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Study of Autoregressive (AR) Spectrum Estimation Algorithm for Vibration Signals of Industrial Steam Turbines

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Abstract

Spectral analysis of the vibration signals of industrial steam turbines provides efficient reference for the characterization and discrimination of turbine faults. Conventional power spectrum estimation methods often exhibit contradiction between variance performance and resolution, leading to poor estimation results. In this study, we investigated Levision-Durbin recursive algorithm, Burg algorithm and periodogram power spectrum estimation algorithm, and also chose Akalke Information Criterion (AIC) to identify the optimal order p. Based on MATLAB, we wrote a simulation program for Autoregressive (AR) spectrum estimation algorithm and designed a graphic user interface, formulating the AR spectrum estimation algorithm program for vibration signals of industrial steam turbines. After field measurement of a steam turbine with sampling number of 400 and frequency of 256Hz, as well as order of 10 and 80, simulation was performed. It was demonstrated that AIC provides efficient reference for the identification of proper order. With the optimal order, AR spectrum estimation algorithm produces good variance performance and resolution, providing reference for the spectral analysis of vibration signals of industrial steam turbines.

Keywords: *Steam turbine, Vibration signal, Autoregressive (AR) model, Power spectrum estimation, MATLAB*

1. Introduction

The power spectral density (PSD) of signals is important for the signal analysis and identification. PSD-related power spectrum estimation technologies are widely employed in areas like radar, sonar, audio and fault diagnosis [1]. Conventional power spectrum estimation is often constrained by the Discrete Fourier Transform (DFT), leading to defects that prohibit high resolution and accuracy, which are required in some cases [2]. These defects include leakage error, aliasing error, low resolution, and unsuitability for short data processing, rough spectral lines, violent fluctuation, and difficulty in fitting smooth curves [3]. In modern spectrum estimation, parameter model is first estimated by observing data, and then the power spectrum of signal is estimated by calculating the output power of the parameter model [4]. Autoregressive (AR) model, an all-pole model that can effectively describe the peaks of narrow-band power spectra, is a typical model in modern spectrum estimation [5]. With an order great enough, AR model can describe a stationary random sequence in a relatively precise fashion [6].

Steam turbine is a type of rotating machinery widely used in industrial field. The conditions of turbines influence both their normal operations and the production safety and economic benefits. When faults occur to a turbine, the spectral energy distribution of its vibration signal often changes. Therefore, spectral analysis of the vibration signal can provide efficient reference for the fault diagnosis [7]. In this study, we investigated AR power

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spectrum estimation algorithm, performed comparative analysis using MATLAB simulation and designed a graphical user interface (GUI). As a result, a set of simulation programs, which offers flexible signal generation, sampling frequency selection and parameter setup and provides estimation result comparison and analysis between different parameter setups, were designed. On the basis of these programs, we analyzed the performances of different algorithms using actual vibration signal of an industrial steam turbine, hoping to provide reference for the spectral analysis of vibration signals of steam turbines.

2. Algorithms

2.1. Periodogram Power Spectrum Estimation Algorithm

Periodogram method is to perform Fast Fourier Transform (FFT) to the definite number of samples x(n)={x(0), x(1), ⋯, x(N-1)} of observed signal directly for power spectrum estimation[8]. The N-periodogram of x (n) can be calculated by Formula (1).

$$I_N(k) = I_N(\omega)\Big|_{\omega=\frac{2\pi}{N}k} = \frac{1}{N}\left|X(k)\right|^2 \tag{1}$$

Where, N is the length of data and X(k) is the discrete Fourier transform of signal sequence x(n). X(k) is calculated through FFT and it should be called in the format of Xk = fft(xn, NFFT). The algorithm can be described by the flowchart in Figure 1.

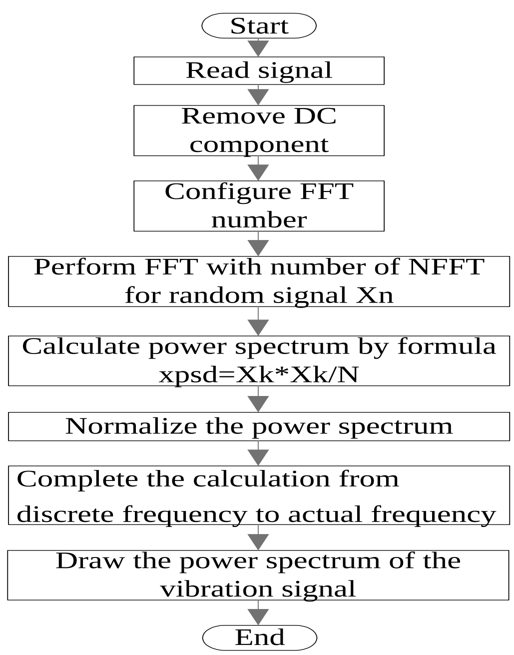

Figure 1. Periodogram Spectrum Estimation Algorithm for Steam Turbine

The code for this process is as below.

```
mid=sum(xn)/length(xn); xn=xn-mid; %Remove DC component
N=length (xn);
fs =256;NFFT=1024; %Configure sampling frequency and FFT number
Xk=fft(xn,NFFT); %Perform FFT with number of NFFT for Xn
```

```
xpsd=Xk.*Xk/N; %Calculate power spectrum
pmax=max(xpsd);
xpsd=xpsd/pmax;
xpsd=10*log10(xpsd+0.000001); %Normalize the power spectrum and convert it into logarithmic spectrum
k= 0:1:(NFFT/2-1);
f=fs*k/NFFT; %Convert the discrete frequency to actual frequency
plot(f,xpsd(1: NFFT/2)); grid on;xlabel('f/Hz'); ylabel('PSD/dB'); %Draw the power spectrum
```

2.2. AR Power Spectrum Estimation Algorithm

2.2.1. Algorithm Flow: AR power spectrum estimation algorithm is established on the basis of performing linear prediction modeling to the signal sequence x(n) to be estimated. The sequence is treated as a white noise sequence with mean of 0 and variance of σ_w^2, and it is generated by a Linear Time Invariant (LTI) system with system function of H(z). It can be expressed by the difference equation below.

$$x(n) = -\sum_{k=1}^{p} a_k x(n-k) + w(n) \tag{2}$$

This model is denoted by AR(p), and the system transition function H(z), as expressed below, is a p-order AR model.

(3)

In power spectrum estimation, if the observed data x(n) is a stationary random process, the input w(n) of the system can be considered stationary[9]. According to the response theory of linear systems to stationary random signals, the power spectrum of the observed data can be expressed by Equation (4).

$$P_x(\omega) = \sigma_w^2 \left| H(e^{j\omega}) \right|^2 = \frac{\sigma_w^2}{\left| 1 + \sum_{k=1}^{p} a_k e^{-j\omega k} \right|^2} \tag{4}$$

The denominator of Equation (4) can be calculated through FFT. In this algorithm, a signal prediction model is established to signal sequence x(n) through linear prediction to predict the data outside the sampling intervals, so that spectral leakage in conventional spectrum estimation algorithms, caused by the window truncating of data, is prevented. This way, the estimation result is improved comparing with conventional algorithms. Figure 2 presents the flow of this algorithm.

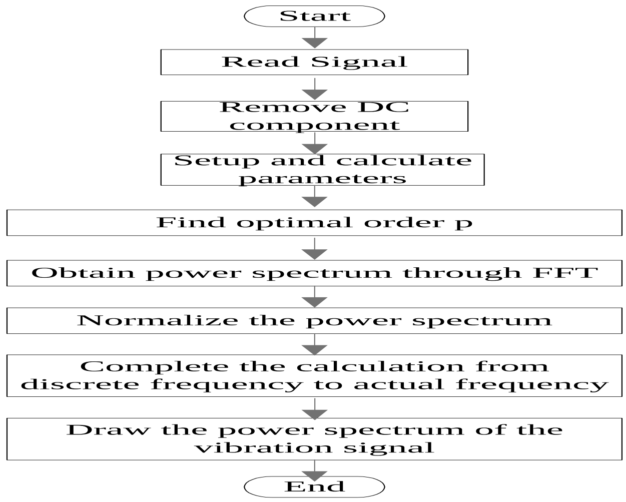

Figure 2. AR Power Spectrum Estimation Algorithms

2.2.2. Identification of Optimal Order through AIC: To use the AR power spectrum estimation algorithm for vibration signals of industrial turbines, the identification of the model's order p is crucial. In practical application, there exist optimal orders, which can be identified according to the Akalke Information Criterion (AIC).

$$AIC(p) = \ln[\sigma_p^2] + \frac{2(p+1)}{N} \quad (5)$$

Where, N is the length of data x(n), and σ_p^2 is the prediction error rate of AR model with order p [10]. When a model's AIC function has the minimal value, it is the suitable model. Based on AIC and combining aryule function, the prediction error rate σ_p^2 is calculated. The following program is designed to calculate and plot the AIC (p) curve for the convenience of deciding the optimal order p.

2.2.3. L-D recursive Algorithm-based AR Spectrum Estimation: Assume that the observed data x(n) is obtained by stimulating an all-pole linear time invariant system H(z) using a zero-mean white noise sequence W(n) with mean square error of σ_w^2 [11-12]. On the premise of keeping the mean square error of forward prediction minimal, Levision-Durbin (L-D) recursive algorithm acquires the auto-correlation function of the observed data, obtains the model's parameters through the recursive property of Yule-Walker (Y-W) function, and then calculates the estimated power spectrum using Equation(4) [13]. First, the predicting coefficients $\{a_m(k)\} = a_1(1)$ and σ_{w1}^2 when the order m=1 are calculated; then the coefficients $a_2(1)$, $a_2(2)$ and σ_{w2}^2 when the order m=2 are calculated; in the same manner coefficients are calculated until $a_p(1)$, $a_p(2)$, $\ldots a_p(p)$ and σ_{wp}^2 for m=p, when σ_p^2 satisfies the requirements for precision. The recursive formula is as below.

$$a_m(m) = -\frac{R(m) + \sum_{k=1}^{m-1} a_{m-1}(k) R(m-k)}{E_{m-1}} \quad (6)$$

$$a_m(k) = a_{m-1}(k) + a_m(m) a_{m-1}(m-k), \quad k = 1, 2, \ldots m-1 \quad (7)$$

$$E_m = \sigma^2_{wm} = \left[1-\left|a_m(m)\right|^2\right]E_{m-1} = R(0)\prod_{k=1}^{m}\left[1-\left|a_k(k)\right|^2\right] \quad (8)$$

The computational labor of L-D algorithm is in the magnitude of p^2. With parameters AR(0) and AR(1) of the model as initial conditions, AR(2) is calculated, and then AR(3) to AR(P) in likewise manner. After the iterative computation, the parameters for the low-order models are also obtained [14]. In MATLAB, this algorithm can be realized with pyulear function as the core. The pyulear function should be called in the format of xpsd=pyulear(xn, p,NFFT), where xpsd indicates the calculated power spectrum of the signal, xn is the signal sequence to be estimated, p is the order of AR model, and NFFT is the number of Fast Fourier Transform (FFT), which must be greater than or equal to the sampling number of the signal. The following program details the L-D recursive algorithm.

```
Mid=sum (xn)/length (xn);
xn=xn-mid;
N=length (xn);
fs=1000; NFFT=1024;
xpsd=pyulear (xn,minp,NFFT); %Calculate power spectrum using pyulear function
pmax=max(xpsd);
xpsd=xpsd/pmax;
xpsd=10*log10(xpsd+0.000001)-0.5;
k=0:1: (NFFT/2-1);
f=fs*k/NFFT;
figure (1);  plot(f,xpsd(1:NFFT/2)); grid on;xlabel('f/Hz'); ylabel('PSD/dB');
```

2.2.4. Burg Algorithm-based AR Spectrum Estimation: The basic idea of Burg algorithm is to use linear predictor to directly calculate the total mean square error of the forward and backward predictions of the observed data, keep the total mean square error minimal in order to estimate the reflection coefficient, and then find the optimizing parameters for AR model through the recursive formula of L-D algorithm [15]. For N observed data x(0), x(1), …, x(N-1), the algorithm executes in the flow presented by Figure 3.

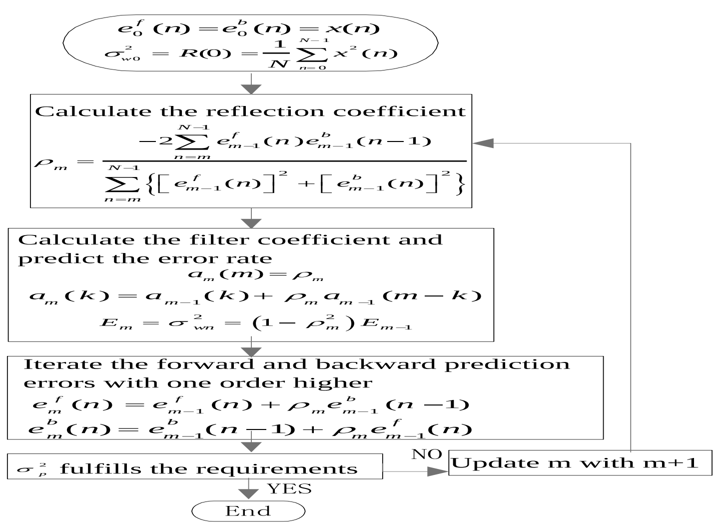

Figure 3. Flowchart for Burg Algorithm-Based AR Spectrum Estimation

In MATLAB, function pburg should be called for this process. The calling of pburg function should be in the format of xpsd=burg (xn, p,NFFT), similar to the calling of L-D recursive algorithm, and the program code is as below.

```
Mid=sum(xn)/length(xn);
xn=xn-mid;
N=length(xn);
fs=1000; NFFT=1024;
xpsd=pburg(xn,minp,NFFT);
pmax=max(xpsd); xpsd=xpsd/pmax;
xpsd=10*log10(xpsd+0.000001)-0.5;
k=0:1:(NFFT/2-1);
f=fs*k/NFFT;
figure(2);
plot(f,xpsd(1:NFFT/2)); grid on;xlabel('f/Hz'); ylabel('PSD/dB');
```

3. Design of GUI and Program

The design of the graphic user interface (GUI) includes the arrangement of components, the compiling of properties and the compiling of the callback function. In MATLAB, typing command ‘guide’ can create an initial GUI page. With the appearance editing function of GUIDE, necessary controls can be drew to the interface with properties configured. A single click of the ‘Run’ button in the toolbar of GUIDE will activate the graphic user interface.

3.1. Signal Selection Function

The realization of signal selection function is described with signal source 4-256Hz (as presented in Figure 4) as an example.

7936	6830	6891	7490	7759	8022	6854	6893	7398	7748	8128	7021	6804	7307	7717	8059
7024	6754	7177	7661	8143	7305	6753	7220	7626	8076	7204	6807	7126	7804	8047	7585
6721	7117	7709	8077	7652	6696	6963	7679	8024	7784	6675	6941	7580	7723	7927	6767
6891	7492	7808	8021	6873	6929	7437	7730	8181	6981	6819	7329	7757	8065	7040	6863
7188	7612	8135	7240	6734	7204	7611	8099	7187	6816	7127	7811	8079	7489	6730	7157
7753	8076	7571	6707	6970	7656	8014	7770	6692	6972	7614	7835	7884	6745	6943	7569
7874	8011	6871	6832	7429	7713	8053	6922	6846	7350	7787	8050	7061	6848	7168	7598
8125	7172	6744	7144	7640	8120	7156	6802	7240	7762	8027	7479	6761	7188	7804	8053
7633	6728	7058	7708	8040	7741	6663	6950	7567	7941	7866	6754	6912	7560	7851	8037
6850	6873	7512	7736	8048	6898	6911	7381	7762	8079	7087	6853	7131	7636	8106	7104
6844	7105	7736	8168	7259	6793	7188	7716	8107	7281	6760	7149	7789	8028	7648	6732
7150	7774	8079	7806	6681	6947	7626	7909	7856	6760	7040	7556	7828	7961	6833	6880
7470	7765	8004	6837	6959	7377	7709	8123	7040	6841	7178	7632	8035	7027	6741	7109
7692	8068	7309	6780	7164	7687	8100	7244	6790	7122	7782	8111	7537	6737	7088	7746
8019	7730	6695	6973	7671	7980	7891	6756	7015	7567	7791	7982	6791	6901	7483	7779
8057	6863	6986	7375	7703	8104	6996	6809	7247	7684	8033	7037	6735	7172	7683	8117
7345	6748	7193	7619	8070	7210	6823	7150	7802	7968	7495	6727	7122	7780	8110	7668
6696	6989	7668	8012	7827	6718	6943	7554	7698	7890	6728	6887	7520	7792	8066	6891
6895	7397	7756	8121	7042	6825	7330	7729	8055	7003	6768	7261	7641	8141	7329	6756
7207	7661	8089	7217	6823	7147	7844	8068	7643	6770	7144	7738	8122	7612	6680	6941
7605	7956	7723	6636	6929	7566	7766	7895	6824	6926	7543	7871	8052	6910	6819	7479
7735	8098	6935	6817	7305	7748	8053	7042	6839	7313	7662	8174	7253	6788	7221	7642
8137	7190	6793	7115	7755	8059	7481	6751	7170	7762	8063	7593	6727	6987	7714	8049
7787	6680	6953	7622	7872	7875	6732	6951	7506	7792	8023	6836	6815	7408	7721	8049
6903	6966	7352	7789	8129	7064	6861	7151	7609	8088	7126	6744	7086	7677	8120	7214

Figure 4. Signal Source of 256Hz

In MATLAB, type ‘guide main.fig’ in Command Window and double click the ‘vibration signal sample selection’ module, the property compiler will appear. Set the value of ‘string’ as ‘vibration signal sample selection’ and ‘tag’ as ‘signalselect’, single click the ‘vibration signal sample selection’ module and choose the ‘callback’ button in ‘View callbacks’ of the pull down list, and type the following code:

```
[FileName,PathName] = uigetfile('*.txt');
datafile=fullfile(PathName,FileName);
```

```
xn=textread(datafile,'%f');
mid=sum(xn)/length(xn);
xn=xn-mid;plot(xn);
grid on;
\
```

Then, save the code and execute, signal source 4-256Hz is selected.

3.2. Parameter Display Function

The function of parameter display should be configured in the 'vibration signal sample selection' module. The main program for this function is as below.

```
N=length(xn);
if (N==400) fs=256;
end
if (N==128) fs=1600;
end
set(handles.N,'String',num2str(N));
set(handles.FS,'String',num2str(fs));
```

3.3. Single Selection of Mutual Exclusion

To detail the realization of this function, assume that during the algorithm selection of AR spectrum estimation, L-D recursive algorithm was chosen. Set the value of 'string' of periodogram method as 'perodogram method' and 'Tag' as 'PER', and set the values of 'Tag' of 'AR model (L-D)' and 'AR model (BURG) as 'ARLD' and 'ARBURG', respectively. Choose the module corresponding to 'AR model (L-D)' and click the 'callback' button in 'View callbacks' of the pull down list, and input the following code:

```
set(findobj('Tag','PER'),'value',0);
set(findobj('Tag','ARBURG'),'value',0);
```

Set the value of Object with 'Tag' of 'PER' as 0, and the value of Object with 'Tag' of 'ARBURG' as 0, then when the 'AR model (L-D)' control is selected for spectrum estimation, periodogram method and AR model (BURG) are chosen for exclusion.

3.4. Parameter Setup Function

The realization of parameter setup function is detailed here with the specification of order as an example. In the parameter setup of controls, single click on the SN (specified order) and the AICN (optimal order) modules, and click the 'callback' buttons in 'View callbacks' of the pull down lists, input the following two lines of code respectively.

```
set(findobj('Tag','AICN'),'value',0);
set(findobj('Tag','SN'),'value',0);
```

Then, save and execute, the parameter setup function is realized.

3.5. Power Spectrum Estimation Function

For the calculation of optimal order for signal source of 4-256Hz and L-D recursive algorithm as an example, execute the L-D recursive algorithm-based AR spectrum estimation, and the following program identifies the optimal order.


```
if get(findobj('Tag','ARLD'),'value')
if get(findobj('Tag','SN'),'value')
ARN=str2num(get(findobj('Tag','N1'),'string'));
end
if get(findobj('Tag','AICN'),'value')
P=N/2; AIC=zeros(1,length(P));
for p=1:P
[A,E]=aryule(xn,p); AIC(p)=N*log(E)+2*p;
end
for p=1:P
if (AIC(p)==min(AIC))  ARN=p; end
end
set(handles.N2,'String',num2str(ARN))
end
xpsd=pyulear(xn,ARN,NFFT);
pmax=max(xpsd); xpsd=xpsd/pmax;
xpsd=10*log10(xpsd+eps);
k=1:1:(NFFT/2-1);
f=fs*k/NFFT;
plot(f,xpsd(2:NFFT/2));xlabel('f/Hz');ylabel('PSD/dB');grid on;
end
```

After executing this program, the result as shown in Figure 5 is obtained.

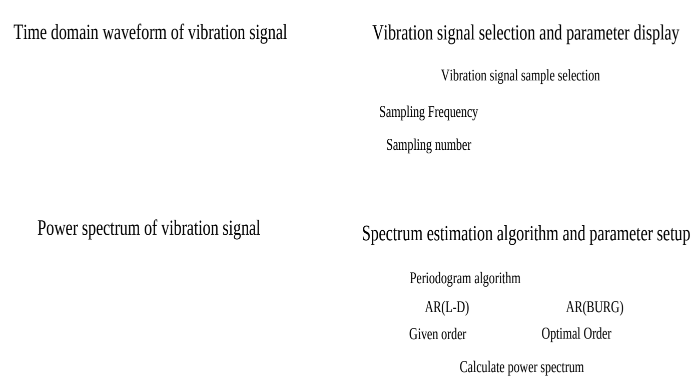

Figure 5. Power Spectrum Estimation Function

4. Performance Analysis of the Algorithm

4.1. Signal Collection

Through field measurement, vibration signals of an industrial turbine were collected. Electronic vortex sensor with ideal shaft rotating frequency of 50Hz was used. During the signal collection, for fixed-frequency sampling, the highest frequency was 256Hz, while for frequency multiplication sampling the highest sampling frequency was the 128 times of the rotating rate.

In this study, we investigated the variance performance and resolution of periodogram method and AR spectrum estimation algorithm, compared their performances with different parameter setup, chose the optimal algorithm and related parameters and applied them to the analysis of the measured signals. The signals were obtained through fixed-frequency sampling with frequency of 256Hz and 32 times-frequency multiplication sampling. The time domain waveform of the vibration signal collected with sampling frequency of 256Hz and sampling number of 400 is presented in Figure 6.

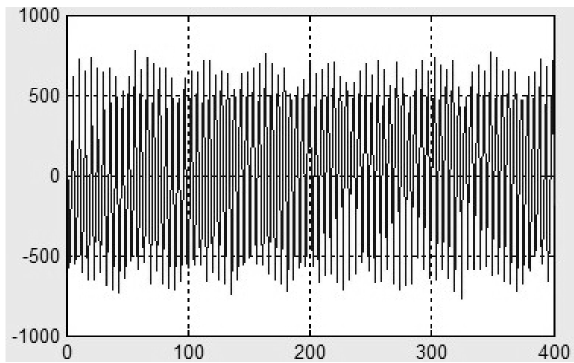

Figure 6. Time Domain Waveform of Measured Vibration Signal

The time domain waveform of the vibration signal collected by 32 times-frequency multiplication sampling with frequency of $f_s = 50 \times 32 = 1600Hz$ and sampling number of 128 is presented in Figure 7.

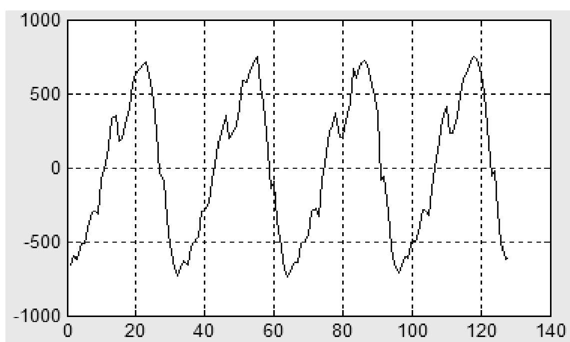

Figure 7. Time Domain Waveform of Measured Vibration Signal with Sampling Number of 128

With the waveforms in Figure 6 and 7, it is difficult to analyze the characteristics of the vibration signals accurately from the perspective of time domain and to discover and locate faults. Therefore, the aid from power spectrum analysis tools is needed.

4.2. Result and Analysis of Periodogram Estimation

With sampling number of 400 and sampling frequency of 256Hz, the simulation result of periodogram method is as shown in Figure 8.

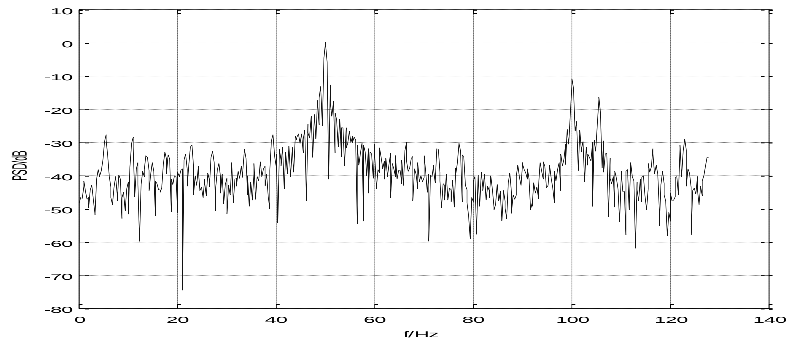

Figure 8. Estimation Result of Periodogram Method

It can be seen from the result that the spectrum obtained by periodogram method has good resolution and sharp peaks. However, the variance performance is poor, and the spectrum shows violent fluctuations, making it hard to ensure the accuracy of spectral analysis. In addition, the spectrum has poor tolerance to noises. Such contradiction between the variance and resolution makes the application of periodogram method in turbine vibration signal analysis limited. When it is impossible to collect and process longer vibration signal data because of the constraint of real-time performance and processing speed, such limitation is particularly obvious. In such case, the random sequence x(n) is treated as periodic extension of a section of finite sequence, thus causing spectral leakage and affecting the spectrum estimation performance. It seems that the smaller the sampling number, i.e. the shorter the windowing length, the more obvious the spectral leakage.

4.3. Results of L-D recursive algorithm- and Burg algorithm-based AR spectrum estimations

With sampling number of 400, sampling frequency of 256Hz, and optimal order of 52, the simulation result of L-D recursive algorithm-based AR spectrum estimation is as shown in Figure 9.

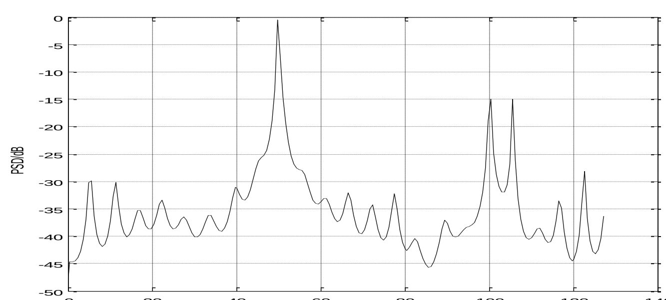

Figure 9. L-D Recursive Algorithm-Based AR Spectrum Estimation Result

It can be seen that the spectrum has good resolution, sharp peaks and accurate harmonic location. The fluctuation is not violent, indicating good variance performance, and the tolerance to noises is improved. The simulation shows that the L-D recursive algorithm-based AR spectrum estimation is suitable for vibration signals of steam turbines. The simulation result of Burg algorithm-based AR spectrum estimation is as shown in Figure 10.

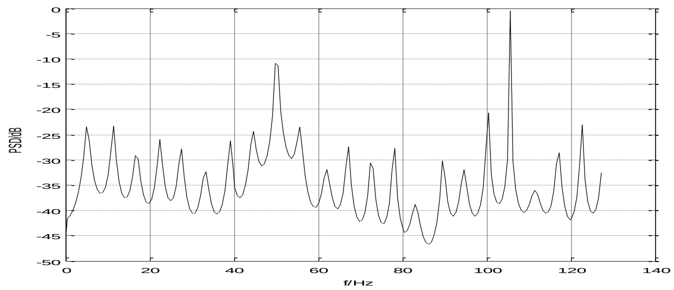

Figure 10. Burg Algorithm-Based AR Spectrum Estimation Result

It can be seen that the spectrum has good resolution and sharp peaks. The fluctuation is relatively violent, which means the variance performance is less satisfying, yet the harmonic components can be located from the noises. This simulation result demonstrates that Burg algorithm-based AR spectrum estimation is also suitable for vibration signals of steam turbines.

4.4. Comparison between Periodogram Method and AR Spectrum Estimation

Comparing Figure 8, 9 and 10, it can be found that AR model has comparable frequency resolution with periodogram method but much better variance performance. Through comparative analysis, we found that with proper selection of order, AR spectrum estimation algorithm can ensure both good resolution and variance performance, with much better estimation result. In the analysis of vibration signals of steam turbines, AR model can perform relatively accurate harmonic analysis even with short sampling data, overcoming the limitation of conventional algorithms.

4.5. Comparison between L-D recursive Algorithm and Burg Algorithm

It can be seen from Figure 9 and 10 that comparing with L-D recursive algorithm, Burg algorithm has better resolution, slightly displaced frequency and less satisfying variance performance [16]. Since when performing auto-correlation sequence estimation, L-D recursive algorithm assumes the data outside the range of 0~N-1 as 0, the estimated power spectrum are more smooth, with peaks less sharp than those estimated by Burg algorithm, and the displacement is greater. In practical application, L-D recursive algorithm-based AR spectrum estimation is more suitable for the estimations with higher requirement of variance performance, whereas Burg algorithm-based AR spectrum estimation is more suitable for estimations with higher requirement of resolution.

4.6. Influences of Order on AR Spectrum Estimation Result

With L-D recursive algorithm-based AR spectrum estimation, simulation analyses are performed to the signal in Figure 11, with given order of 10 and 80 and identified optimal order of 52. The estimated power spectra are presented in Figure 11, 12 and 13, respectively.

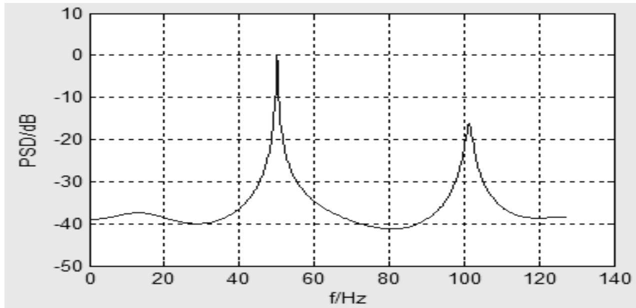

Figure 11. Power Spectrum Estimated with Order of 10

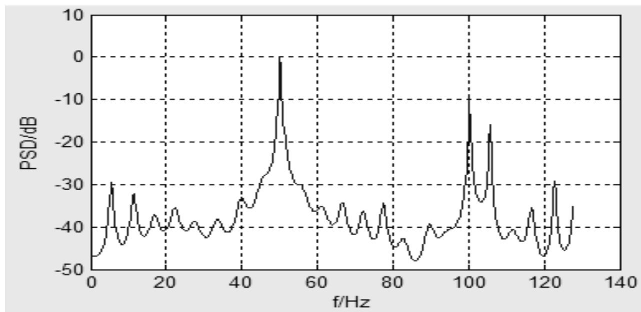

Figure 12. Power Spectrum Estimated with Optimal Order of 52

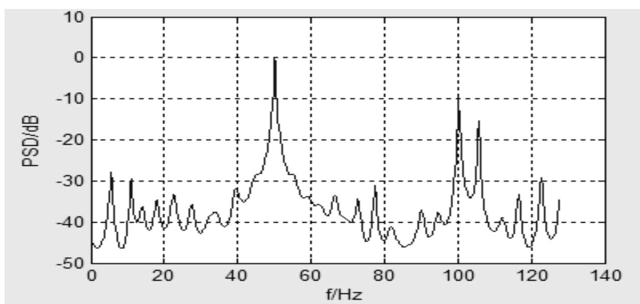

Figure 13. Power Spectrum Estimated with Order of 80

Comparing Figure 11, 12 and 13, the following findings were made. With overly low order p, the estimated spectrum is too smooth, which reduces the resolution and causes some harmonic components to be unidentifiable. With overly high order p, noise and other interference signals would be prominent in the spectrum as useful signals, creating false peaks and increasing the computational labor. With optimal order, the waveform is smoother, peaks sharper, and resolution and variance performance more balanced. For the processing and analysis of vibration signals, AR spectrum estimation algorithm shows good balance between resolution and variance performance.

5. Conclusions

Based on field measurements of vibration signals of an industrial steam turbine, comparative analysis was performed between AR spectrum estimation and conventional spectrum estimation algorithms. Through theoretical study, algorithm analysis and actual simulation, we came to the following conclusions. Conventional spectral estimation algorithm exhibits contradiction between resolution and variance performance. With smaller sampling number, the algorithm shows poor performance for vibration signals of turbines, thus it has some limitation in application. For the spectrum estimation of turbine vibration signals, conventional algorithms are unable to perform short data spectral analysis in practical application, whereas this limitation is o overcome by AR spectrum estimation algorithm. Satisfying harmonic analysis result can be obtained by AR model. In AR spectrum estimation, the order of the model greatly influences the estimation result for turbine vibration signals, thus it is an important parameter of the model. In the spectrum estimation of turbine vibration signals, AIC provides good theoretical basis for the identification of optimal order.

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