Time-Frequency Analysis Method for Railway Rolling-Element Bearing Fault Diagnosis

R10942062 盧志賢

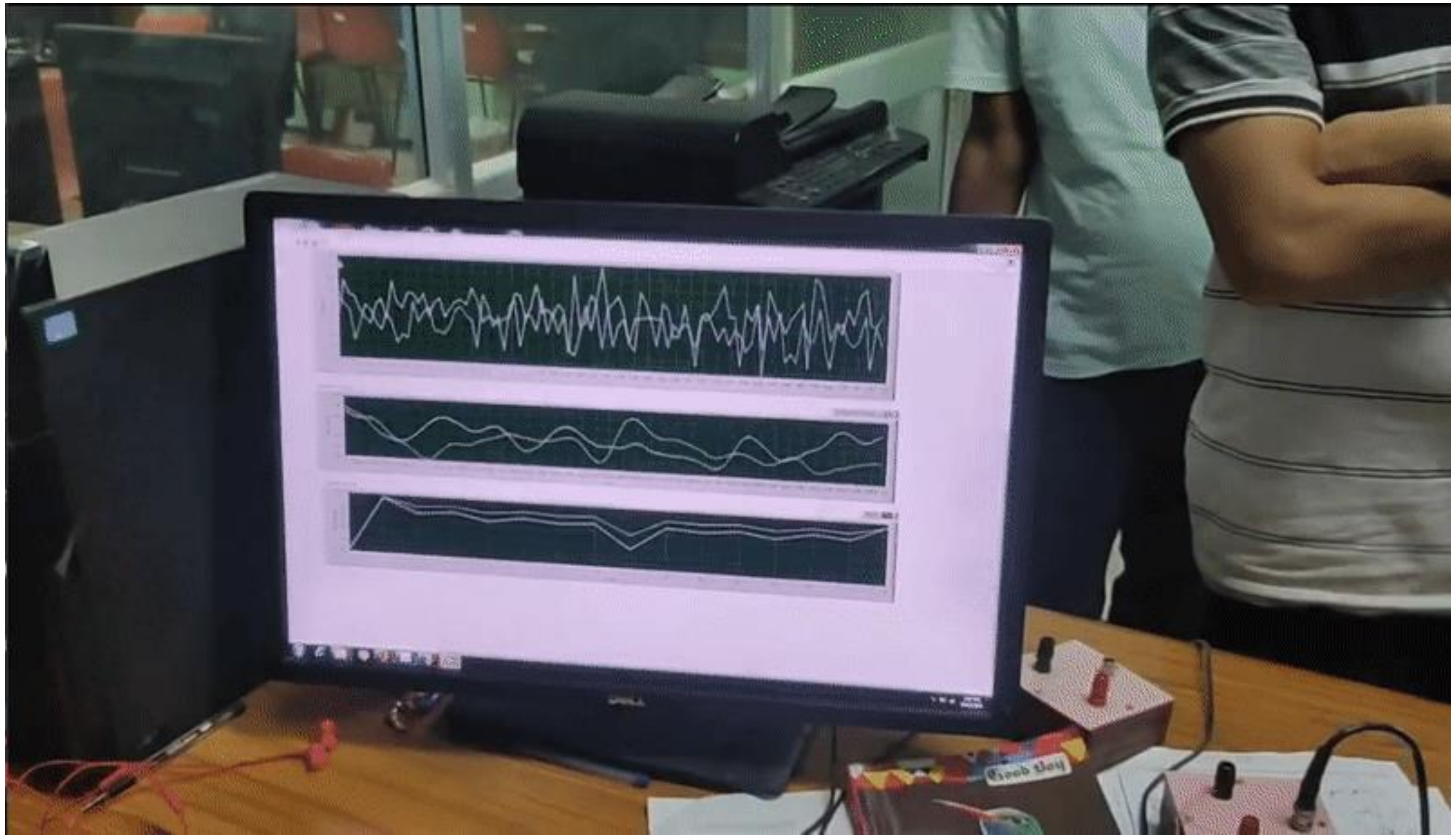
Outline

- Introduction
- Background Theories
  - LMD/ELMD
  - TKEO
- Combination
- Results
- References

Introduction

https://www.youtube.com/watch?v=tJNqpcsvlqI

Introduction



https://www.youtube.com/watch?v=usWgTUAv9Ng

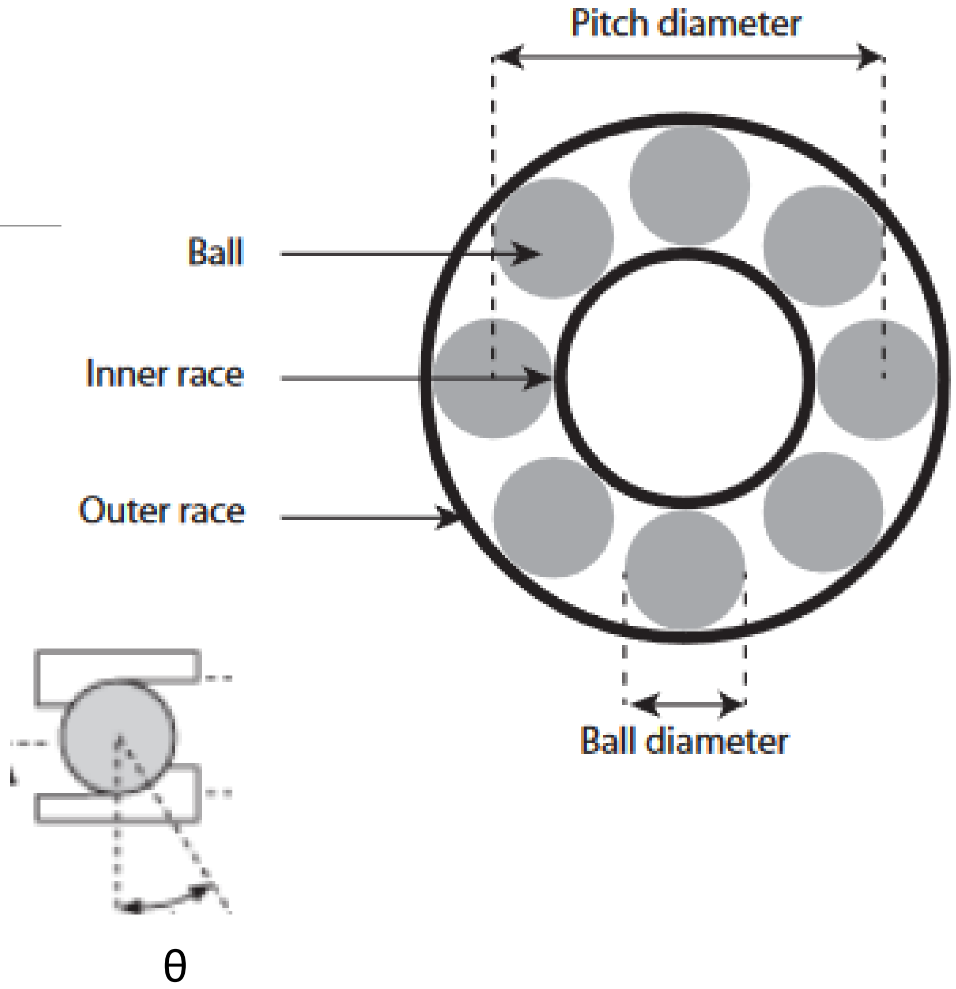
Introduction

$$BPFI = \frac{N_b}{2} f_r \left(1 + \frac{B}{P}\cos(\theta)\right)$$

$$BPFO = \frac{N_b}{2} f_r \left(1 - \frac{B}{P}\cos(\theta)\right)$$

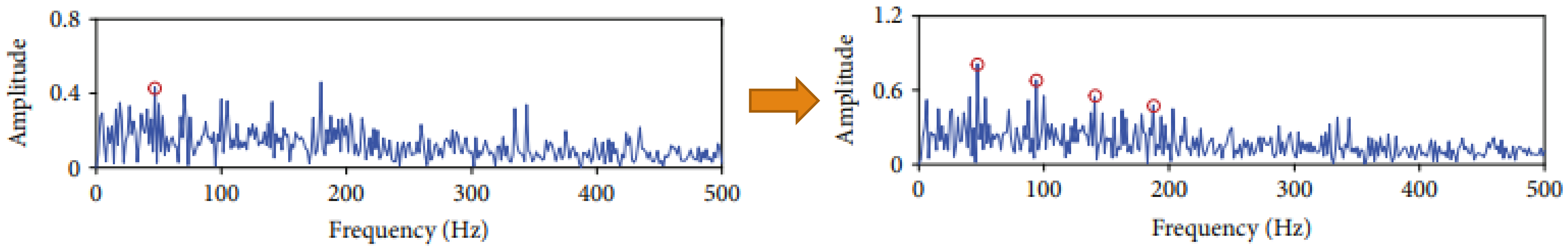
$$FTF = \frac{f_r}{2}(1 - \frac{B}{P}\cos(\theta))$$

$$BSF = \frac{P}{2B} f_r [1 - (\frac{B}{P}\cos(\theta))^2]$$



G. Gautier, R. Serra, and J.-M. Mencik, "Subspace-based damage identification of roller bearing," *Matec Web of Conferences*, vol. 20, 2015

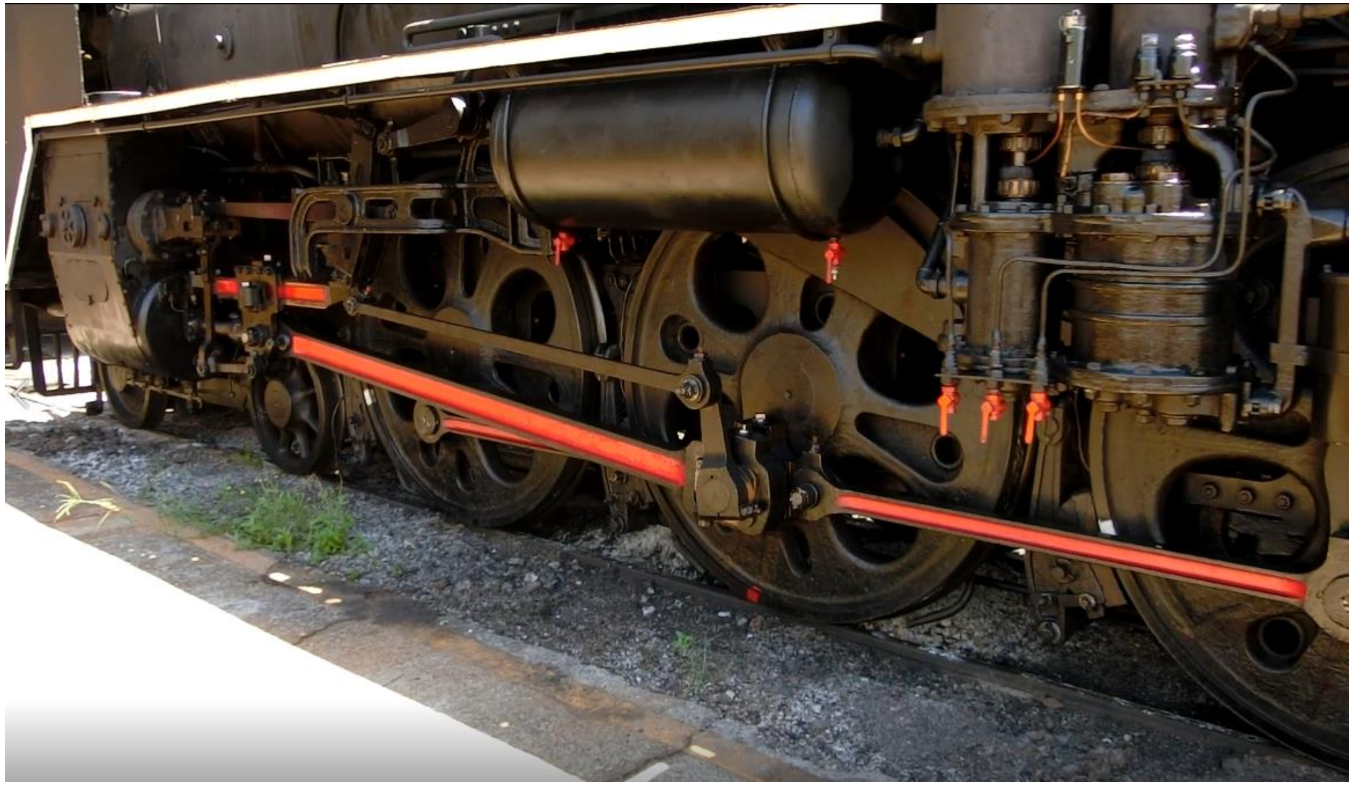
Introduction



Cheng, Y.; Zou, D.; Wang, Z. A Hybrid Time-Frequency Analysis Method for Railway Rolling-Element Bearing Fault Diagnosis. J. Sens. **2019**, *2019*, 8498496.

Background Theory

- LMD/ELMD
- TKEO

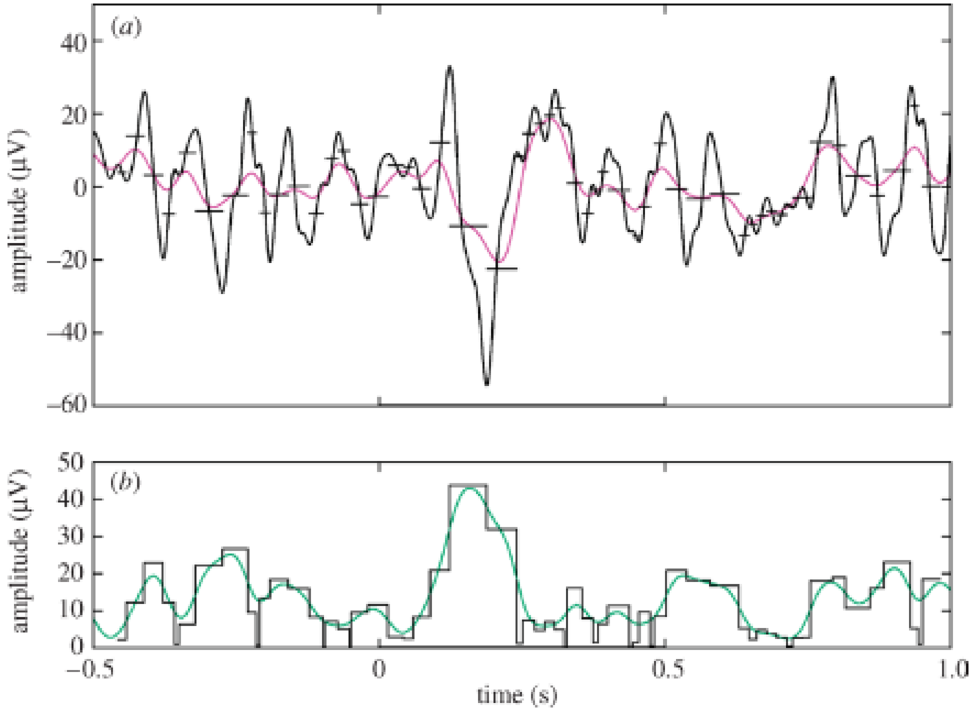


LMD (Local Mean Decomposition)

- Decompose a raw signal into a series of product functions (PF)
- Step 1.
  - Find the local extreme points n_i (i = 1, 2,..., M) of the target signal x(t)
  - Calculate the local mean value m_i and local envelope magnitude a_i
  - $m_i = \frac{n_i+n_{i+1}}{2}$
  - $a_i = \frac{|n_i-n_{i+1}|}{2}$

LMD

Step 2. Connect all m_i and a_i by using straight lines. Then obtain a varying continuous local mean function $m_{1,1}(t)$ and local amplitude function $a_{1,1}(t)$ via the moving average method.



J. Smith, "The local mean decomposition and its application to EEG perception data", *J. Roy. Soc. Interface*, vol. 22, no. 5, pp. 434-454, 2005.

LMD

- Step 3. $h_{1,1}(t) = x(t) - m_{1,1}(t)$

$$s_{1,1}(t) = \frac{h_{1,1}(t)}{a_{1,1}(t)}$$

- Step 4. Set $s_{1,1}(t)$ as the target signal and repeat steps (1-3) until $a_{1,n}(t) = 1$

$$\begin{cases} h_{1,1}(t) = x(t) - m_{1,1}(t), \\ h_{1,2}(t) = s_{1,1}(t) - m_{1,2}(t), \\ \qquad \ddots \\ h_{1,n}(t) = s_{1,(n-1)}(t) - m_{1,n}(t), \end{cases}$$

where

$$\begin{cases} s_{1,1}(t) = \dfrac{h_{1,1}(t)}{a_{1,1}(t)}, \\ s_{1,2}(t) = \dfrac{h_{1,2}(t)}{a_{1,2}(t)}, \\ \qquad \ddots \\ s_{1,n}(t) = \dfrac{h_{1,n}(t)}{a_{1,n}(t)}. \end{cases}$$

LMD

Step 5.

- The envelope signal $a_1(t) = \prod_{i=1}^{n} a_{1,i}(t)$
- The first PF is given as $PF_1(t) = a_1(t)s_{1,n}(t)$
- Corresponding instantaneous phase $\varphi_1(t) = cos^{-1}\left(s_{1,n}(t)\right)$
- Corresponding instantaneous frequency $f_1(t) = \frac{f_s d\varphi_1(t)}{2\pi dt}$

LMD

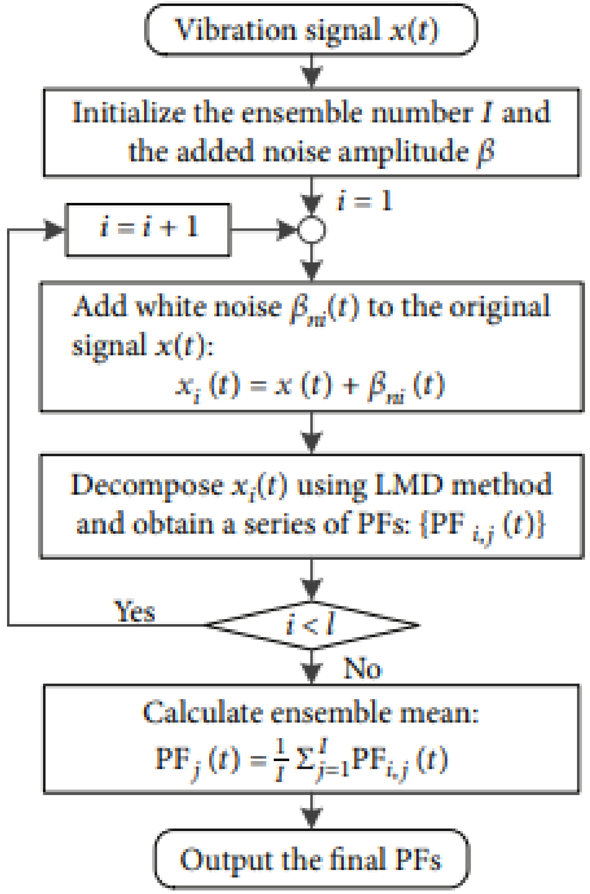
Step 6.

- $u_1(t) = x(t) - PF_1(t)$
- Set $u_1(t)$ as target signal and repeat the steps (1-5) until $u_J(t)$ contains no oscillations
- $$\begin{cases} u_1(t) = x(t) - PF_1(t) \\ u_2(t) = u_1(t) - PF_2(t) \\ \quad \ddots \\ u_J(t) = u_{J-1}(t) - PF_{J-1}(t) \end{cases}$$
- $x(t) = \sum_{j=1}^{J} PF_j(t) + u_J(t)$

ELMD (Ensemble LMD)

- Step 1. $x_i(t) = x(t) + \beta n_i(t), n_i(t): white\ noise$
- Step 2. Using LMD: $x_i(t) = \sum_{j=1}^{J} PF_{i,j}(t) + u_i(t)$
- Step 3. $PF_j(t) = \frac{1}{I}\sum_{i=1}^{I} PF_{i,j}(t)$

ELMD



Cheng, Y.; Zou, D.; Wang, Z. A Hybrid Time-Frequency Analysis Method for Railway Rolling-Element Bearing Fault Diagnosis. J. Sens. **2019**, *2019*, 8498496.

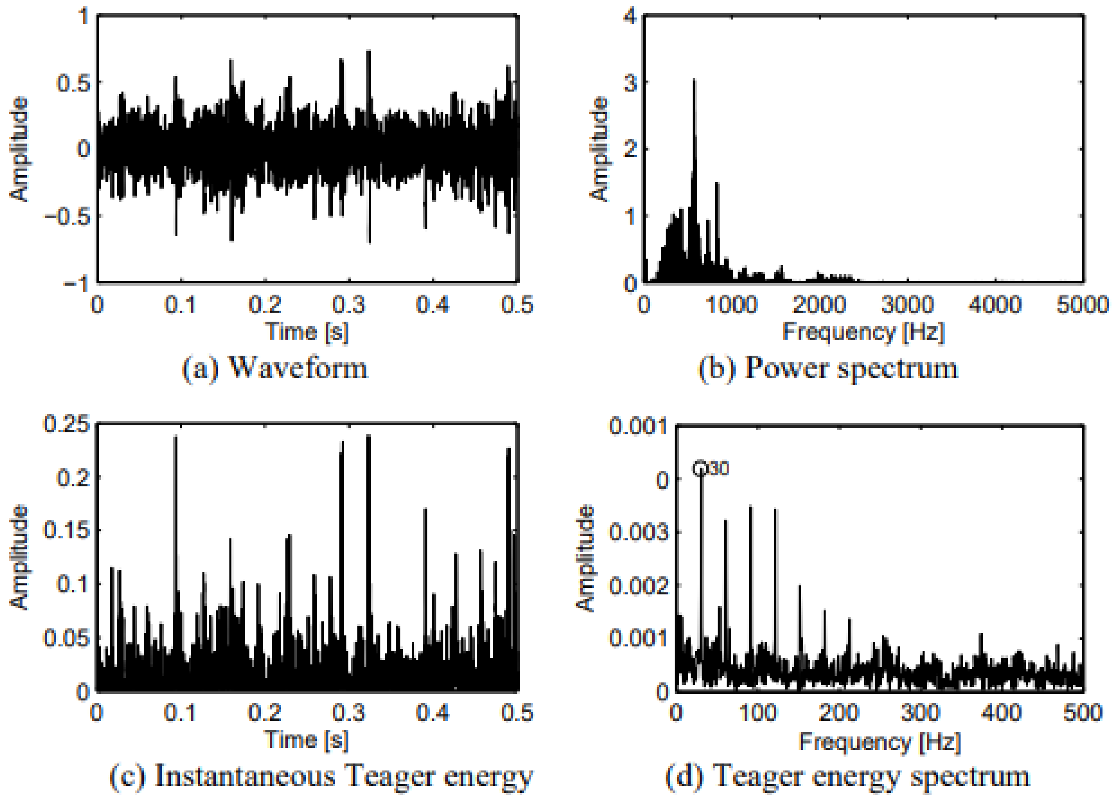
TKEO (Teager-Kaiser Energy Operator)

- continuous form: $\Psi[x(t)] = (\frac{dx(t)}{dt})^2 - x(t)\frac{d^2x(t)}{dt^2}$
- discrete form: $\Psi[x(n)] = [x(n)]^2 - x(n+1)x(n-1)$

TKEO

- Consider an undumped linear mass-spring oscillator with mass m and spring stiffness k
- Motion of the mass: $m\ddot{x}(t) + kx(t) = 0$
- Solution: $x(t) = Acos(\omega t + \theta), \omega = (k/m)^{1/2}, \theta: arbitrary\ initial\ phase$
- $\dot{x}(t) = -A\omega \sin(\omega t + \theta), \ddot{x}(t) = -A\omega^2 \cos(\omega t + \theta)$
- Total mechanical energy $E = \frac{1}{2}k[x(t)]^2 + \frac{1}{2}m[\dot{x}(t)]^2 = \frac{1}{2}mA^2\omega^2$
- $\Psi[x(t)] = (\frac{dx(t)}{dt})^2 - x(t)\frac{d^2x(t)}{dt^2} = A^2\omega^2$

TKEO

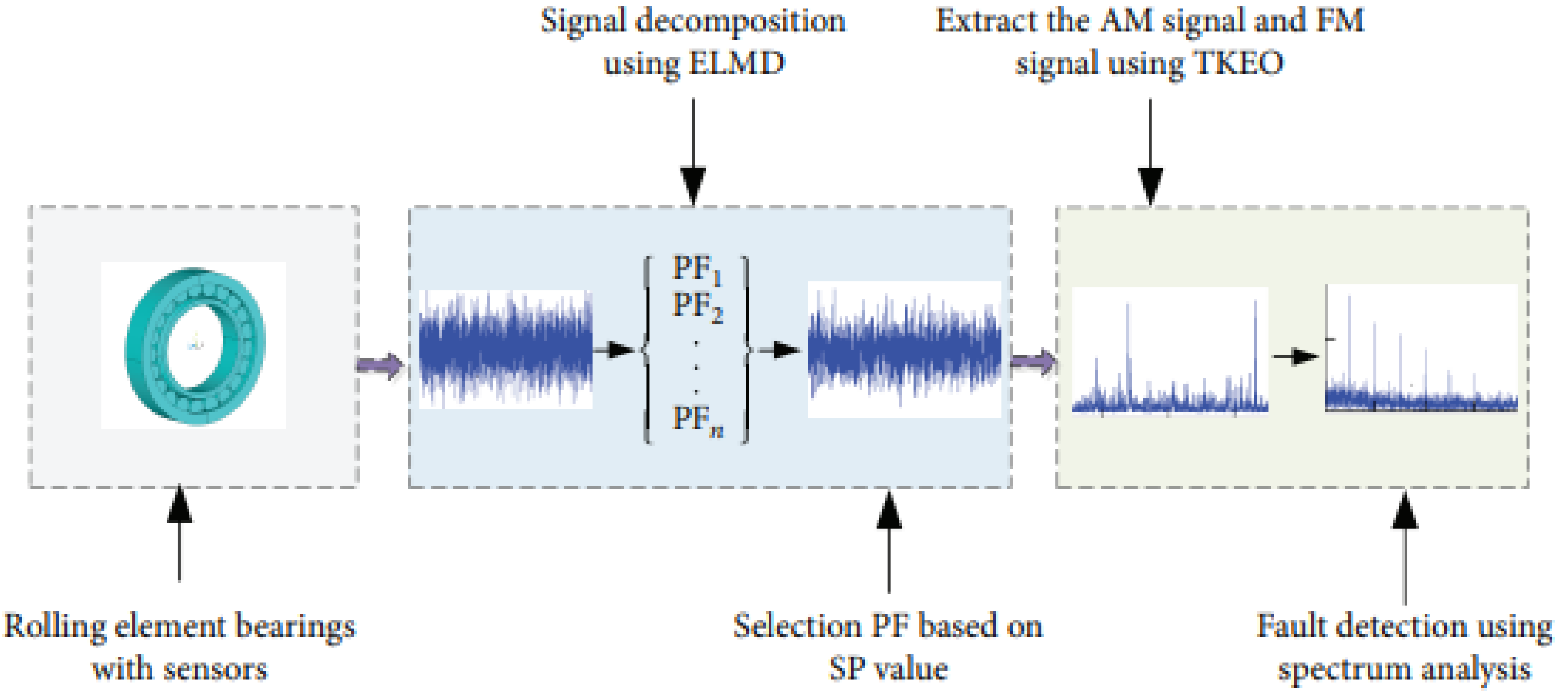


Feng, Z.P.; Wang, T.J.; Zuo, M.J.; Chu, F.L.; Yan, S.Z. Teager Energy Spectrum for Fault Diagnosis of Rolling Element Bearings. *J. Phys.: Confer. Ser*. **2011**, 305, 012129:1-012129:7.

Combination

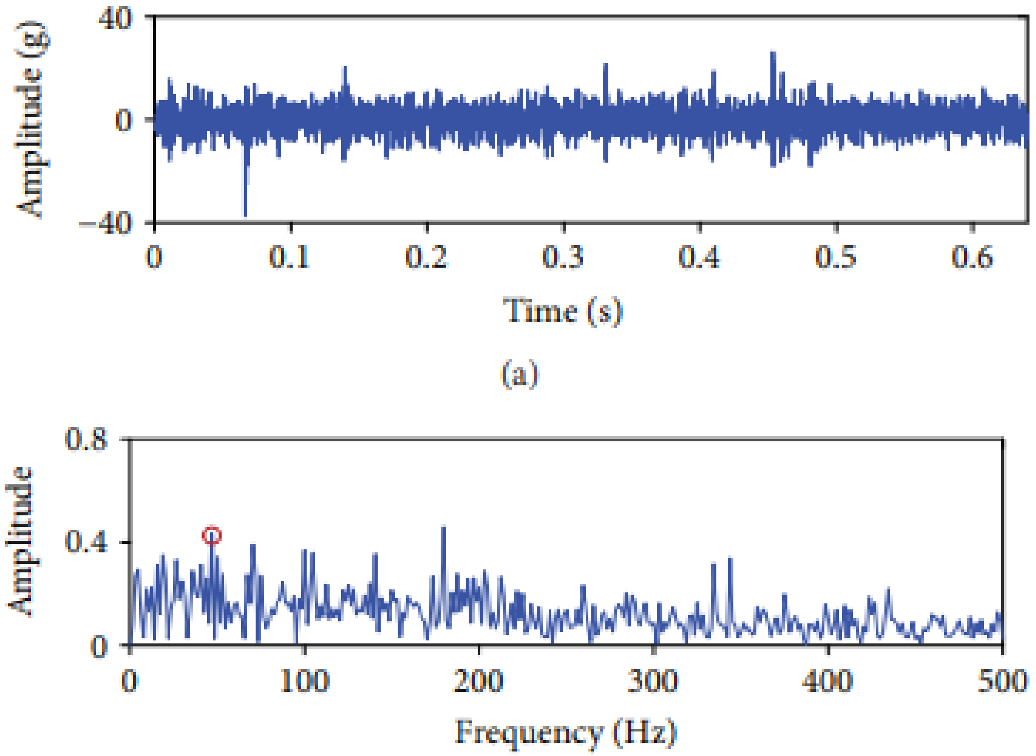
- ELMD => Select PF =>>=> TKEO
- First-shift Correlated kurtosis $CK_j = \frac{\sum_{n=1}^{N}(PF_j(n)PF_j(n-T))^2}{(\sum_{n=1}^{N} PF_j^2(n))^2}$
- $T = \frac{F_s}{f_m}, F_s: sampling\ frequency, f_m: fault\ frequency$
- Pearson’s correlation coefficient $PCC_j = \frac{\left(x(n)-\bar{x}(n)\right)^T (PF_j-\overline{PF}_j)}{\left|\left|x(n)-\bar{x}(n)\right|\right| \cdot \left|\left|PF_j-\overline{PF}_j\right|\right|}$
- Sensitive Parameter $SP_j = PCC_j \cdot f_j, where\ f_j = \frac{CK_j-\min(CK)}{\max(CK)-\min(CK)}$

Results



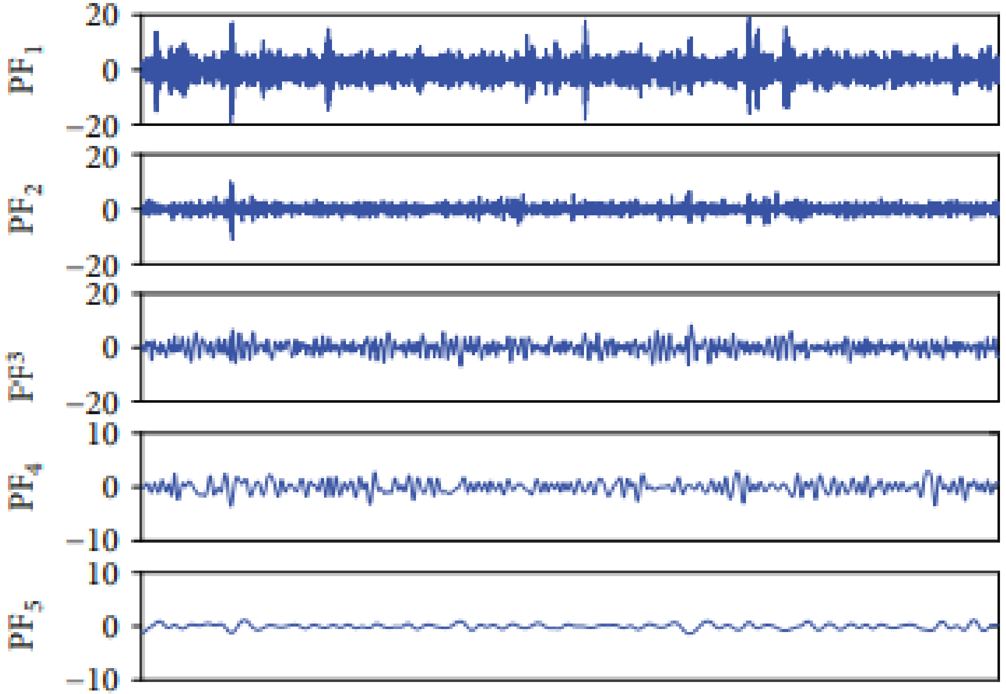
Cheng, Y.; Zou, D.; Wang, Z. A Hybrid Time-Frequency Analysis Method for Railway Rolling-Element Bearing Fault Diagnosis. J. Sens. **2019**, *2019*, 8498496.

Results [1]



Cheng, Y.; Zou, D.; Wang, Z. A Hybrid Time-Frequency Analysis Method for Railway Rolling-Element Bearing Fault Diagnosis. J. Sens. **2019**, *2019*, 8498496.

Results [1]



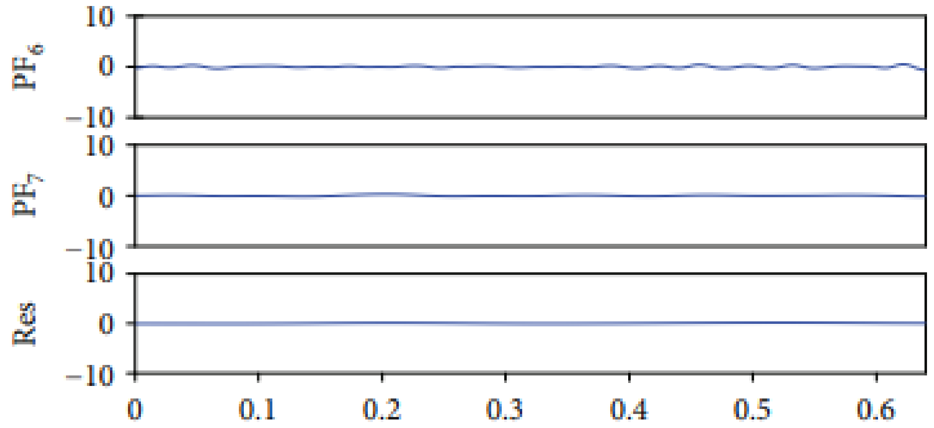
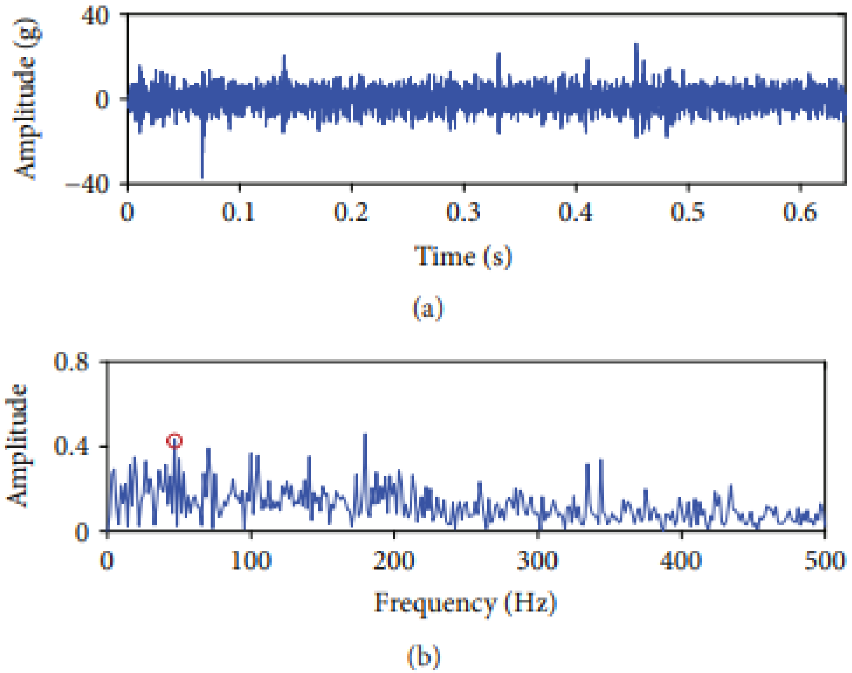


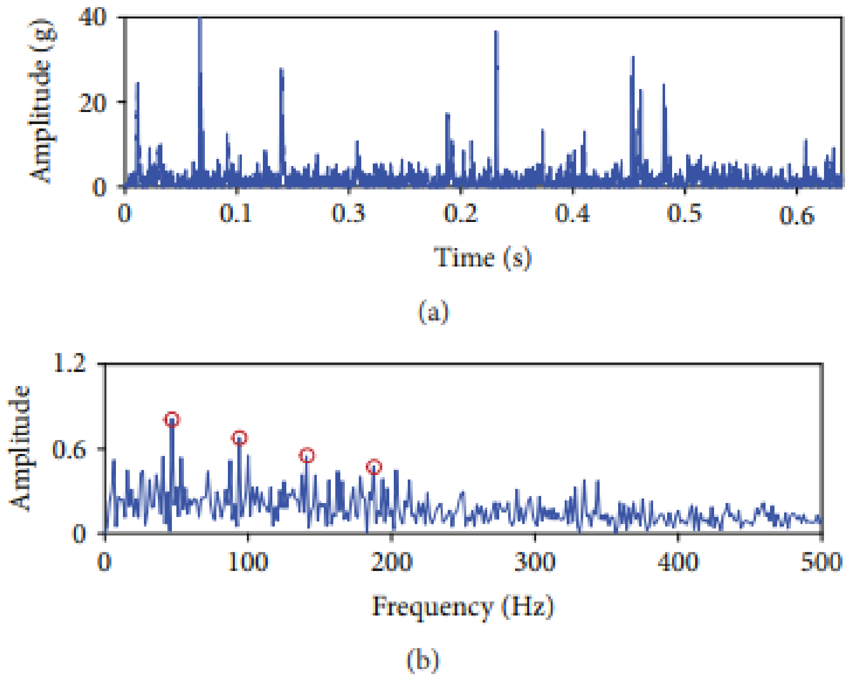
TABLE 1: SP values of the first six PFs obtained using ELMD.

Mode	PF_1	PF_2	PF_3	PF_4	PF_5	PF_6
SP	0.4182	0.1152	0.1289	0.0764	0	0.0185

Cheng, Y.; Zou, D.; Wang, Z. A Hybrid Time-Frequency Analysis Method for Railway Rolling-Element Bearing Fault Diagnosis. J. Sens. **2019**, *2019*, 8498496.

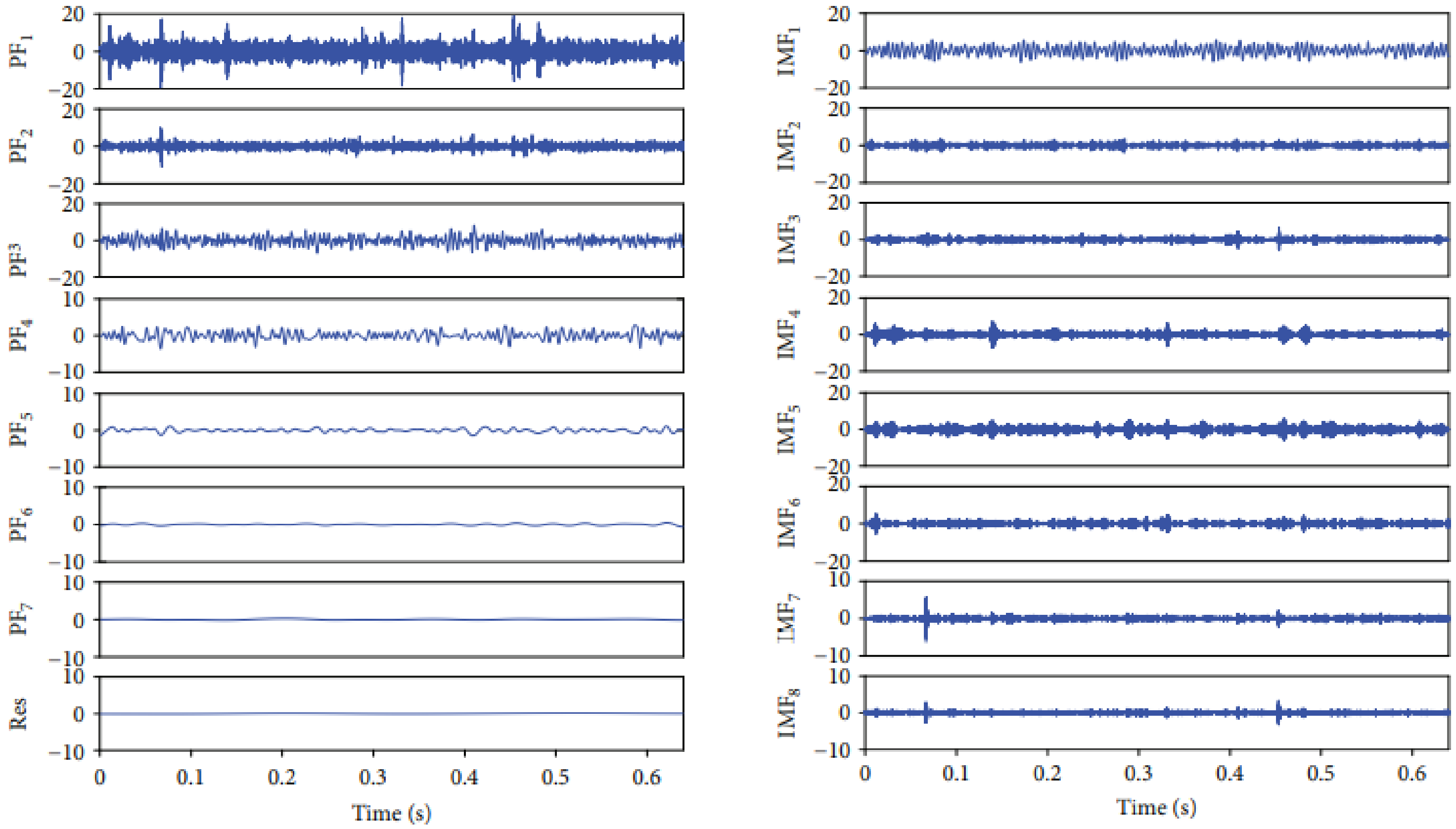
Results [1]





Cheng, Y.; Zou, D.; Wang, Z. A Hybrid Time-Frequency Analysis Method for Railway Rolling-Element Bearing Fault Diagnosis. J. Sens. **2019**, *2019*, 8498496.

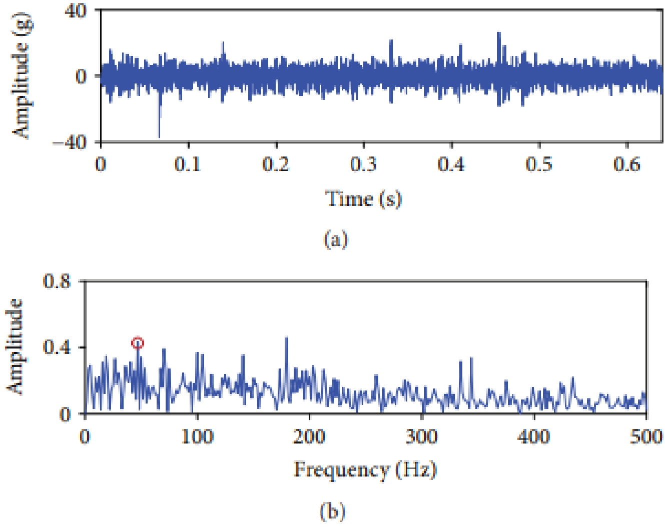
Results [1]



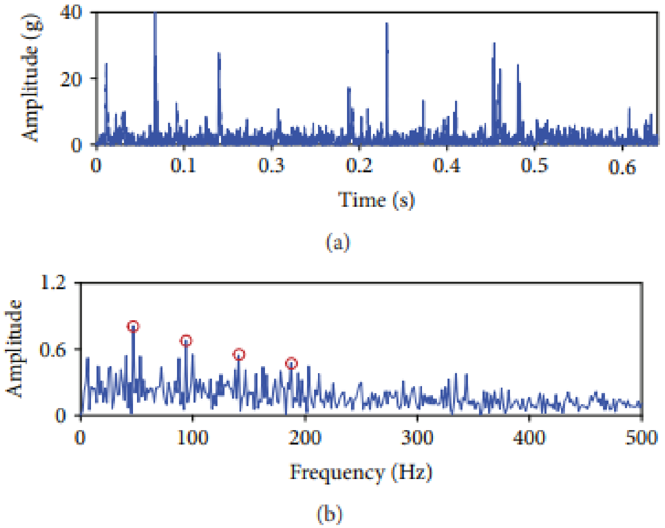
Cheng, Y.; Zou, D.; Wang, Z. A Hybrid Time-Frequency Analysis Method for Railway Rolling-Element Bearing Fault Diagnosis. J. Sens. **2019**, *2019*, 8498496.

Results [1]

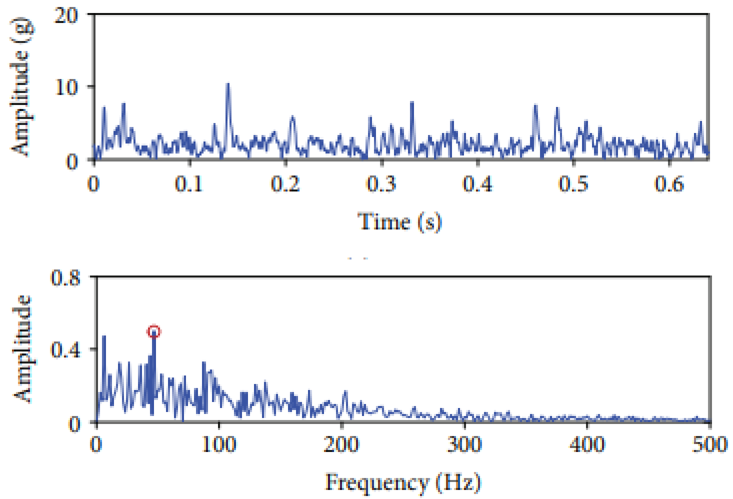
origin



ELMD

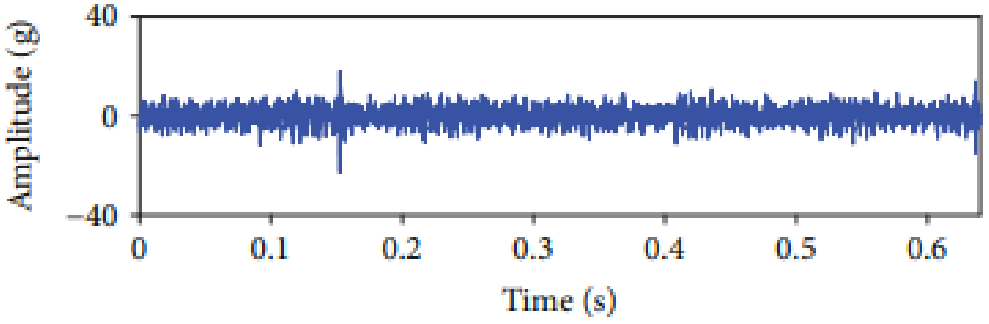


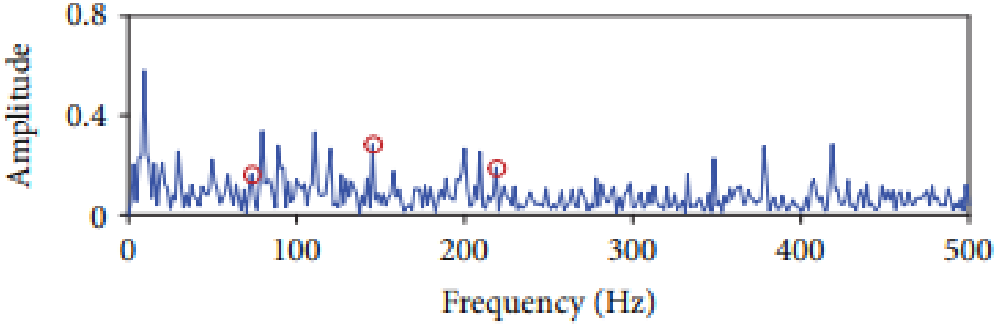
IMF



Cheng, Y.; Zou, D.; Wang, Z. A Hybrid Time-Frequency Analysis Method for Railway Rolling-Element Bearing Fault Diagnosis. J. Sens. **2019**, *2019*, 8498496.

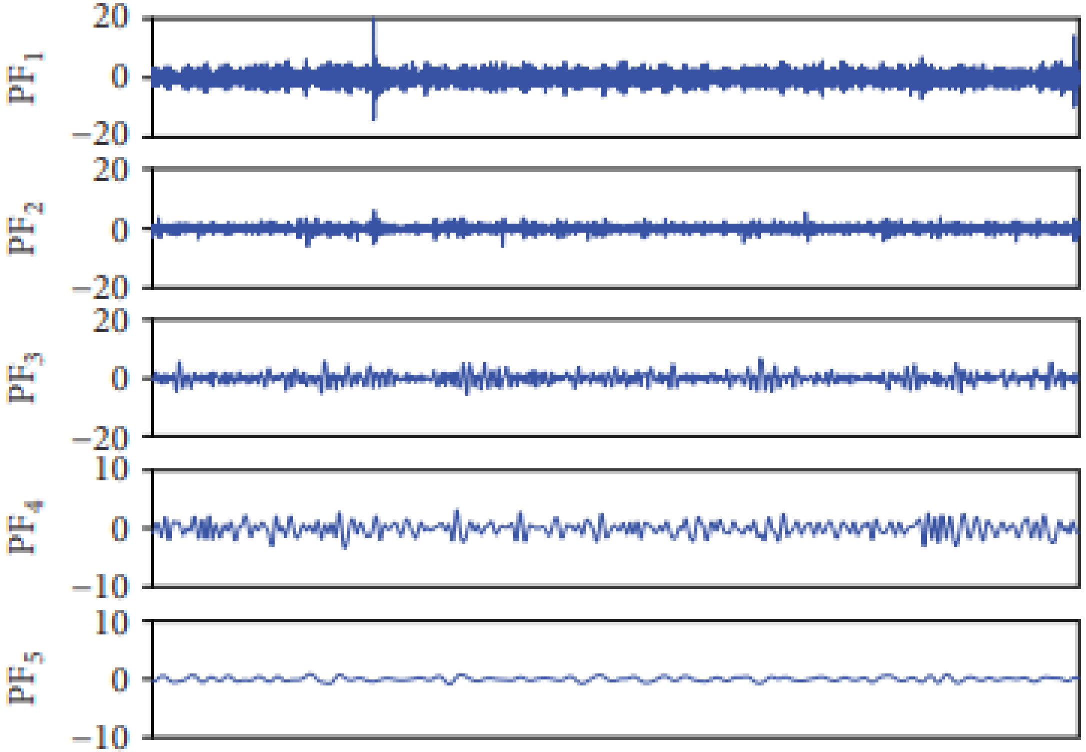
Results [2]

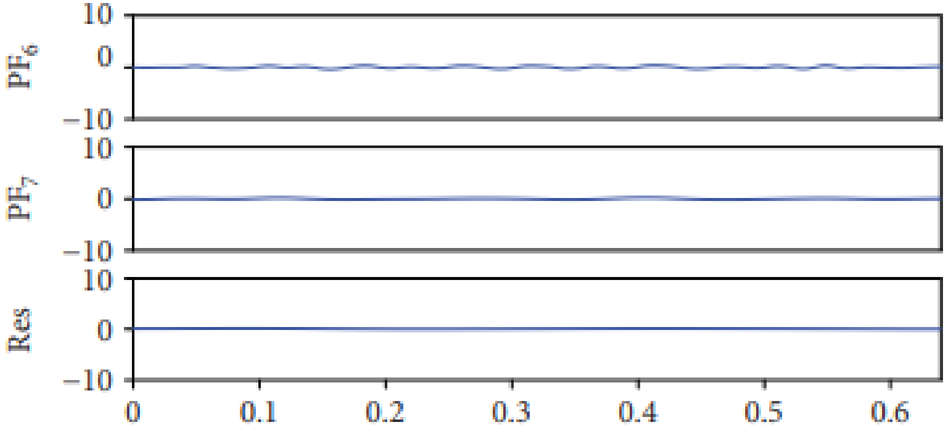




Cheng, Y.; Zou, D.; Wang, Z. A Hybrid Time-Frequency Analysis Method for Railway Rolling-Element Bearing Fault Diagnosis. J. Sens. **2019**, *2019*, 8498496.

Results [2]

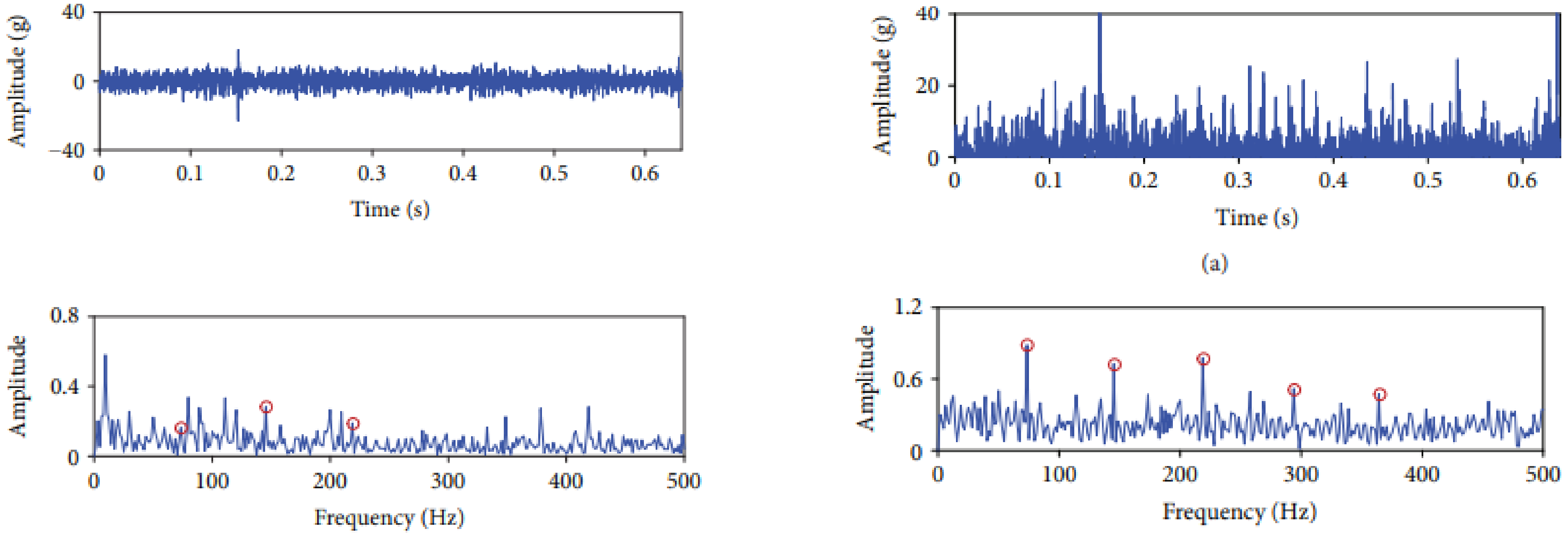




Mode	PF_1	PF_2	PF_3	PF_4	PF_5	PF_6
SP	0.4403	0.1914	0.0538	0.1725	0.0873	0

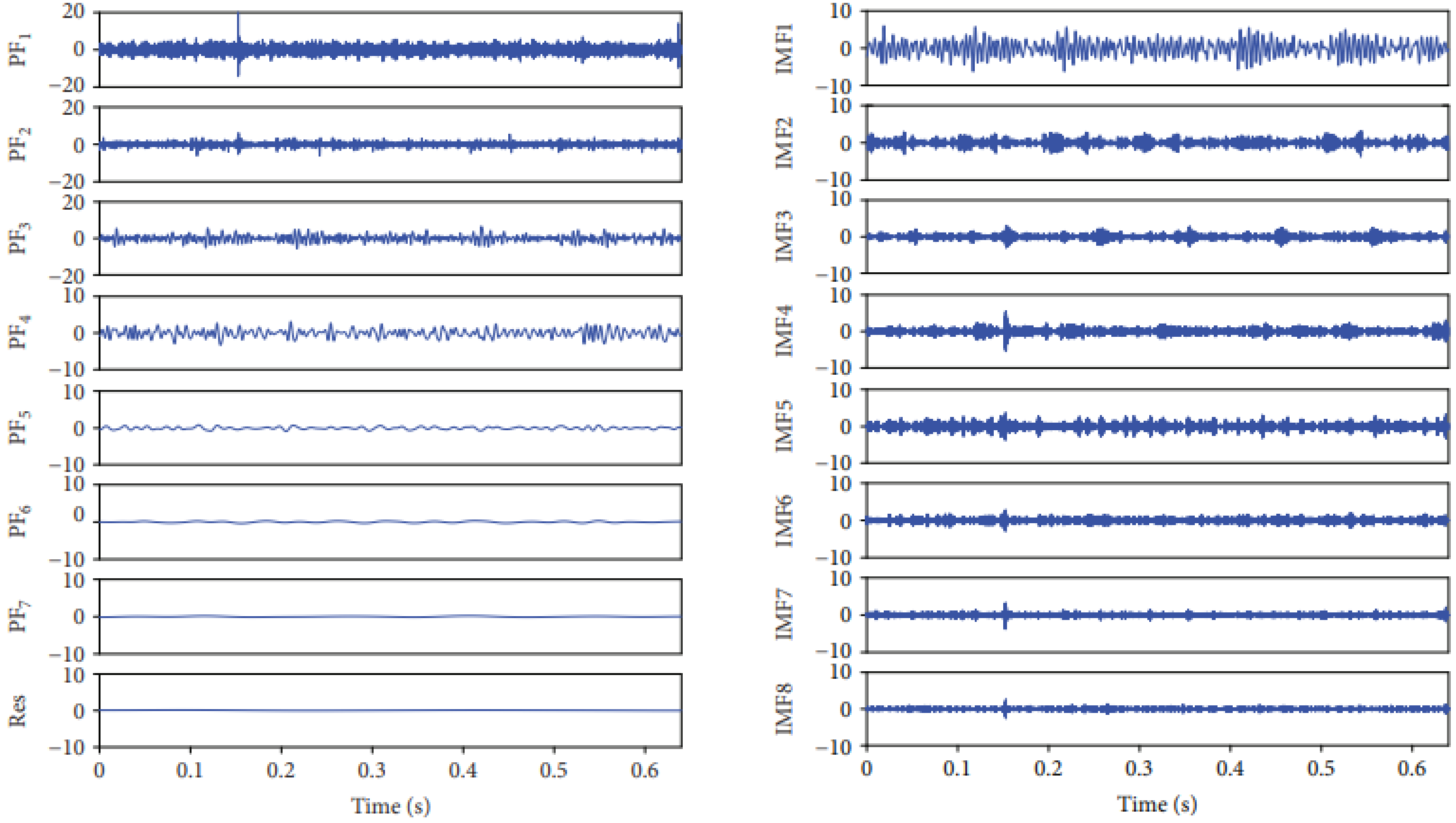
Cheng, Y.; Zou, D.; Wang, Z. A Hybrid Time-Frequency Analysis Method for Railway Rolling-Element Bearing Fault Diagnosis. J. Sens. **2019**, *2019*, 8498496.

Results [2]



Cheng, Y.; Zou, D.; Wang, Z. A Hybrid Time-Frequency Analysis Method for Railway Rolling-Element Bearing Fault Diagnosis. J. Sens. **2019**, *2019*, 8498496.

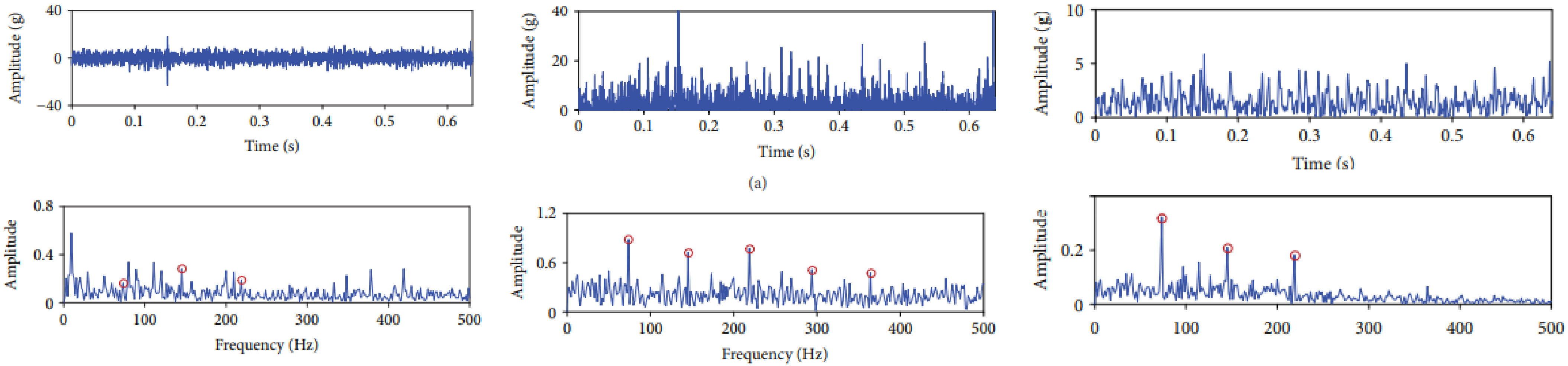
Results [2]



Cheng, Y.; Zou, D.; Wang, Z. A Hybrid Time-Frequency Analysis Method for Railway Rolling-Element Bearing Fault Diagnosis. J. Sens. **2019**, *2019*, 8498496.

Results [2]

origin ELMD IMF



Cheng, Y.; Zou, D.; Wang, Z. A Hybrid Time-Frequency Analysis Method for Railway Rolling-Element Bearing Fault Diagnosis. J. Sens. **2019**, *2019*, 8498496.

References

- Cheng, Y.; Zou, D.; Wang, Z. A Hybrid Time-Frequency Analysis Method for Railway Rolling-Element Bearing Fault Diagnosis. J. Sens. **2019**, *2019*, 8498496.
- Feng, Z.P.; Wang, T.J.; Zuo, M.J.; Chu, F.L.; Yan, S.Z. Teager Energy Spectrum for Fault Diagnosis of Rolling Element Bearings. *J. Phys.: Confer. Ser*. **2011**, 305, 012129:1-012129:7.
- J. Smith, “The local mean decomposition and its application to EEG perception data”, *J. Roy. Soc. Interface*, vol. 22, no. 5, pp. 434-454, 2005.
- G. Gautier, R. Serra, and J.-M. Mencik, “Subspace-based damage identification of roller bearing,” *Matec Web of Conferences*, vol. 20, 2015
- https://www.youtube.com/watch?v=usWgTUAv9Ng
- https://www.youtube.com/watch?v=tJNqpcsvlqI