

Wavelet Transform Noise Elimination and Its Application in City Heating Load

Prediction

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Abstract: In this paper, the real-time measuring data with noise undergo wavelet transformation. With the treated data and an internal time-delay Elman network, city heating supply predictive models are established and short-term real-time predictions are realized. The result indicates that selecting the proper level of decomposition to denoise measuring signals can eliminate high frequency noise disturbance, improve identification precision, shorten identification time and meet the demands of real-time identification.

Key words: wavelet transform; data denoising; Elman network; heat load prediction

0. INTRODUCTION

For various measuring signal, its information could be analyzed with Fourier analysis. However Fourier transform has serious shortages. It would lose time information and result in disjunction between frequency-domain and time-domain analysis. Wavelet analysis is a method of information analysis developed in recent years, it overcomes insufficiency of Fourier transform, and has good characterization capacity of local signal characteristic in frequency and time domain.

As a method of information analysis, wavelets transform is paid much attention by science, technology and engineering and develops rapidly in various fields. In this paper to forecast city heating load, wavelet transform is applied to denoise measuring signal to deal with noise pollution. It shortens identification time, increases identification precision, and popularizes neural network identification.

1. the BASIC CONCEPT of WAVWLETS

TRANSFORM

Suppose a continuous wavelets transform^[1] is as following:

$$\psi_{a,b}(t) = |a|^{-\frac{1}{2}} \psi\left(\frac{t-b}{a}\right) \quad (1)$$

Where a is scale factor, b is shift factor, $\psi \in L^2 \cap L^1$ and

$$C_\psi = \int_{\mathbb{R}} \frac{|\psi(\omega)|^2}{|\omega|} d\omega < \infty \quad (2)$$

then ψ is basic wavelet. $f(t)$ could be modified by continuous wavelets transform as following:

$$W_f(a,b) = \langle f, \psi_{a,b} \rangle = |a|^{-\frac{1}{2}} \int_{\mathbb{R}} f(t) \psi\left(\frac{t-b}{a}\right) dt \quad (3)$$

and reverse transformation formula of wavelets transform is:

$$f(t) = C_\psi^{-1} \iint_{\mathbb{R}^2} W_f(a,b) \psi_{a,b}(t) \frac{dadb}{a^2} \quad (4)$$

2. the FUNDAMENTAL PRINCIPLES of WAVELETS TRANSFORM DENOISE TECHNICAL

2.1 Wavelets Transform and Signal Denoise Principles

Fourier transform is to get the projections of $f(t)$ in $e^{-j\omega t}$, those transform results are called Fourier coefficient. To multiply those Fourier coefficients by $e^{j\omega t}$, we could obtain original signals. While wavelets transform is to get the projections of $f(t)$ in each wavelet, the transform results are coefficients corresponding to each wavelet. To multiply those coefficients by each wavelets transform function, we

could obtain original signals.

In the measuring data of industrial process, there are characteristic information of basic parameters (generally low frequency) and interference noise

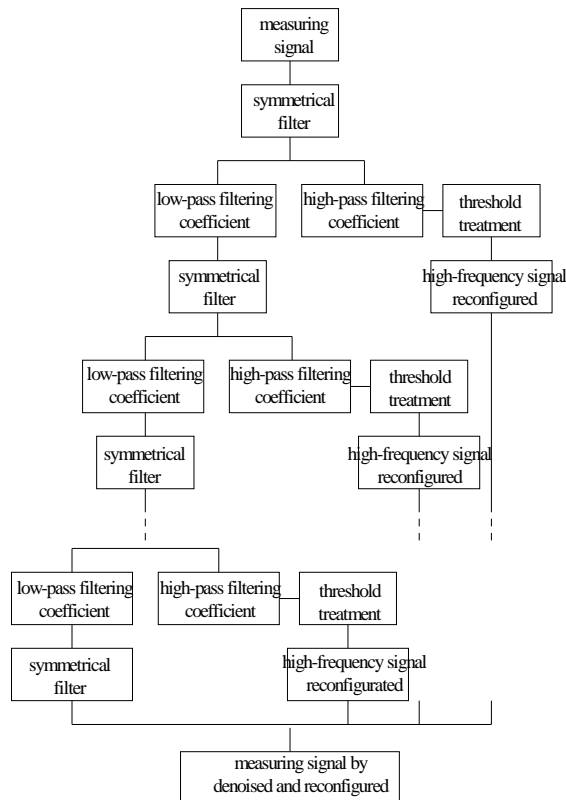


Fig.1 the Signal Denoising Process by Wavelet

from various industrial equipments (generally high frequency). Those measuring information could be multi-criteria decomposed by wavelets transform and filtered out high-frequency noise under certain thresholds range, then reconfigured and smooth information of industrial process could be obtained. Above all are the basic principles of wavelets transform and signal denoise.

2.2 Wavelets Transform and Signal Denoise Process

Measurement information of industry process is independent variable with time and one-dimensional signal. The process of wavelets denoise is as following. Firstly those one-dimensional signals are filtered by two complementary symmetry filters and two decomposition signals in low-frequency and high-frequency are gotten. Further the low-frequency signals would be treated by the same means and two more decomposition signals in low-frequency and

high-frequency are obtained. The decomposition layers N could be determined according to polluting noise level. Secondly, the thresholds value of each layer should be set to filter out high-frequency coefficient. Lastly, the low-frequency coefficients and the high-frequency coefficients fit to thresholds limit would be reconfiguration, thus the denoised signals are obtained. We can choose hard or soft thresholds value based on the characteristic of high-frequency noise^[2]. Figure 1 displays denoise process with wavelets transform.

3. the APPLICATION of DENOISE TECHNICAL with WAVWLETS TRANSFORM

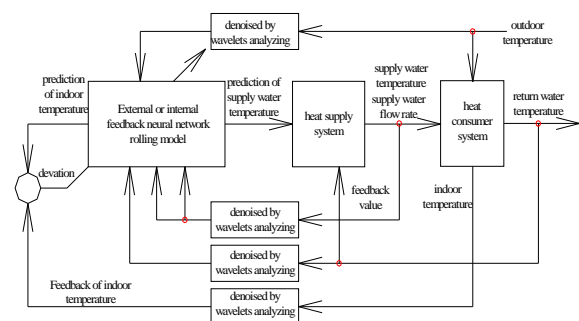


Fig.2 Heating Supply Predictive Models with Wavelet Transforms Denoising

External BP and internal Elman network could be used to predict heating load^[3]. While in practical application, the model identification and heating load prediction should depend on real-time sample data. Thus the predictive model should have strong anti-interference capability to eliminate local noise. Limited memory method is applied to avoid data saturated and the length of measurement signals for identification is fixed^[4]. Heating load would be predicted 1~4 times everyday, and the model should be re-identified if prediction error over limit. Those input signals should be denoised by wavelets transform before heating load prediction and model

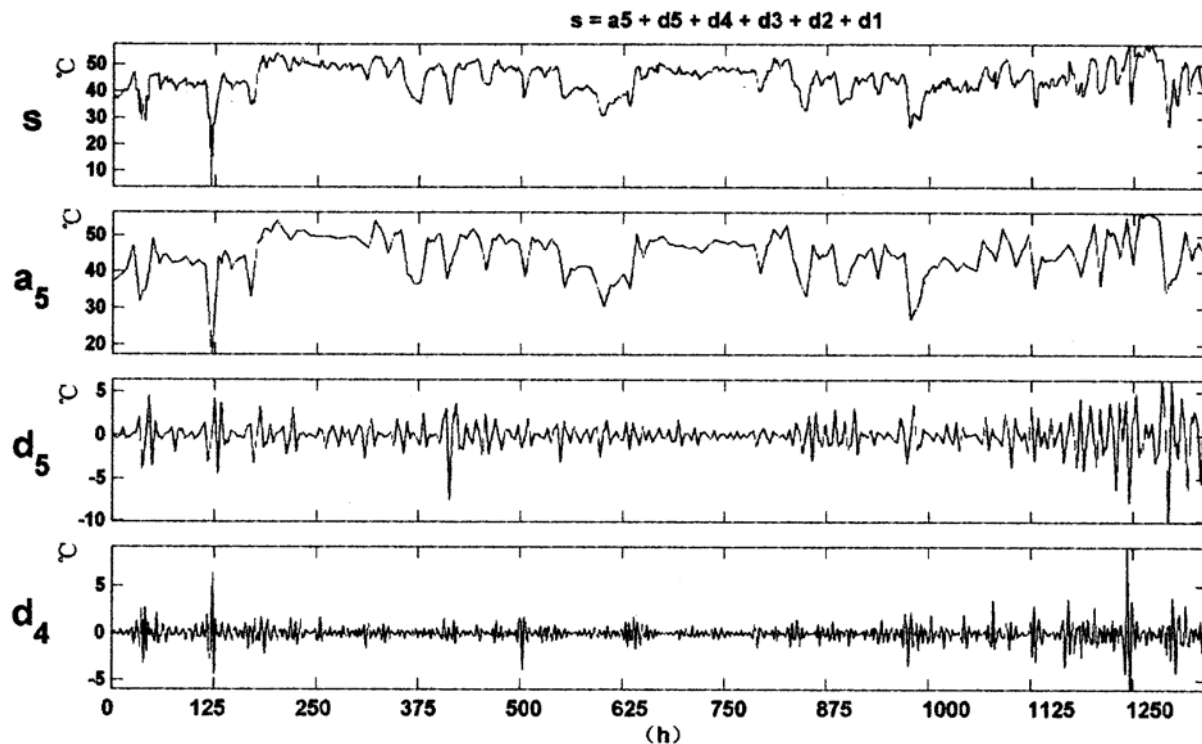


Fig. 3 The initial signal of heat network return water temperature and reconstructed partial low and high frequency signals

identification, so the results would be more accurate. Figure 2 shows the identification and prediction principles.

Heating load of Xihailin is predicted in the paper. Figure 3 shows the signals of heating network return water temperature which is denoised by wavelets transform and reconstructed with partial low and high frequency signals. s is initial data of heating network return water temperature, a_5 is low-frequency reconstructed signals, and d_5 , d_4 is high-frequency reconstructed signals. Wavelets function db3 which provided by MATLAB6.5 is applied and the decomposition layer is five. Figure 3 displays that low-frequency reconstructed signals by five-level decomposition could well predict. While six-level decomposition would cause large distorted of low-frequency signals, and it should reconstructed with high-frequency signals to ensure information accurate. Thus five-level decomposition is applied in this paper.

Table 1 shows the results which are pre-treated by wavelets transform and predicted by internal Elman network. The former 500 data is to identify the model and the last 500 data is to predict. The structure of

Elman network is 5 input nodes, 25 hidden nodes and 6 output nodes^[3]. Table 1 shows that if based on low-frequency signals which is five-level decomposition and reconstructed, the identification precision is higher, the identification is faster and test error is larger. While the identification precision is lower, the identification is slower and test error is smaller if based on low-frequency signals which is one-level decomposition and reconstructed. Low-frequency signals which is three-level decomposition and reconstructed is best fit identification.

4. CONCLUSION

The results show that dynamical system could be well predicted by reconfiguration low-frequency information which is multi-level decomposed. Multi-level high-frequency information is filtered out, so identification time is shortened and identification precision is increased. While if high-frequency was excessively filtered out, the model would be poor generalized and the measurement error would increased. Therefore we should appropriate choose decomposition layers according to the signal characteristics, and then achieve optimum integrated

Tab.1 Contrasting to the Results with Wavelet Transforms Denoising Process

predictive model identification and test data	training times	training period (s)	training precise	identification data error	test data error
low-frequency signals which was five-level decomposition and reconstructed	166	15.22	0.0010	0.2509	9.167
low-frequency signals which was four-level decomposition and reconstructed	247	22.04	0.0010	0.3145	3.089
low-frequency signals which was three-level decomposition and reconstructed	474	41.29	0.0010	0.3936	2.863
low-frequency signals which was two-level decomposition and reconstructed	2422	207.84	0.0010	0.5263	2.584
low-frequency signals which was one-level decomposition and reconstructed	5000	430.48	0.0015	0.8516	2.388
Initial signals	5000	430.67	0.0019	1.1507	8.246

results of identification precision, identification time and generalization ability.

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