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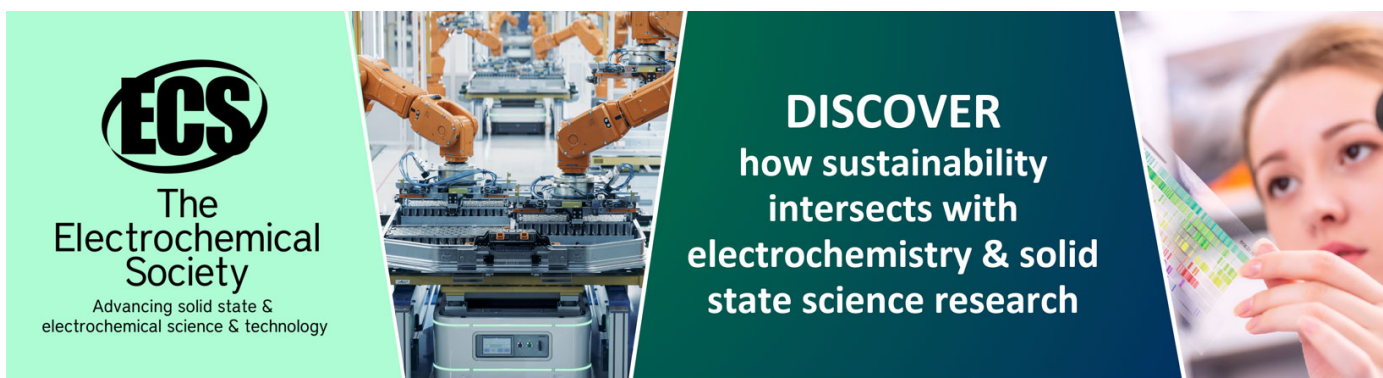
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Real-time prediction of sub-item building energy consumption based on PCA-AR-BP method

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Abstract. In this paper, a new method for real-time prediction of building energy consumption is proposed, this method solves the problem that the kinds of energy consumption are not distinguished and the prediction accuracy is low in the current energy consumption prediction algorithms. This paper divides the total energy consumption into four sections. Firstly, three main influencing factors of building energy consumption are extracted using PCA to realize real-time prediction; Secondly, the method of lighting energy consumption prediction based on time series analysis is constructed, the lighting energy consumption of the building is predicted in real time. Finally, the energy consumption prediction model based on BP network is established to predict the air conditioning, power and special energy consumption of the building. The experimental results show that the prediction model can predict energy consumption in every part of a building more accurately and effectively.

1. Introduction

With the rapidly increasing of annual energy consumption in office buildings and public buildings, building energy consumption has become the main target of building energy efficiency regulation and transformation [1]. At present, the main building energy consumption prediction methods are multiple linear regression [2], artificial neural network [3-5], time series method, genetic algorithm [6] and so on. Some scholars have also studied the prediction of building energy consumption through time series analysis [7-9]. However, the total energy consumption is used to structure the prediction model in almost all existing literatures, and most of the predictions are long-term energy consumption prediction. Therefore, the direction of the whole building energy consumption can't be predicted, and the real-time prediction of energy consumption can't be well achieved.

In this paper, a new method for real-time prediction of building energy consumption based on sub-item measurement is proposed. Firstly, 3 main influencing factor of building energy consumption was extracted by PCA. Then the real-time prediction of lighting energy consumption can be achieved. At the same time, energy consumption, energy consumption building air conditioning (lift, water supply etc.) and special energy (computer room, kitchen etc.) prediction model can also be structured, which achieve the real-time prediction of the sub term energy consumption. The real time prediction system of building energy consumption can optimize the imbalance between energy consumption systems and power supply systems (municipal power supply system, solar power system and building ontology building wind power system etc.) of large public buildings, which ensure the stability and utilization efficiency of municipal power grid renewable energy.



2. Prediction feature selection based on PCA

In order to realize the real time prediction of sub item energy consumption of construction, this paper uses PCA to extract the main prediction features.

For the given 7 prediction features $C = [C_1, C_2, \dots, C_7]$, the normalization is made according to the formula (1).

$$T_i(k) = \frac{1}{C_{\max}(i) - C_{\min}(i)} [C_i(k) - C_{\min}(i)] \quad (1)$$

$C_i(k)$ is the k th sample point of i th influence factors, $C_{\max}(i)$ and $C_{\min}(i)$ are the maximum and minimum of all the sampling points of i th influence factors, $T_i(k)$ is standardized target data, The covariance of $T_i = [T_i(1), T_i(2), \dots, T_i(n)]$ and the correlation coefficient matrix ρ_i are as follows:

$$\delta_i(s, t) = \frac{1}{n-1} \sum_{j=1}^n [(T_i(s) - \bar{T}_i)(T_i(t) - \bar{T}_i)] \quad (2)$$

$$\rho_i = \left[\frac{\delta_i(s, t)}{\delta_i(s, s) \delta_i(t, t)} \right] \quad (3)$$

Among them, $\bar{T}_i = \frac{\sum_{j=1}^n T_i(j)}{n}$ is the number of samples. By calculating the eigenvalues λ_i of the correlation coefficient matrix ρ_i , the calculation formula of the variance contribution rate and the cumulative variance contribution rate of each principal element of the PCA algorithm is as follows:

$$\alpha_i = \frac{\lambda_i}{\sum_{i=1}^7 \lambda_i} \quad (4)$$

$$\eta_i = \sum_{k=1}^i \alpha_k, \quad i = 1, 2, \dots, 7 \quad (5)$$

The contribution rate and cumulative contribution rate of all principal components are shown in Figure 1. In this paper, when $\eta_i \geq 85\%$, the first 3 principal components with the largest contribution rate are used as the prediction and prediction characteristics of building energy consumption. The prediction features of the selection are lighting energy consumption, indoor temperature, and 24 clocks in one day.

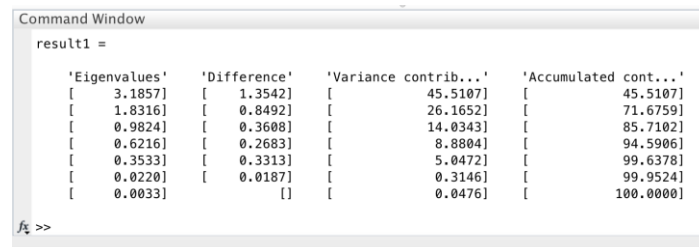


Figure 1. The main element contribution rate

3. Prediction of lighting energy consumption based on time series

3.1. The analysis of time series about lighting energy consumption

Although the lighting energy consumption often appears as a random fluctuation on the basis of past energy consumption in a short time, it belongs to the non-stationary time series, but the high-order difference of lighting energy consumption is stable. Such as, collecting the 24 hours lighting energy value of one day is $[x_1, x_2, \dots, x_{24}] = [49.8, 51.6, \dots, 218.2]$ unit(Kwh), which x_i represents the energy consumption value of the lighting at time i . As shown in Figure 2, the seven order difference of lighting energy consumption is shown to be stationary, so the time series analysis method can be used to predict lighting energy consumption.

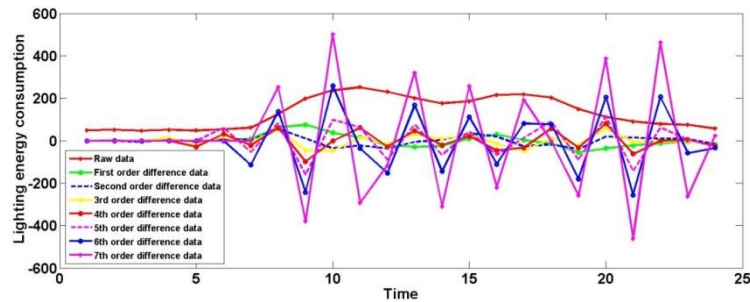


Figure 2. The high-order difference graph of lighting energy consumption

3.2. Construction of real-time prediction model for lighting energy consumption

In this section, we use the P order autoregressive model to build the prediction model of lighting energy consumption. The following is the definition of the auto correlation coefficient and partial auto-correlation coefficient of lighting energy consumption, so as to determine the value of order P .

Definition 1 Auto-correlation of lighting energy consumption

The 7-order difference value of lighting energy consumption during the 24 hours of a day is $[df_1, df_2, \dots, df_{24}]$, and the linear dependence between df_{i+k} and df_i is defined by:

$$p(k) = \frac{r(k)}{\sqrt{\text{Var}(x_i)\text{Var}(x_{i+k})}} \quad (6)$$

where $r(k) = \text{Cov}(df_i, df_{i+k})$ is the self-covariance, $\text{Var}(df_i)$ is the variance, which represents k lag number. Because the variance of the stationary time series is equal, $\text{Var}(df_{i+k})$ is then given by:

$$\text{Var}(df_{i+k}) = \text{Var}(df_i) = \dots \text{Var}(0) \quad (7)$$

Based on $\text{Var}(0) = r(0) = \sigma^2$, formula (6) can be written as:

$$p(k) = \frac{r(k)}{r(0)} \quad (8)$$

So, $p(k)$ can be calculated by the recursive formula (8).

Definition 2 Partial auto-correlation coefficient of lighting energy consumption

Defining the $k-1$ random difference variables in the middle of all the variables as $[df_i, df_{i+1}, \dots, df_{i-k+1}]$, the correlation from df_{i+k} to df_{i-1} is defined by:

$$\phi(k) = \frac{D(k)}{D} \quad (9)$$

where,
$$D = \begin{bmatrix} 1 & \rho_1 & \cdots & \rho_{k-1} \\ \rho_1 & 1 & \cdots & \rho_{k-1} \\ \cdots & \cdots & \cdots & \cdots \\ \rho_6 & \rho_5 & \cdots & 1 \end{bmatrix}, \quad D(k) = \begin{bmatrix} 1 & \rho_1 & \cdots & \rho_1 \\ \rho_1 & 1 & \cdots & \rho_2 \\ \cdots & \cdots & \cdots & \cdots \\ \rho_{k-1} & \rho_{k-2} & \cdots & \rho_k \end{bmatrix}$$

4. Experimental verification and analysis

The experimental data come from an hourly collected energy consumption from a building from July 1st to July 31st, 2016. It uses the BP neural network for prediction.

4.1. Real-time prediction results analysis of lighting energy consumption

The actual value of lighting energy consumption of $24 \times 4 = 96$ whole hours from July 27th to July 30th, 2016 were randomly selected as the training samples to predict the lighting energy consumption value at every 24 whole hours on July 31st.

4.1.1. Verification of lighting energy consumption prediction model. Figure 3 and Figure 4 show the auto-correlation analysis and partial auto-correlation analysis respectively. As can be seen from Figure 3, the process of the auto-correlation coefficient decays to small value fluctuations is slow and continuous, it shows a long tail dragged behind, which is in accordance with the trailing nature. As can be seen from Figure 4, the value of the partial auto-correlation coefficient is damped oscillatory, and the critical value would converge to 0 suddenly when the lag order is 7, and the partial auto-correlation coefficient values are all 0 after the 7th order, it is consistent with truncation. Therefore, the order of auto-regressive model $AR(P)$ is $P = 7$, it further verifies that the lighting energy consumption prediction is in line with the auto-regressive model $AR(7)$.

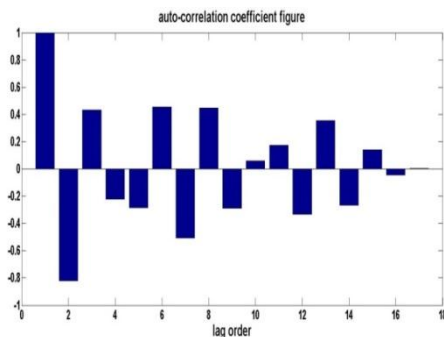


Figure 3. Auto-correlation coefficient analysis

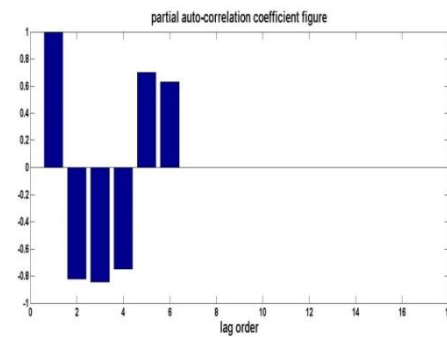


Figure 4. Partial auto-correlation coefficient analysis

4.1.2. The prediction results of lighting energy consumption. Figure 5 presents the predicted and actual lighting energy consumption profiles at 24 whole hours on July 31st. It can be concluded from Figure 5 that the predicted value is in good agreement with the actual value, and the average absolute error (MAE) is 0.0249, and the root mean square error (RMSE) is 5.6778, so it reaches the satisfactory prediction effect.

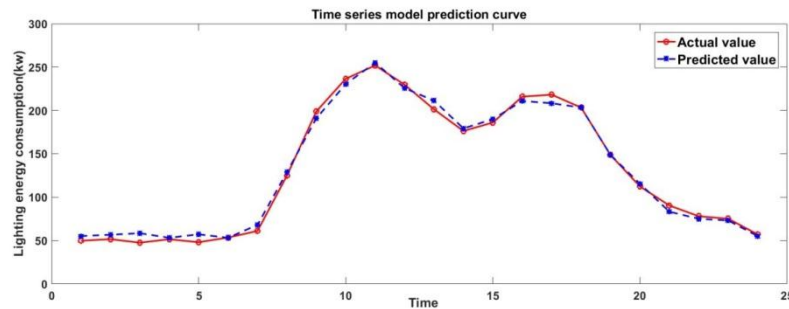


Figure 5. The results of lighting energy consumption prediction

4.2. Verification of air conditioning, power and special energy consumption prediction

The data of a week (from Monday to Sunday) are randomly selected as the training samples, and the energy consumption values of the 24 whole hours in the following week are predicted by the proposed model. The prediction results are shown in Table 1. Table 1 shows the predicted and actual values for working days (e.g. Monday and Tuesday) and non-working days (e.g. Sunday).

Table1. The results of air conditioning, power and special energy consumption prediction

		0 am		3 am		6 am		9 am		12 pm		15 pm		18 pm	
		A ¹	P ²	A	P	A	P	A	P	A	P	A	P	A	P
ACEC ³	Mon.	45.50	46.81	47.17	46.23	50.12	55.14	178.11	170.09	185.71	186.03	163.34	165.09	108.50	110.12
	Tue.	48.90	47.12	48.34	49.13	53.84	54.78	192.17	190.21	184.31	186.17	152.81	150.06	100.91	98.43
	Sun.	62.50	63.41	62.21	60.93	63.52	60.43	96.43	97.05	90.63	90.08	76.63	78.87	51.83	50.52
PEC ⁴	Mon.	9.40	9.31	10.35	9.12	11.85	10.12	60.65	66.21	52.85	50.54	60.72	61.03	45.34	47.97
	Tue.	9.20	9.17	10.82	10.91	12.52	13.01	64.52	66.05	53.35	55.02	55.25	55.23	50.71	46.89
	Sun.	9.80	10.30	8.35	8.07	11.12	11.14	14.25	14.65	11.43	11.67	14.44	13.09	11.41	11.00
SEC ⁵	Mon.	12.98	12.76	14.92	15.11	21.33	20.01	31.53	31.21	40.73	43.91	34.33	32.99	41.57	40.41
	Tue.	13.93	13.81	14.93	14.32	30.48	30.91	39.98	40.32	39.12	40.09	32.13	32.32	40.58	40.21
	Sun.	34.80	35.61	38.62	35.21	32.21	32.13	38.24	37.87	47.81	50.08	56.63	55.32	31.24	30.93

¹ A-Actual. ² P-Predicted. ³ ACEC-Air conditioning energy consumption.

⁴ PEC-Power energy consumption. ⁵ SEC-Special energy consumption.

The average relative error of the 7-day prediction of air conditioning energy consumption, power consumption and special energy consumption are calculated respectively. The results are shown in Figure 6, where the average relative error of the three kinds of energy consumption prediction is within 0.08, especially the prediction error of air conditioning energy consumption is generally within 0.04, it means that a better prediction effect is achieved.

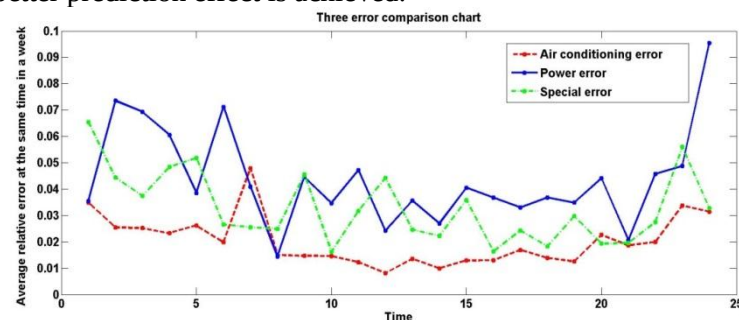


Figure 6. The average relative error of air-conditioning energy consumption, power consumption and special energy consumption prediction

5. Conclusions

This paper constructs an auto-regressive model for predicting building energy consumption, where the lighting energy consumption at 24 whole hours in a day is real-time predicted. The principal component analysis is applied to select the main factors that affect the prediction of sub-item energy consumption, and the speed and accuracy of prediction are improved. Experiments are conducted to test and verify the rationality of the auto-regressive model of lighting energy consumption and the accuracy of the sub-item energy consumption prediction.

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References

- [1] LI Dao-yang, MENG Yan-mei, HU Ying-ning, et al. Numerical analysis of building energy consumption based on separate real-time monitoring[J]. Journal of Guangxi University: Nat Sci Ed 2012, 37(5):965-971.
- [2] A Aranda, G Ferreira, M.D. Mainar-Toledo, et al. Multiple regression models to predict the annual energy consumption in the Spanish banking sector[J]. Energy and Buildings, 2012, 49(49):380-387.
- [3] LU Kuo, ZHONG Bochong. Online Forecast of Building Energy Consumption Based on LM BP Neural Network[J]. Journal of Shanghai University of Engineering Science, 2014, 28(4):347-350.
- [4] Kangji Li, Chenglei Hu, Guohai Liu, et al. Building's electricity consumption prediction using optimized artificial neural networks and principal component analysis [J]. Energy and Buildings, 2015, 108(10):106-113.
- [5] R Mena, F. Rodri'guez, M. Castilla, et al. A prediction model based on neural networks for the energy consumption of a bioclimatic building[J]. Energy and Buildings, 2014, 82(5):142-155.
- [6] Zhang Zhen-ya, Cheng Hong-mei, Liu Jia, et al. Research on the Minimum Number of Mobile Node for Sweep Coverage in Wireless Sensor Network Based on Genetic Algorithm[J]. Journal of Chinese Computer Systems, 2013, 34(10):2388-2392.
- [7] Zhou Rui-jin, Pan Yi-qun, Huang Zhi-zhong. Time Series Analysis Method and Its Application in Energy Consumption Forecast of an Actual Office Building[J]. Building energy conservation, 2012, 252(2):55-62.
- [8] Zhou Rui-jin, Pan Yi-qun, Huang Zhi-zhong. Building energy consumption prediction method based on time series analysis[J]. HV&AC, 2013, 43(8):71-77.
- [9] OUYANG Qian-wu, LI Hui, LI Jun. Application of the ARMA Model in Energy Consumption Forecast of Commercial Buildings[J]. Building Energy & Environment, 2013, 32(3):56-58.