2008年2月 第35卷 第1期
西安电子科技大学学报(自然科学版)
JOURNAL OF XIDIAN UNIVERSITY
Feb. 2008 Vol. 35 No. 1

最大熵原理的供热负荷预报研究

陈 烈，齐维贵，邓盛川
(哈尔滨工业大学 电气工程及自动化学院，黑龙江 哈尔滨 150001)

摘要： 根据建筑供热的特点和供热节能控制的需要，提出应用最大熵法进行负荷预报，介绍了最大熵谱法原理及Burg算法，对从热力站采集的历史随机负荷序列进行预处理，将其中的确定性部分和随机部分进行分离；并对负荷样本序列，分别用相关法和最大熵谱法进行负荷预报，对两种结果进行了分析比较，采用最大熵谱法进行负荷预报，其预报精度、自适应性和算法的实时性均能较好地满足建筑分户计量节能供热的要求.

关键词： 最大熵；随机序列；负荷预报；计量供热
中图分类号：TM921.2 **文献标识码：**A **文章编号：**1001-2400(2008)01-0183-06

Study of heat load forecasting based on the maximum entropy principle

CHEN Lie, *QI Wei-gui*, *DENG Sheng-chuan*
(School of Electrical Engineering and Automation,
Harbin Institute of Technology, Harbin 150001, China)

Abstract: According to the characteristics of architecture heat supply and the demands for energy-saving control, load forecasting based on the maximum entropy method is proposed. By using the least square fitting and the pretreatment approach, the historical random load series collected from the heat supply station are separated into the certain part and the random part. Then the load series is dealt with by the auto-correlation method and the maximum entropy method respectively. Comparing the results of these two methods shows that the load forecasting based on the maximum entropy theory can meet the demands for heating energy-saving control in terms of the forecasting accuracy, auto-adaptive and real-time ability better.

Key Words: maximum entropy; random series; load forecasting; heat metering

Due to the large consumption of energy in the heating system, effective energy-saving control systems are desirable to decrease the total cost. Accurate forecast of heat load in heating system is a key to heat supply control system design. Mattias B. O. Ohlsson[1] described a method using artificial neural network to forecast the heat load of a large building in America. The inputs of the ANN model were time, temperature, sunlight and wind speed, while the output was the heat load. Zhou En-ze[2] applied the time series to accomplish short-term forecasting of heat load, and utilized correlation method for metaphase forecasting. The results were used as an instruction of the energy management of heating network. Outdoor equivalent equation whose parameters could be estimated was applied to the heat load forecasting[3]. Cao Yu-qiang et al.[4] presented a method to adjust the average temperature of supply water along with fluctuation of the temperature outdoor. However, the method in ref. [1] is more feasible in macroscopic administration than in real-time control. Reference [2] has the disadvantage of low forecasting

收稿日期：2007-06-10
基金项目：哈尔滨市科技创新人才研究专项资金资助(RC2006XK007001)
作者简介：陈 烈(1982-)，男，哈尔滨工业大学博士研究生，E-mail: chenliehit@hit.edu.cn.

precise. The forecasting in reference [3] and [4] which merely has the relationship with weather is not fit for the measured heating system. Based on the above background, a load forecasting method using maximum entropy theory is proposed, which considers two main random factors: weather and consumers' needs. The simulation results show that this method is more accurate than the method which using traditional time series. In addition, it is more efficient and can meet the demand of real-time of the heat supply system, especially in the case the heat load is uncertain.

1 Maximum entropy principle

1.1 Principles of entropy

Information principle is described: if the event is happen surely, the entropy will equal to zero. The value of entropy will increase along with the uncertain of event.

Suppose matrix $\boldsymbol{X}$ is a discrete random variable, and p_i is the probability while the random variable is x_i, $i=1,2,3,\cdots n$.

$$P\{\boldsymbol{X}=x_i\}=p_i \quad , \quad i=1,2,\cdots,n \quad , \tag{1}$$

The entropy is defined as follows:

$$H(\boldsymbol{X})=H(p_1,p_2,\cdots,p_n)=-\sum_{i=1}^{n} P_i \ln P_i \quad . \tag{2}$$

If the random variable is continuous distributed and its probability density function is $p(x)$, the entropy is defined:

$$H(\boldsymbol{X})=-\int_{-\infty}^{+\infty} p(x) \ln p(x) \,\mathrm{d}x \quad . \tag{3}$$

1.2 Maximum entropy rule

If the sample is a time series $\boldsymbol{x}=(x_1,x_2,\cdots,x_N)^{\mathrm{T}}$, the entropy of this random process can be written as:

$$H_x=-\int_{-\infty}^{+\infty} p(\boldsymbol{x}) \ln p(\boldsymbol{x}) \,\mathrm{d}\boldsymbol{x} \quad , \tag{4}$$

where $p(x)$ is joint probability density function $p(x_1,x_2,\cdots,x_N)$. Suppose the time series is Gaussian process whose average is zero, thus

$$p(x_1,x_2,\cdots,x_N)=(2\pi)^{-N/2}(\det R_x(N)^{-1/2})\exp\left(-\frac{1}{2}\boldsymbol{x}^{\mathrm{T}} R_x^{-1}(N)\boldsymbol{x}\right) \quad , \tag{5}$$

where the $R_x(N)$ is auto-correlation matrix.

Equation (4) can also be substituted by (5):

$$H_x=\frac{1}{2}\ln[\det R_x(N)]+N\ln(2\pi e)^{1/2} \quad . \tag{6}$$

If nonstationary time series has been described as $r_x(0),r_x(1),\cdots,r_x(N)$, the course which extrapolates the next auto-correlation value $r_x(N+1)$ above the premise H_x is maximized, is named maximum entropy rule.

Thus $r_x(N+1)$ can be obtained by solving the following equation:

$$\partial \det R_x[(N+1)]/(\partial r_x(N+1))=0 \quad , \tag{7}$$

where,

$$R_x(N+1)=\begin{vmatrix} r_x(1) & r_x(0) & \cdots & r_x(1-N) \\ r_x(2) & r_x(1) & \cdots & r_x(2-N) \\ \vdots & \vdots & & \vdots \\ r_x(N+1) & r_x(N) & \cdots & r_x(1) \end{vmatrix}=0 \quad . \tag{8}$$

1.3 Maximum entropy spectrum estimate

Maximum entropy spectrum estimate[5] is a modern spectrum estimate based on maximum entropy theory. The data outside the observation area can be forecasted by extrapolating the auto-correlation function of process infinitely. The method can solve the low resolution problem caused by adding window with classical spectrum estimate.

In fact, according to Fejer-Ries theorem, maximum entropy spectrum estimate is equivalent to AR signal analysis and linear forecasting error filter, and

$$S_x(m) = P_N \Big/ \left(2f_N \left|1 - \sum_{k=1}^{N} a_k \exp(-\mathrm{j}k\omega)\right|^2\right) \quad , \tag{9}$$

where a_k is also the AR model parameters can be acquired by solving Yule-Walker equation which has $N+1$ auto-correlation function values. P_N is the output power of N ranks forecasting error filter.

The coefficient of forecasting error filter $1, -a_1, -a_2, \cdots, -a_N$ can be obtained by following matrix,

$$\boldsymbol{R}_x(N) = \begin{bmatrix} r_x(0) & r_x(-1) & \cdots & r_x(-N+1) \\ r_x(1) & r_x(0) & \cdots & r_x(-N+2) \\ \vdots & \vdots & & \vdots \\ r_x(N-1) & r_x(N-2) & \cdots & r_x(0) \end{bmatrix} \begin{bmatrix} 1 \\ -a_1 \\ \vdots \\ -a_N \end{bmatrix} = \begin{bmatrix} P_N \\ 0 \\ \vdots \\ 0 \end{bmatrix} \quad . \tag{10}$$

2　Disposal of load sample

2.1　Choice of experiment sample

Data collected from a certain heat supply station of Harbin are treated as original data for load forecasting. The sample includes 70 days data between December 1th, 2005 and February 8th, 2006. The data are shown in Table 1.

Table 1　Day-Average Heat Load From Dec. 1th,2005 To Feb. 8th,2006

Date/day	Dec. 1st, 2005	Dec. 2nd, 2005	Dec. 3nd, 2005	…	Dec. 26th, 2005	Dec. 27th, 2005	…	Feb. 7th, 2006	Feb. 8th, 2006
Load/ ($MJ \cdot h^{-1}$)	44.250	45.750	45.625	…	48.750	45.250	…	59.250	59.625

2.2　Pretreatment of random process

The certain part can be estimated by using least square and the random part can be separated from the same part simultaneously.

Before modeling, the random part should be pretreated.

1) zero mean value method　For the time series $x(i)$ $(i = 1,2,\cdots,n)$, the data should be disposed by zero mean value method if $E[x(i)] \neq 0$.

2) Stabilization　Run test is utilized to realize steady test. It's practicable to small sample observation series without considering the distribution rule of the data.

The time series needs to be stabilized if the heat load is non-stationary series. In this paper trend items are removed by using first-order difference method.

The random signal separated above is dealt by the zero mean method and stabilization. And the final random signal separated is shown in Fig. 1.

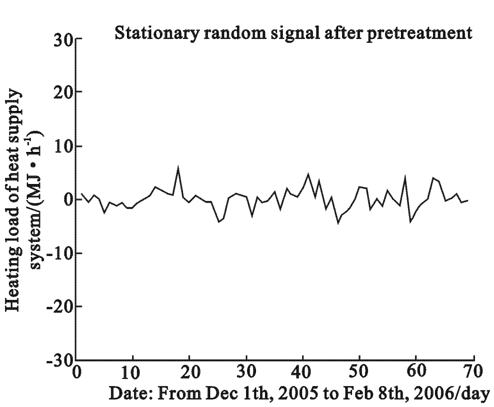


Fig. 1　Random signal after pretreatment.

3 Heat load forecasting with maximum entropy method

3.1 Burg algorithm

According to Burg algorithm[6], reflectance is calculated under the rule that both the average power of the forward and backward forecasting errors are minimized. Thus the power spectrum of signal can be acquired restrictedly by Levinson recursive algorithm. The detailed approach involves six steps (see below):

1) The initial value of forecasting error power can be calculated by:

$$P_0 = \frac{1}{N}\sum_{n=1}^{N} |x(n)|^2 \quad , \tag{11}$$

and the initial value of forward and backward error

$$f_0(n) = g_0(n) = x(n) \quad . \tag{12}$$

2) Let $m = 1$, then the reflectance is

$$K_m = -\sum_{n=m+1}^{N} f_{m-1}(n) g^*_{m-1}(n-1) \Big/ \left(\frac{1}{2} \sum_{n=m+1}^{N} \left[|f_{m-1}(n)|^2 + |g_{m-1}(n)|^2 \right] \right) \quad . \tag{13}$$

3) Coefficient of filter can be expressed as follows:

$$a_k^m = a_k^{(m-1)} + K_m a_{m-k}^{(m-1)} \quad , \tag{14}$$

and then let the reflectance $K_m = a_m^m$.

4) Forecasting error power can be calculated by:

$$P_m = (1 - |K_m|^2) P_{m-1} \quad . \tag{15}$$

5) Outputs of filter are obtained:

$$f_m(n) = f_{m-1}(n) + K_m g_{m-1}(n-1) \quad , \tag{16}$$

$$g_m(n) = g_{m-1}(n-1) + K_m^* f_{m-1}(n) \quad . \tag{17}$$

6) In addition, $m \leftarrow m+1$, and repeat step 2)~5) until $m = p$.

3.2 Forecasting applying maximum entropy method

The algorithm based on maximum entropy theory, which is utilized to forecast the load of heat supply system, solves the inconsequence problem that the values of time series outside "window" are set to zero by traditional algorithm. Thus the forecasting zone is extended to infinite.

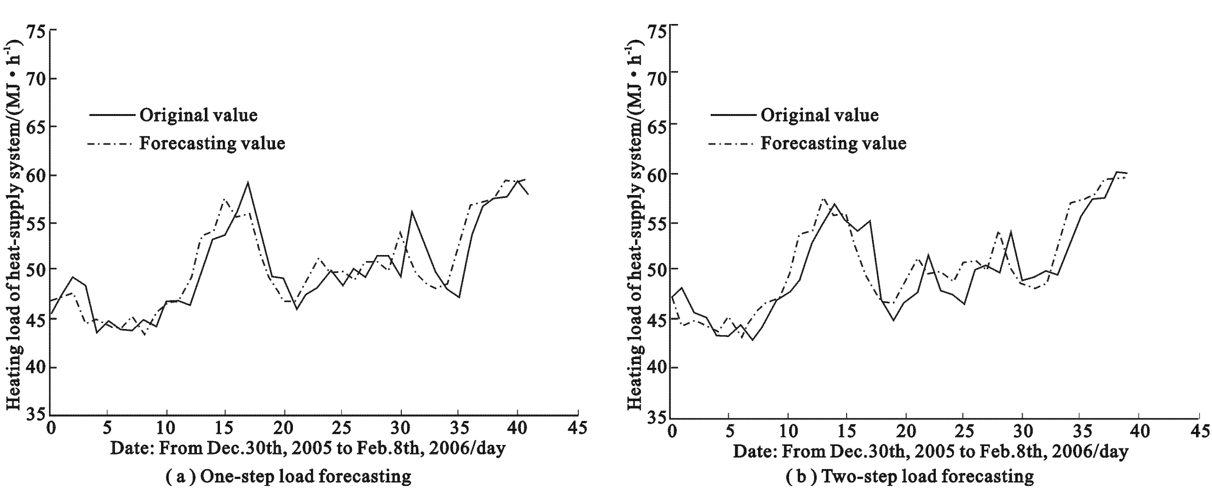


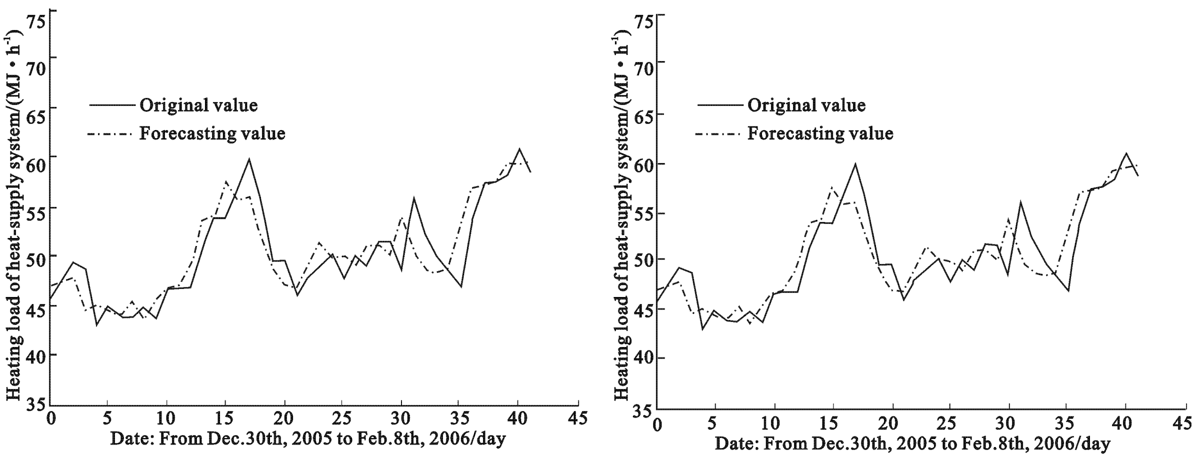
Fig. 2 Load forecasting based on maximum entropy method.

The time series from Dec. 30th, 2005 to Feb. 8th, 2006 is dealt with Burg algorithm forecasting, while the number of the time series is 40. The simulation results are shown in Fig. 2.

According to Fig. 2, to the heat supply system which has the characters of random, nonlinear, and time-varying, the accuracy of heat load forecasting is improved obviously by using maximum entropy principle.

3.3 Results comparison between maximum entropy method and auto-correlation method

Through simulating, the one-step and two-step heat load forecasting with auto-correlation method are shown in Fig. 3. And comparison of those two methods is shown in Table 2.



(a) One-step load forecasting　　(b) Two-step load forecasting

Fig. 3　Load forecasting with auto-correlation method.

Table 2　Comparison of load forecasting using maximum entropy method and auto-correlation method

Load forecasting method	Accumulative Absolute Error/(MJ • h^{-1})	Average Absolute Error/(MJ • h^{-1})	Average Absolute Relative Error/%
One-step maximum entropy method	150.89	3.77	7.69
Two-step maximum entropy method	152.71	3.82	7.80
One-step auto-correlation method	175.59	4.39	8.96
Two-step auto-correlation method	178.92	4.47	9.13

Through the comparison of the accumulative absolute error, the average accumulative absolute error, and the average absolute relative error in Table 2, it can be concluded that the accuracy of the method this paper introduced is higher than using auto-correlation method.

4 Conclusion

In this paper, the heat supply forecasting based on maximum entropy principle is proposed. The results show this method can be advantageously employed in heat supply control system. The conclusion can be obtained as follows:

1) The sample data are pretreated to improve the accuracy of forecasting.

2) The algorithm, which based on maximum entropy theory, can be processed online. It can meet the demands of the real-time system.

3) Comparing the results, heat load forecasting based on maximum entropy method has higher accuracy than using auto-correlation method.

4) The forecasting method based on the maximum entropy has the same effect as AR method in stationary process. Furthermore it's also suitable to parameters estimate for non-stationary process.

Reference:

[1] Ohlsson M B O. Predicting System Loads with Artificial Neural Network-methods From the Great Energy Predictor Shootout[J]. ASHARE Trans, 1994,100(2): 1063-1074.
[2] Zhou Enze, Fang Xiumu. The Study on Heat Load Forecast of the Heating Boiler House[J]. Journal of Harbin University of Civil Engineering and Architecture, 2000, 33(3): 56-60.
[3] Jonsson G R, Jonsson V K. Equivalent Outdoor Temperature for District Heating System[J]. Ashare Trans, 1995,101(1): 394-399.
[4] Cao Yuqiang, Shen Jin'an. An Energy-saving Type Intelligent Heating Control System[J]. Industrial Instrumentation & Automation, 2002, 14(1): 44-46.
[5] Burg J P. Maximum Entropy Spectral Analysis[C]//37th Ann Int Explor Geophysics Meeting. New York: IEEE Press, 1978: 34-39.
[6] Zhang Xianda. Modern Signal Processing[M]. Beijing: Tsinghua Publishing Company, 2002.

(编辑:齐淑娟)

(上接第124页)

[2] Roerdink J B T M, Meijster A. The Watershed Transform: Definitions, Algorithms and Parallelization Strategies [J]. Fundamental Informaticae, 2001, 41(2): 187-228.
[3] Jackway P T. Gradient Watershed in Morphological Scale-space [J]. IEEE Trans on Image Processing, 1996, 5(6): 913-921.
[4] Gauch J H. Image Segmentation and Analysis Via Multiscale Gradient Watershed Hierarchies [J]. IEEE Trans on Image Processing, 1999, 8(1): 69-79.
[5] 王养利, 吴成柯. 基于V氏图的图像分割及表示[J]. 西安电子科技大学学报, 2000, 27(3): 340-344.
Wang Yangli, Wu Chengke. Image Segmentation and Representation Based on Voronoi Diagrams[J]. Journal of Xidian Unviersity, 2000, 27(3): 340-344.
[6] 任获荣, 王家礼, 张平. 形态金字塔图像分割算法[J]. 西安电子科技大学学报, 2004, 31(2):248-252.
Ren Huorong, Wang Jiali, Zhang Ping. Image Segmentation Algorithm Based on the Morphological Pyramid[J]. Journal of Xidian Unviersity, 2004, 31(2):248-252.
[7] 崔明, 孙守迁, 潘云鹤. 基于改进快速分水岭变换的图像区域融合[J]. 计算机辅助设计与图形学学报, 2005, 17(3): 546-552.
Cui Ming, Sun Shouqian, Pan Yunhe. An Image Region Merging Algorithm Based on Modified Fast Watershed Transform [J]. Journal of Computer-Aided Design & Computer Graphics, 2005, 17(3): 546-552.

(编辑:郭 华)