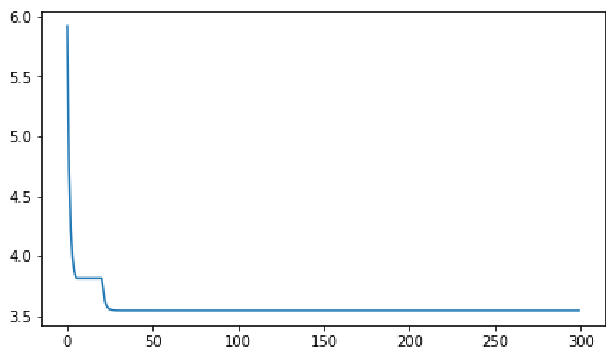


Fig 4 PSO iterative process

When (α, β, γ) = (0.192, 0.364, 0.337), RMSE is the smallest, RMSE=3.545. Fig. 5 shows the HW prediction results.

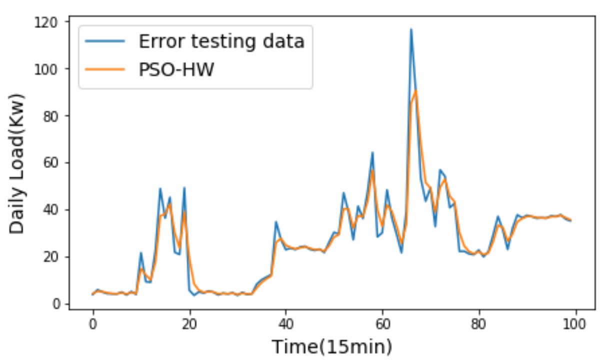


Fig 5 HW prediction with optimal parameter

The forecasting error dataset is calculated by subtracting the HW forecasting dataset from the error

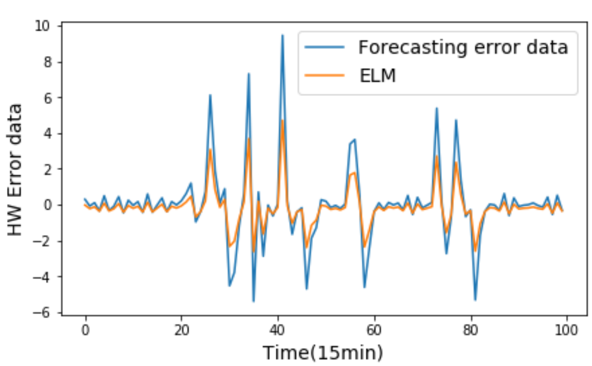


Fig 6 Error forecasting based on ELM network

testing dataset. The error prediction model is built by ELM network based on the forecasting error dataset. The ELM model is set as 40 neurons in the hidden layer and the sigma function as activation function.

The PSO-HW model and the ELM model are combined to get the combined forecasting model. Performances of models are evaluated using testing data, as shown in Fig. 7.

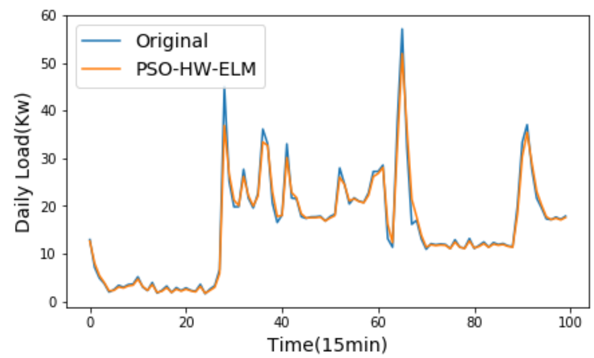


Fig 7 Combined prediction result by PSO-HW-ELM

4. COMPARISON AND DISCUSSION

To verify the feasibility of the model proposed in this paper, PSO-HW, ELM and PSO-HW-ELM models are selected to predict the same time series data. Fig. 8 shows the prediction results of the three models for 200 load data (50 h) selected at an interval of 15 min in the same group.

Table 2 Indexes of different models

Indexes	RMSE	MAE	MAPE(%)	R^2(%)
PSO-HW	3.545	1.85	14.91	0.99
ELM	7.85	4.53	55.19	0.96
PSO-HW-ELM	1.97	0.93	8.43	0.99

In order to compare model performance more intuitively, evaluation indexes of those models as shown in Table 2. Table 3 shows the performance improvement parameters of PSO-HW-ELM compared with other models.

Table 3 Performance improvement parameters

Indexes	PSO-HW-ELM	PSO-HW	ELM
PRMSE(%)	0	-79.95	-298.48
PMAE(%)	0	-98.92	-387.10
PMAPE(%)	0	-76.86	-554.69
PR2(%)	0	0	3.03

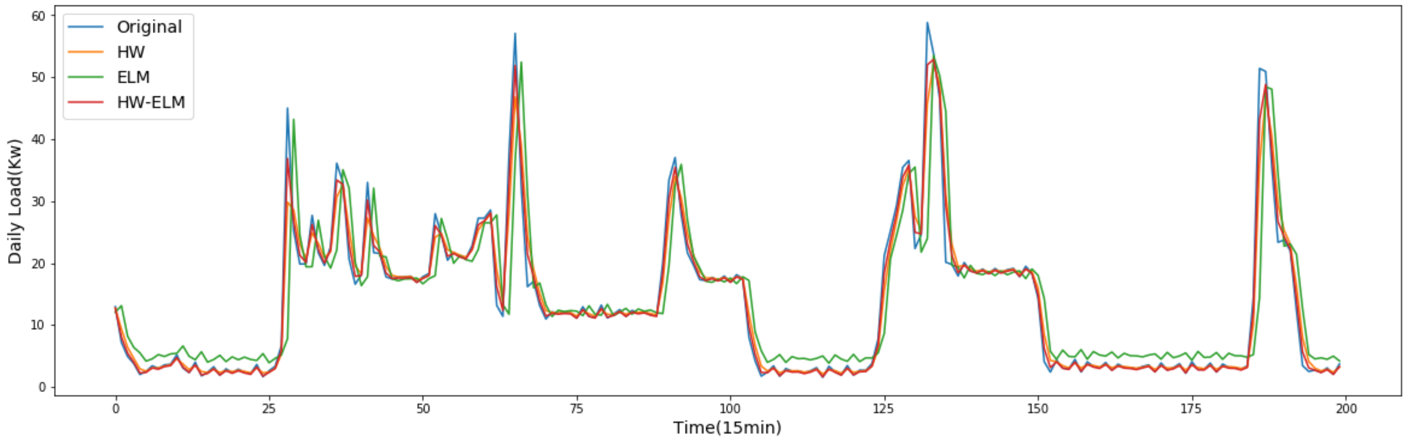


Fig 8 The prediction resluts of different models

According to the above results, the minimum error indexes (RMSE, MAE and MAPE) of PSO-HE-ELM model are minimum, which are 1.97, 0.93, and 8.43, respectively. And R^2 = 99% shows that the PSO-HW-ELM model predict results are maximum similarity with the original data. Table 3 shows that compared with the PSO-HW model, RMSE, MAE, and MAPE of the PSO-HW-ELM model decrease by 79.95%, 98.92%, and 76.86%, respectively. Compared with the ELM model, the performance of the PSO-HW-ELM model improvement is more significant. The experimental results show that the PSO-HW-ELM model can better track the load sequence and has better prediction results than the single HW and ELM model.

5. CONCLUSION

In this paper, a multi-step household power consumption prediction model was proposed, which takes into account the periodicity and seasonality of load time series data and adds prediction correction simultaneously. Firstly, considering the advantages of HW method in dealing with periodic and seasonal time series, HW is taken as the main predictor, and the parameters of HW model are optimized by PSO to obtain the PSO-HW prediction model. Then, the prediction error data of PSO-HW are used to train the ELM model, and the error correction prediction model is obtained. Finally, PSO-HW-ELM prediction model is obtained by combining the two models. The experimental results show that compared with the single HW or ELM method, the proposed model significantly improved the accuracy and stability of load forecasting.

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