Crank Identification of the Rotary Kiln Based on WTD-EEMD Using Vibration Monitoring of the Supporting Rollers

Kai Zheng, Member, IAENG, Yun Zhang, Hong Xiao, Jiufei Luo, Zuqiang Su and Zhiyong Ye

***Abstract*—It is impending to identify the kiln crank as it greatly influences the safety operation of the rotary kiln. In this paper, a novel strategy based on WTD-EEMD method to extract the effective information of the cyclic loading caused by the kiln crank in the vibration signals of the supporting rollers was proposed. Firstly, the vibration model of the supporting rollers was established on the basis of the operation principle of the rotary kiln and the characteristic frequencies of the cyclic loading were obtained. Secondly, the WTD-EEMD method is employed to denoise the vibration signals and the sensitive Intrinsic Mode Functions (IMFs) components contain the rich cyclic loading information were selected. Finally, the new signals were constructed by the selected sensitive IMF components, and the degree of the kiln crank in the supporting stations was evaluated by the energy of the constructed signal. The proposed method is verified with the designed measurement system in the industry field. The experiment results indicated that the proposed method is effective to identify the crank of the rotary kiln.**

***Index Terms*— Kiln crank identification, Cyclic loading, Numerical analysis, WTD-EEMD, Sensitive IMF components**

I. INTRODUCTION

Rotary kiln is large slow-speed mechanical equipment, which is mainly composed by transmission system, kiln cylinder, supporting rollers and tyres, as shown in Fig. 1.

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Kai Zheng is with the School of Advanced Manufacturing Engineering, Chongqing University of Posts and Telecommunication Technology, Chongqing, China. Phone: +008615872410576; e-mail:zhengkai2001@163.com.

Yun Zhang is with the School of Mechanical and Electronic Engineering, Wuhan University of Technology, Wuhan, China (corresponding author to provide phone: +008613871445062; e-mail: whkasco@aliyun.com).

Hong Xiao, Jiufei Luo and Zuqiang Su are with the School of Advanced Manufacturing Engineering, Chongqing University of Posts and Telecommunication Technology, Chongqing.

Zhiyong Ye are with the School of Mechanical and Electronic Engineering, Wuhan University of Technology, Wuhan.

It is key equipment in the cement and metallurgical industry. During the long-time operation, with the factors such as the aging of the rotary kiln cylinder, uneven temperature distribution on the shell, the profile of the cross sections of the kiln cylinder deformed seriously. This kind of phenomenon was called kiln crank [1]. In the supporting stations, the kiln crank will produce the cyclic loading [2]. When such loadings transmitted to the tyre and the supporting rollers, it leaded to the problems such as the fatigue failure in the contacting surface of the supporting rollers, overheating of the plain bearing and overload of the driven system [2]-[4]. In severe cases, it even ruptures the rotary kiln cylinder. Therefore, it is significant important to monitor the kiln crank in the supporting stations.

Currently, there were two methods to monitor the kiln crank: (1) The geometric method to monitor the deformation of the kiln cylinder [1]. With this method, the kiln cylinder was divided into several cross sections. Laser measurement system was used to measure the geometric deformation of each section. Finally, the eccentricity of each cross section was calculated. And the kiln crank could be monitored. This method is applicable to periodic detection. However, rotary kiln is typical low-speed rotating machinery equipment and the kiln crank is a process of slow aging. It is impossible to monitor the instantaneous and cumulative effects of kiln crank in real time to the supporting rollers using this periodic detection method. (2) The method for monitoring the vibration of the supporting rollers [4]. With this method, the vibrations of the supporting rollers were monitored to reflect the kiln crank at the supporting stations. This method is applicable for long-term and real-time monitoring of the kiln crank. As that the kiln crank at the supporting stations would produce cyclic load and it could be transmitted to the supporting rollers. Therefore, the kiln crank could be estimated by extracting the feature information of the cyclic loading in the vibration signals of the supporting rollers, thereby providing a basis for the crank identification of the rotary kiln.

One important problem needs to be solved was analysis the kiln crank effect to the supporting rollers when using the vibration-based monitoring method. In [1], researchers proposed that when doing rotary movements, the shell of the kiln cylinder will deform caused by the kiln crank, which will lead to the load between the tyres and supporting rollers change periodically. In [4], authors presented that when there is kiln crank, there would be deflection of the supporting roller shaft. Therefore, the loading of the supporting rollers and the kiln crank can be evaluated by the displacement of the supporting rollers. In [2], authors proposed that when the kiln cranks happens, the tyre will pushes the rollers outwards. If expansion occurs too fast, the plain bearing may fail to compensate for the movement of the roller axis in the stable housing bushing, which will lead to the overheating of the bearing. Further more, the kiln crank will produce cyclic load and vibrate the supporting rollers. However, the above analysis did not calculate the time-frequency characteristics of the supporting roller's vibration response under the kiln crank. And it was difficult for us to extract the effective feature information of cyclic loading in the vibration signals.

Another problem need to be solved is choosing the appropriate signal processing method to extract the feature of the cyclic loading from the vibration signals. The vibration signals of the supporting rollers collected by the monitoring system are interfered by noise and other vibration signals. These disturbed components and noises may drown the weak effective feature information in the vibration signals, leading to the difficulty to estimate the degree of the kiln crank in the supporting stations. The traditional feature extraction and signal filtering method was based on the Fast Fourier transform, which require a linear, stationary or smooth signal. For example, in [2], researchers proposed the FFT method to process the vibration signals of the supporting rollers. However, the noise frequency components and the effective frequency components may overlap in the frequency spectrum. Also, FFT based method is not suitable for processing the nonlinear and non stationary signal. The wavelet transform (WT) [5] can be used to process the nonlinear no stationary signal and for signal de-noising, and it has been successfully applied to the fault diagnosis of the gearbox [6] and rotors [7], [8]. However, as for wavelet transform, it is difficult to select the suitable wavelet base. And the process results largely depended on the chosen of the wavelet base by using the WT method [9],[10]. Moreover, when using the WT method, the noise reduction effect remains poor for non-stationary signals [11]. As a typical adaptive signal decomposition method, empirical mode decomposition (EMD) method has been widely used in the feature extraction of the vibration signals [12]-[15]. However, one of the major drawbacks of EMD is the mode mixing problem, which is defined as either a single IMF consisting of components of widely disparate scales, or a component of a similar scale residing in different IMF components. As a result, the decomposed IMF components cannot reflect the true physical meanings of the information, thus affecting the effective feature extraction of the signals [16]-[18]. In order to overcome the above-mentioned drawbacks, an ensemble empirical mode decomposition (EEMD) method was proposed. In this method, the Gaussian White Noise was added in to supplement the missing frequency scale of the analyzed signals. By using the statistical properties of uniform distribution with frequency of the Gaussian White Noise, the EEMD method can eliminate the mode mixing problem automatically [17], [18]. However, as that the noises in the signals often influence the processing result, it is inadequate to extract the feature information using only one approach for the signals which include noise more or less. De-noising must be made before the feature extraction of the original signals [19].

For the above analysis, this paper presents a hybrid approach based on WTD-EEMD method for kiln crank identification. Firstly, a dynamical model of the supporting rollers was established, and the vibration response pattern under the kiln crank was analyzed. Secondly, the vibration signals of the supporting rollers were collected by the monitoring system. And the wavelet threshold denoising (WTD) method is taken as the pre-filter process. Afterwards, the de-noised signals were decomposed into a serial of IMFs components by the EEMD method. Based on the vibration characteristic of the supporting rollers under the kiln crank, the sensitive IMF components containing rich cyclic loading information are selected for feature extraction. Finally, the degree of the kiln crank can be evaluated by the energy of the signals reconstructed based on the sensitive IMF components.

The remainder of the paper is organized as follows: sections II analysis the kiln crank effect to the supporting rollers, and a vibration model for the supporting rollers was established. Section III gives a brief review to the WTD and EEMD method. A kiln crank identification method based on the WTD-EEMD method was proposed in Section IV. Section V gives the kiln crank identification results based on the proposed approach. Finally, Section VI makes several conclusions.

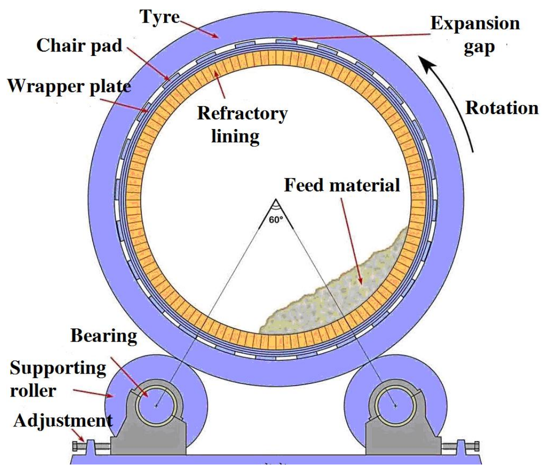


Fig.1. The physical map of the rotary kiln

II. THE KILN CRANK EFFECT TO THE SUPPORTING ROLLERS

The cyclic loading caused by the kiln crank gives rise to the vibration of the supporting rollers, as shown in Fig.2. The snowball effect in the rotary kiln's cylinder will further intensify the vibration of the supporting rollers [2]. To establish the vibration model of the supporting rollers, it is very important to describe the cyclic loading resulting by the kiln crank. The change of the kiln cylinder profile is the most important factor resulting in the cyclic loading, therefore, the eccentricity e can be used as a main parameter for assessing the cyclic loading. To establish the dynamic model of the supporting rollers, a simplified formula was put forward for the cyclic loading calculation. And it can be expressed as:

$$f = m\omega^2 e \tag{1}$$

Where m is the equivalent unbalance mass at the supporting station, ω is the rotational speed of the kiln cylinder and e is the eccentricity of the cross section.

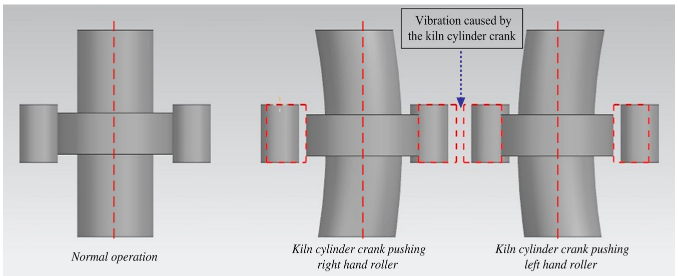


Fig. 2. The supporting rollers' vibration resulting from the kiln crank

A. Vibration model of the supporting rollers

To establish the vibration model of rotary kiln's rollers caused by the kiln crank, a simplified model was established, as shown in Fig. 3. The system contains a disk with mass unbalance and is supported by two plain bearings. The rotary kiln's supporting roller is a disc with a mass m and the supporting shaft is an isotropic shaft without mass; the left and right rollers at the same position of the rotary kiln bear the same load, and Oxy is the rotating coordinate system; O is the whirling center (rotation center) of the supporting roller and G is the center of mass of the supporting roller; ω is the rotating speed of the supporting roller and e is the eccentricity of the center section of the supporting roller.

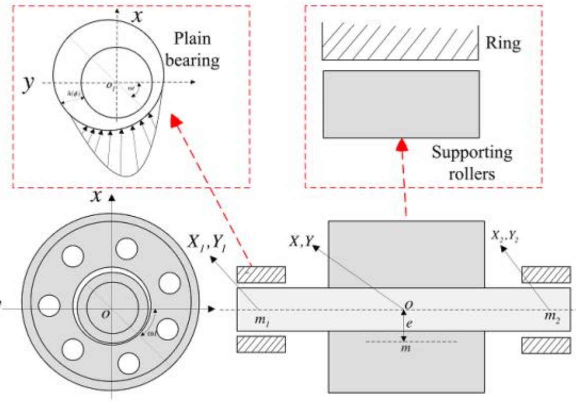


Fig.3 The model schematic of supporting rollers

The Lagrange approach is adopted to establish the vibration model of the supporting rollers. The generalized Lagrange equation is presented as follows:

$$\frac{d}{dt}\left(\frac{\partial T}{\partial \dot{x}}\right) - \frac{\partial T}{\partial x} + \frac{\partial U}{\partial x} + \frac{\partial D}{\partial x} = F_x(t) \tag{2}$$

$$\frac{d}{dt}\left(\frac{\partial T}{\partial \dot{y}}\right) - \frac{\partial T}{\partial y} + \frac{\partial U}{\partial y} + \frac{\partial D}{\partial y} = F_y(t) \tag{3}$$

Where T, U and D are the kinetic energy, potential energy and Rayleigh function of the system, respectively. $F_x(t)$ and $F_y(t)$ are the generalized force of the supporting rollers in the x and y direction. Where T, U, D, $F_x(t)$ and $F_y(t)$ can be expressed as follows:

$$\begin{aligned} T = {} & \frac{1}{2}m_2(\dot{x}_2^2 + \dot{y}_2^2) + \frac{1}{2}\left[J_t(\dot{\varphi}_x^2 + \dot{\varphi}_y^2) + me^2(\dot{\varphi}_x^2 + \dot{\varphi}_y^2)\right] + \\ & \frac{1}{2}m_1(\dot{x}_1^2 + \dot{y}_1^2) + \frac{1}{2}m_3(\dot{x}_3^2 + \dot{y}_3^2) \end{aligned} \tag{4}$$

$$\begin{aligned} D = {} & \frac{1}{2}[c_{11.r}(\dot{x} - \dot{x}_1)^2 + c_{22.r}(\dot{y} - \dot{y}_1)^2 + c_{33,r}\dot{\varphi}_x^2 + c_{44,r}\dot{\varphi}_y^2 \\ & + 2c_{14,r}(\dot{x} - \dot{x}_1)\dot{\varphi}_y + 2c_{23,r}(\dot{y} - \dot{y}_1)\dot{\varphi}_x] + \frac{1}{2}[c_{11.b}(\dot{x} - \dot{x}_2)^2 \\ & + c_{22.b}(\dot{y} - \dot{y}_2)^2 + c_{33,b}\dot{\varphi}_x^2 + c_{44,b}\dot{\varphi}_y^2 + 2c_{14,b}(\dot{x} - \dot{x}_2)\dot{\varphi}_y \\ & + 2c_{14,b}(\dot{x} - \dot{x}_2)\dot{\varphi}_y + 2c_{23,b}(\dot{y} - \dot{y}_2)\dot{\varphi}_x] \end{aligned} \tag{5}$$

$$\begin{aligned} U = {} & \frac{1}{2}[k_{11.r}(x - x_1)^2 + k_{22.r}(y - y_1)^2 + k_{33,r}\varphi_x^2 + k_{44,r}\varphi_y^2 + \\ & 2k_{14,r}(x - x_1)\varphi_y + 2k_{23,r}(y - y_1)\varphi_x] + \frac{1}{2}[k_{11.b}(x - x_2)^2 + \\ & k_{22.b}(y - y_2)^2 + k_{33,b}\varphi_x^2 + k_{44,b}\varphi_y^2 + 2k_{14,b}(x - x_2)\varphi_y \\ & + 2k_{23,b}(y - y_2)\varphi_x] \end{aligned} \tag{6}$$

$$\begin{bmatrix} F_x(t) \\ F_y(t) \end{bmatrix} = \begin{bmatrix} m_1 e_1 \omega_1^2 \cos(\omega_1 t + \beta) \\ m_1 e_1 \omega_1^2 \cos(\omega_1 t + \beta) \end{bmatrix} + \begin{bmatrix} f\cos(\omega t) \\ f\sin(\omega t) \end{bmatrix} - \begin{bmatrix} mg\cos(\pi/3) \\ mg\sin(\pi/3) \end{bmatrix} \tag{7}$$

Where x and y denote the generalized coordinate and its derivative including the supporting rollers displacements x_1; y_1; x_2; y_2; x_3; y_3, f is the cyclic loading caused by the kiln crank, ω_1 is the rotation speed of the supporting roller and e_1 is the eccentricity of the supporting roller's section. Substituting the kinetic energy, potential energy, Rayleigh function into Lagrange equation (2) and (3), the dynamic equation of the supporting roller can be obtained as equation (8):

$$\begin{cases} m\ddot{x} + c\dot{x} + k(x_1 - x) = F_x(t) \\ m\ddot{y} + c\dot{y} + k(y_1 - y) = F_y(t) \end{cases} \tag{8}$$

Where k are the stiffness values of the supporting roller in x and y directions; c are the damping forces of the supporting roller in x and y directions; m is the equivalent mass of the supporting roller at the related supporting station.

It is great important to take a careful estimation of the physical parameter values of the supporting rollers to perform a numerical simulation [20]. However, it is difficult to take this task as that the specific parameters of the supporting rollers depend on the production, the length and the tyre number of a rotary kiln. In this research, we take a qualitative analysis to the numerical analysis of a three tryes rotary kiln with the production of 5000-6500 t/d. It supposes that the basic material of the supporting rollers is ZG42GrMo and the elasticity modulus of is 2.09×10^5 Mpa. The mass density of the rollers is 7.86×10^{-6} kg/mm^3 and the radius is 1150mm. The stiffness of the supporting rollers in the x , y axis direction is 1.48×10^5 N/m and the viscous damping is 6.92×10^4 Ns/m [21].The rotating speed of the supporting rollers and the kiln cylinder are $10.7\,r/\min$ and $4\,r/\min$ respectively.

B. Numerical analysis of the vibration model

In this section, the dynamic response of the supporting rollers under the influence of the kiln crank was studied. And the fourth-order Runge-Kutta (RK4) method is selected to solve the equation (8) to obtain the vibration response of the supporting rollers.

The effect on the supporting rollers of the rotary kiln crank was analyzed in this section. As previously pointed out, during the operation of the kiln, it will change the dimensional size as the result of the internal thermal processes. As the rotation center and the center of mass is not overlap in the cylinder section, thus producing section eccentricity. Therefore, the eccentricity of the cross section can be used as a main parameter to represent the kiln crank. The simulation result of the vibration response in time domain and frequency domain of the supporting roller was shown in Fig.4(a) and Fig.4(b), respectively. Furthermore, the relationship between the eccentricity of the kiln cylinder in the supporting station and the energy of the kiln harmonic was analyzed, and the result was shown in Fig.5.

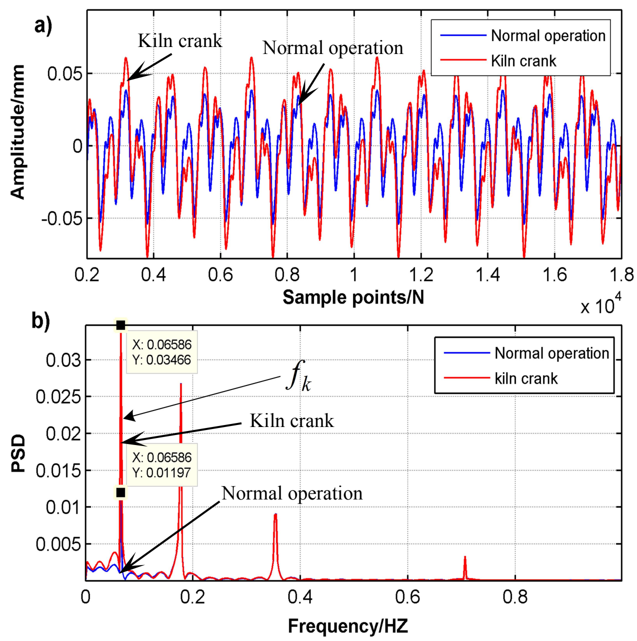


Fig.4. The vibration response in the contact direction of the supporting rollers (a) in time domain and (b) frequency domain

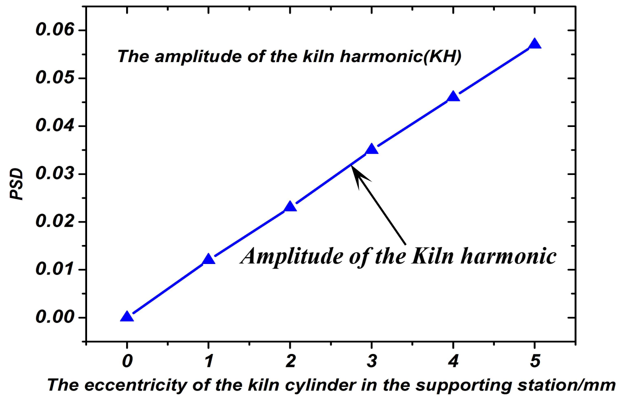


Fig.5. Simulation result of the relationship between the eccentricity of the kiln cylinder in the supporting stations and the amplitude of the kiln harmonic (KH) of the supporting rollers

$$f_k = \frac{n_{kiln}}{60} \tag{9}$$

$$f_r = \frac{n_{roller}}{60} \tag{10}$$

From Fig.4(a), Fig.4(b) and Fig.5, the following conclusions can be made: (1) the frequency of the cyclic loading (kiln harmonic) caused by the kiln crank is consistent with the rotation frequency of the kiln cylinder, while the frequency of the rollers (roller harmonic) is consistent with the rotation frequency of the supporting rollers, and they can be calculated by formula (9) and (10), where n_{kiln} and n_{roller} are the rotating speed of the kiln cylinder and the supporting rollers, respectively. (2) When the value of eccentricity of the cross section near the supporting station increased (the degree of the kiln crank enhanced), the energy of the kiln harmonic (KH) get increased.

II. FUNDAMENTAL OF WTD AND EEMD METHOD

A. WTD method

It is necessary to find an appropriate denoising method to pre-process the vibration signals of the supporting rollers as that they contain lots of noise. The WTD (wavelet threshold denoising) method was selected in this research to filter the high-frequency line noise of the vibration signal. The noise within a WTD method can be suppressed [22], [23]. The useful vibration energy components will be concentrated on a few large wavelet coefficients, and the noise components will be concentrated on small coefficient.

The effect of wavelet threshold filtering is mainly dependent on the selection of the threshold. A too small threshold will be unable to reduce noise, whereas an excessively large threshold will result in the loss of useful information [22]. The Sqtwolog threshold computation was employed in this research for threshold selection. The Sqtwolog threshold can be calculated as following:

$$Thr_i = \sigma\sqrt{2Ln(N)} \tag{11}$$

Where N is the length of the signal, and, σ is the standard deviation of the noise. Considering that the noise is unknown in the vibration signals of the supporting rollers, the σ can be estimated by noise consideration. And it can be calculate by the following formula (12):

$$\sigma = \frac{median\{|d_{i,k}|\}}{0.6745} \tag{12}$$

Where $d_{i,k}$ is the wavelet coefficient of level i .the denominator is depending on the data distribution which in a normal data is 0.6745.

What's more, considering that the symmlet 5 has many advantage such as approximate symmetry, biorthogonality etc. It was used as the mother wavelet to perform discrete wavelet transform in our research.

B. EEMD method

Empirical mode decomposition (EMD) method is first proposed by Huang et al. in 1998. Compared with FFT and Wavelet Transform, EMD method got better result for processing non-stationary and nonlinear signal [24]. It could decompose any time domain signals into a set of zero-mean IMFs which starts from high-frequency to low-frequency components. Each IMF satisfies two basic conditions: (1) The number of extremes and the number of zero-crossings in the data set must either be equal or must differ by no more than one. (2) At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero. The detailed procedure of EMD can be found in literature [25], [26].

EMD is based on the local characteristic time scales of a signal and could self-adaptively decompose the complicated signal into some intrinsic mode functions (IMFs). However, the disadvantages of EMD are the mode mixing problem and the endpoint effect. In certain cases, the IMF component decomposed by EMD method cannot reflect the physical meaning of the feature information to be extracted. To solve this problem, Wu and Huang proposed an improved version of EMD, called ensemble EMD (EEMD). Gaussian white noise is added to the original signal to improve the distribution of extreme points in original signal as that it is evenly distributed throughout time-frequency space [25]-[29]. The mode mixing problem can be well solved by using the EEMD method. And the brief description of EEMD method is as follows:

Step 1) Add a numerically generated white noise $\omega(t)$ with the given amplitude to the original signal $x(t)$ to generate a new signal:

$$X(t) = x(t) + \omega(t) \tag{13}$$

Step 2) Use the EMD algorithm to decompose the newly generated signal $X(t)$.

$$X(t) = \sum_{i=1}^{n} c_i(t) + r_n \tag{14}$$

Step 3) Repeat step 1 and step 2 n times with a different white noise series. The IMF components can be expressed as $C_n(t)$, where

$$C_n(t) = \frac{1}{N}\sum_{i=1}^{N} c_{i,n}(t) \tag{15}$$

Where N is the number of added white noise series which follow the following statistic principle

$$\ln e = \ln a_n - \frac{1}{2}\ln N \tag{16}$$

where e is the standard deviation value of the error.

It can be indicated that e decreased with N , However if N is too large, the overhead computation process will also grow. Generally, the amplitude of added white noise is 0.2 to 0.4 times the standard deviation of original vibration signal [26], [27]. When the signal is mainly composed of high frequency signal, the amplitude of added white noise signal should try to get smaller. On the country, it should take larger amplitude.

III. THE PROCEDURE OF THE CRANK IDENTIFICATION METHOD BASED ON WTD-EEMD

Based on the above theory analysis, in order to realize the crank identification of the rotary kiln, a strategy is proposed. As shown in Fig.6, the main implemented procedure can be described by the following steps:

Step 1) The vibration signals of the supporting rollers were collected by the monitoring system in the real time and the WTD method was applied to preprocessed the signals.

Step 2) The EEMD method is employed to process the vibration signals by the measuring system. A serial of IMF components can be obtained and the sensitive IMF components contain the rich cyclic loading information was selected.

Step 3) The vibration model of the supporting rollers is established according to the operation principle of the rotary kiln. The vibration signals of the supporting rollers with the kiln crank were analyzed. The characteristic frequency of the cyclic loading was obtained which provided a sensitive IMF components selection criteria from the vibration signal.

Step 4) The signals contained the rich cyclic loading information were constructed based on the sensitive IMF components. The degree of the kiln crank can be estimated by the energy of the reconstructed signal. As a result, the crank of the rotary kiln can be identified.

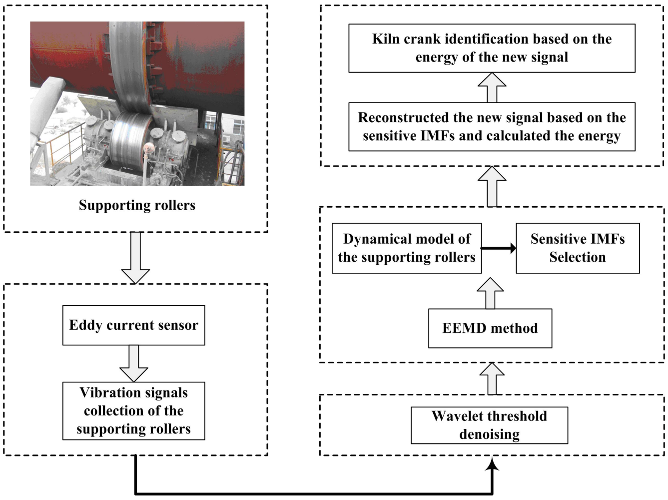


Fig.6. Implemented procedure of the proposed strategy for the kiln crank identification based on WTD-EEMD method.

IV. EXPERIMENT AND RESULTS ANYSIS

The proposed kiln crank identification method is verified is this section. And the analyses of vibration signals collected by the monitoring system were carried out.

A. Experiment in the industry field

As shown in Fig.8, the data acquisition system comprises a 16-bit data acquisition card (DAQ-card), three non-contact eddy current sensors and a hall sensor, the non-contact eddy current sensors are mounted through fixture to keep the probes in the contact direction between the supporting rollers and kiln tyre. The hall sensor is installed in a fixed position of rotary kiln to interact with magnet mounted on the kiln cylinder generating pulse signal per lap which is used to synchronize the collected vibration signals and the rotation of the rotary kiln. The sketch of eddy current sensors and the laser system installation and the system layout in the industry field are shown in Fig.7 and Fig.8, respectively. The vibration signals were collected by the DAQ-card to the upper computer by the monitoring software, as shown in Fig.9.

The experiments were conducted in a cement plant, and the measured object was a rotary kiln which consist three tyres. The rotational speed of the kiln cylinder was 4.02 $r/\min$ while the rotational speed of supporting rollers of the first station, the second station and the third station were 12.87 $r/\min$, 11 $r/\min$ and 12.87 $r/\min$, respectively. The vibration signals of all the supporting rollers were collected based on the designed monitoring system. The sample frequency was settled to 100HZ. Meanwhile, to study the relationship between kiln crank and the cyclic loading, the eccentricity of the cross section near the supporting stations were measured, as shown in Fig.7. The measurement process and calculation methods were introduced in literature [28].

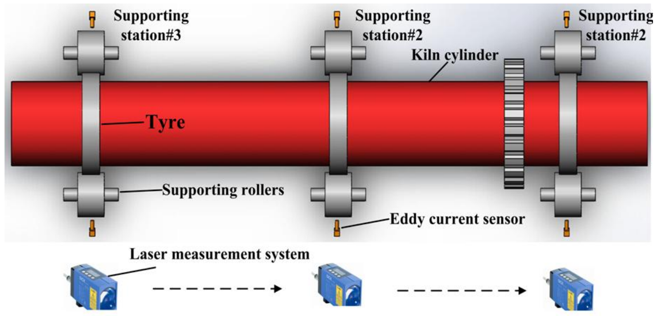


Fig.7 The sketch of eddy current sensors and the laser system installation

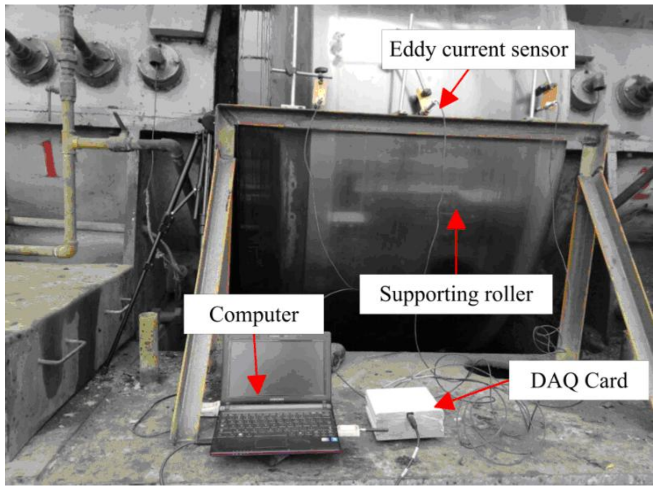


Fig.8 The layout of the measurement system in the industry field

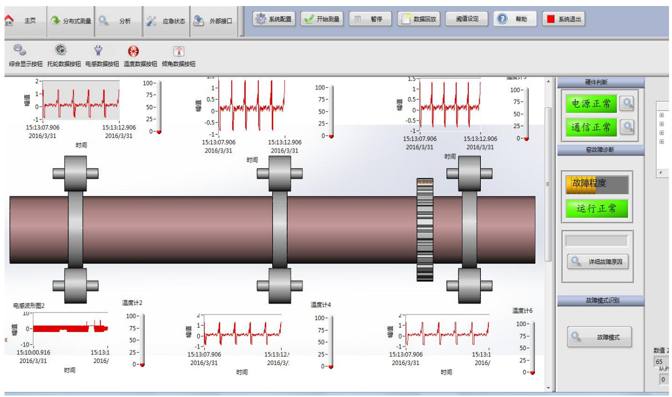


Fig.9 The monitoring software

B. Vibration signals analysis of the supporting rollers using the WTD-EEMD method

The vibration signals of the supporting rollers of the three stations of the rotary kiln were collected by the monitoring system. According to the numerical analysis of the supporting rollers, the vibration signals contained the harmonics originating from the cyclic load caused by the kiln crank (frequency is consistent with the kiln's rotation frequency). As that the rotational speed of the kiln cylinder was 4.02 $r/\min$, therefore, the fault characteristic frequencies of the rotary kiln are shown in Table 1, where f_K is the kiln harmonic, f_{r1}, f_{r2} and f_{r3} are the harmonics of the supporting rollers in the first, second and the third station, respectively. In order to identify the kiln crank, it needs to extract the Kiln harmonic components.

Table 1. The fault characteristic frequencies of the rotary kiln

f_K	f_{r1}	f_{r2}	f_{r3}
0.067HZ	0.213HZ	0.183HZ	0.214HZ

In this section, the results of the experimental investigation are presented. The raw vibration signals of the supporting rollers include noise components, which complicate the feature extraction of the kiln harmonic accurately. Therefore, the WTD (Wavelet threshold de-noising) method was adopted in this section to pre-process the vibration signals to alleviate the interference of the noise components. The decomposition level is set to 5 and symmlet 5 is selected as the wavelet function. All the vibration signals of the supporting rollers were processed by the WTD method. For example, the processing result of the vibration signals with WTD method in the first, second and the third stations are shown in Fig. 10.

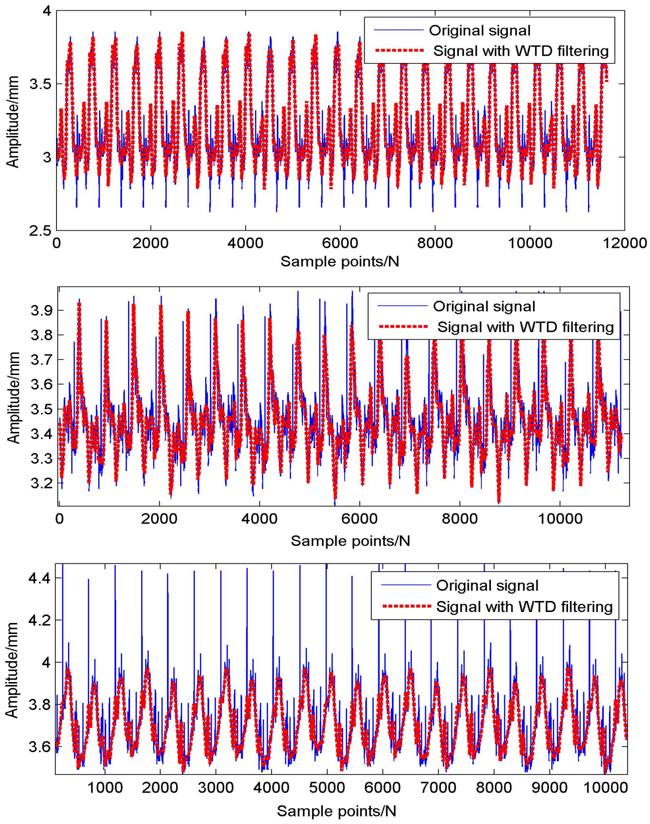


Fig.10. Vibration signals with WTD in time domain and frequency domain of the left supporting rollers in the first (a) second (b) and third(c) station

In order to reveal the frequency characteristic of the vibration signal of the supporting rollers, the de-noised signals were processed by FFT method. Fig. 11 shows the time domain and frequency domain waveform of the vibration signals of the supporting rollers in the first, second and the third stations. According to the results, it can be found that the main frequency components of the vibration signals collected by the monitoring system agreed well with the numerical analysis result. And by using traditional methods of time and frequency domain analysis, we can get the frequency characteristic of the vibration signal f_K . However, the symptoms are not obvious. Moreover, it can be found that the there were a great deal of useless component such as the ripple deformation component and surface roughness component in the vibration signal produced by the fatigue damage of the supporting rollers surface, making the difficulty to extract the components of kiln harmonics.

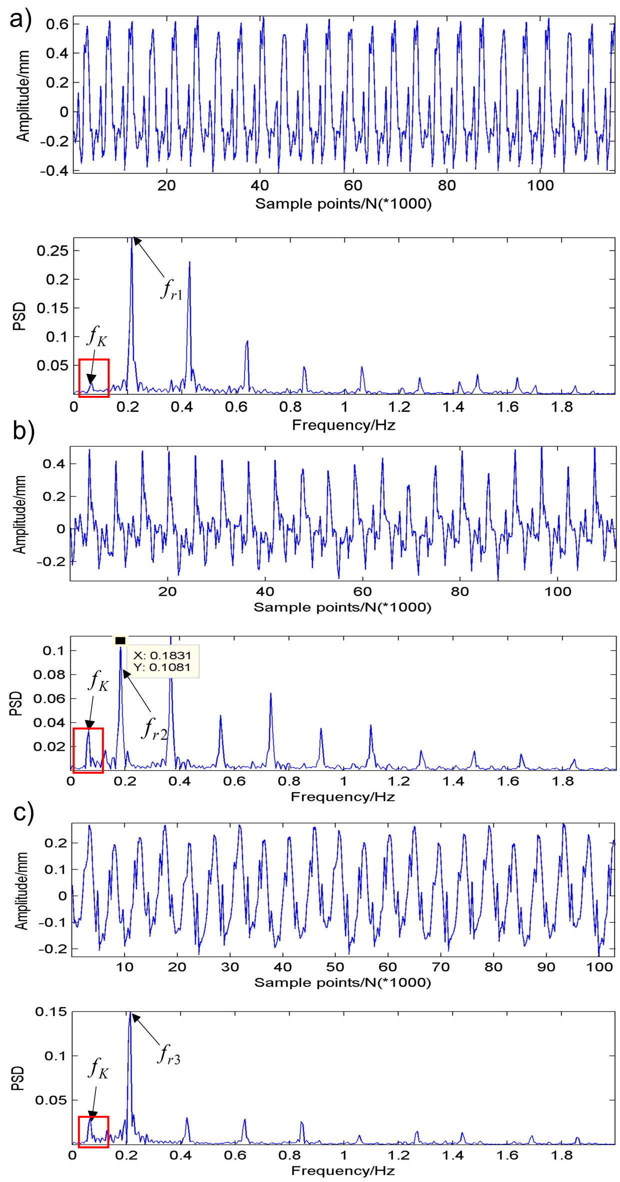
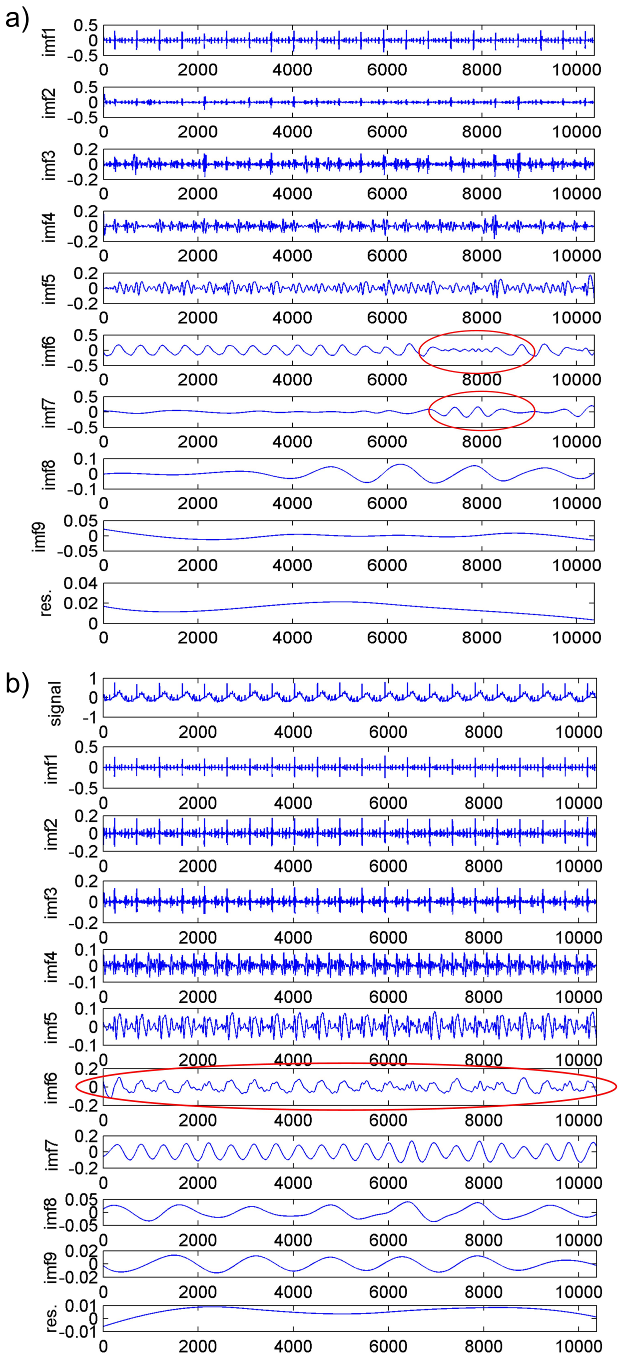


Fig 11. Vibration signal with WTD in time domain and frequency domain of the left supporting rollers in the first (a) second (b) and third(c) station

Therefore, the EEMD method was adopted to extract the kiln crank harmonic in the vibration signals. It should be noted that when using EEMD method, it is very important to set up the reasonable parameter. Considering that the kiln harmonic is concentrated in the low frequency band of the vibration signals, therefore, as for EEMD method, the amplitude of added white noise value is set to $Nstd = 0.4\sigma$, where σ is the standard deviation of the Gaussian white noise added. And the number of added white noise is set to 200 times. Then, a set of IMF components is obtained which contain different time scales to expose the signal's characteristics under different resolutions.

To verify the effectiveness of the WTD-EEMD method, we compared the proposed method with other two cases. Take the vibration signal of Fig.10(c) as an example; it was processed by three scenarios: (1) signals decomposed by the EMD method; (2) signals decomposed by the EEMD method; (3) signals decomposed by the proposed WTD-EEMD method; the results are shown in 12(a)、12(b) and 12(c) respectively.



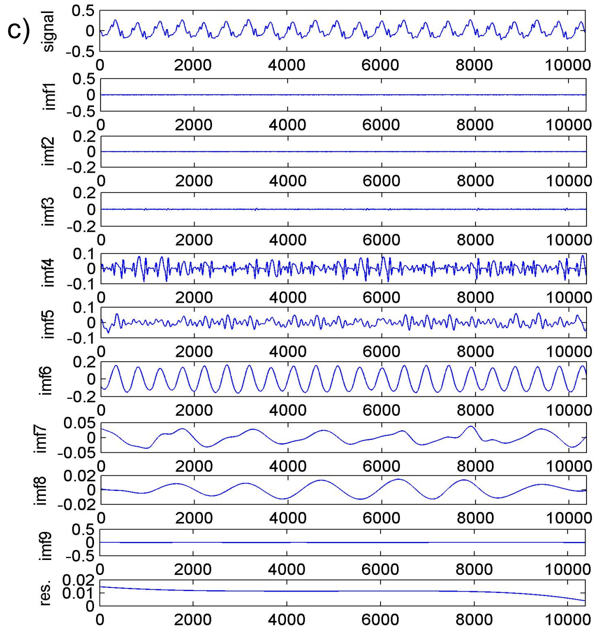


Fig 12. The vibration signal of the supporting rollers in the third station and its Intrinsic Mode Functions by (a) The EMD decomposition (b) The EEMD decomposition (c) The proposed WTD-EEMD method decomposition

Through comparing the process results of EMD and EEMD, it is obvious that IMFs obtained by EMD are distorted seriously. As shown in fig 12(a), the frequency component of IMF6 and IMF7 mixed together. The EEMD method is able to solve the problem of mode mixing and achieves an improved decomposition with physical meaning. However, the noise in the vibration signals made an effect to the decomposition result. As shown in fig 12(b), the IMF6 contains other interfering harmonic frequencies. Shown in fig 12(c), with parameter optimization of EEMD, the characteristic components such as IMF6、IMF7 and IMF8 decomposed by the proposed WTD-EEMD method contain only one low-frequency component, without mixing other disturbed frequency components. As a result, the characteristic frequency components such as kiln harmonic and the rollers harmonic can be extracted accurately. Moreover, the Hilbert spectrum of the three methods can be obtained, as shown in fig.13. In Fig.13, the energy distribution of the kiln harmonic and the rollers harmonic in the Hilbert spectrum obtained by the proposed WTD-EEMD method is much more obviously than EMD and EEMD method, as shown in Fig.13(c).

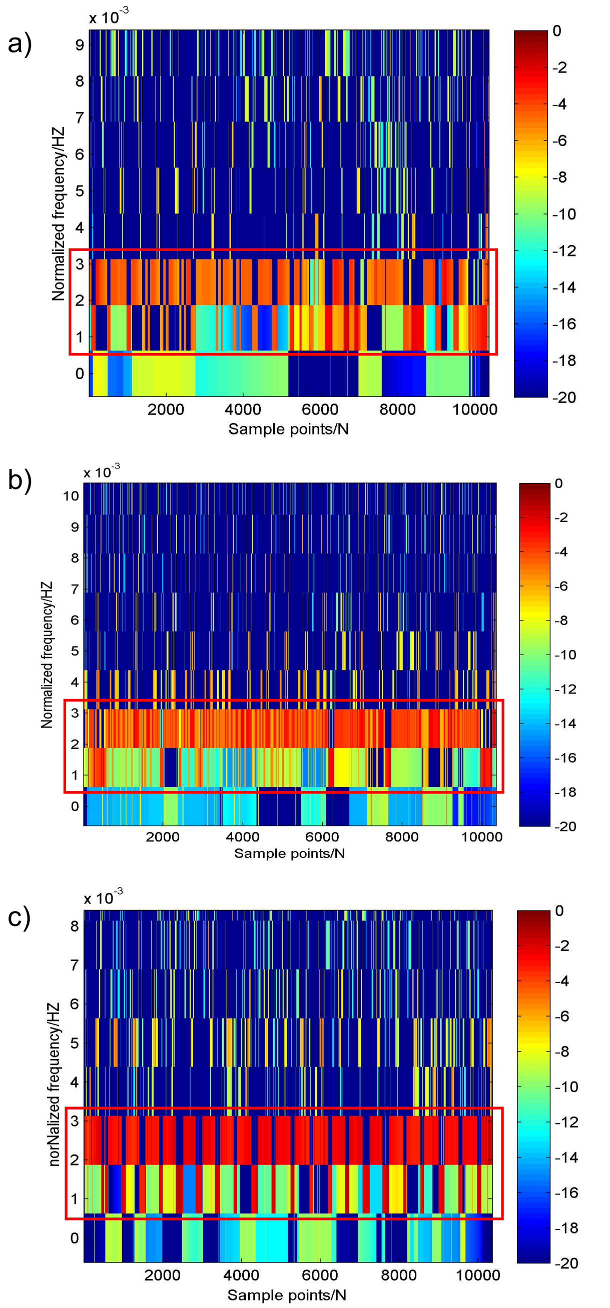


Fig 13. Hilbert spectrum of the three method (a) The EMD result of the vibration signal (b) The EEMD result of the vibration signal (c) The proposed WTD-EEMD method of the vibration signal

Afterwards, the effects of the three methods in the extraction of the kiln crank features were compared. And the comparison is made by two important assessment indicators which are Signal to Noise Ratio (**SNR),** Mean Square Error **(MSE)**[23]. The computational formulas are as shown in Eq. (17). The two assessment indicators can judge the feature extraction effect from different angles.

$$SNR=-10\log\frac{\sum_{i=1}^{n}(s-s')^2}{\sum_{i=1}^{n}(s')^2},\quad MSE=\frac{1}{n}\sum_{i=1}^{n}(s-s') \qquad (17)$$

Where s and s' are the real signals and signal reconstructed by the feature IMFs components, respectively. The results of features extraction performance with SNR and RMSE by the three methods were shown in Table.2. From Table 2, we can find that the SNR of the proposed WTD-EEMD method is maximal value while the RMSE is the minimal value. So it is clear that the proposed method is best method for feature extraction compared with EMD and EEMD method for processing the vibration signals of the supporting rollers.

Table 2. Results of features extraction performance by the three methods.

	EMD	EEMD	WTD-EEMD
SNR	3.7714	3.9890	**11.39015**
RMSE	0.0754	0.0712	**0.0310**

C. Crank identification analysis based on the proposed method

We analyzed the supporting roller's vibration signals according by the method for identifying the kiln crank proposed in section IV. The vibrations of all supporting rollers were processed by the proposed WTD-EEMD method. Also, the IMF components obtained by the EEMD were processed by FFT method. The vibration signal of the right supporting roller in the first supporting station was taken as an example, with the results shown in Fig.14.

The numerical analysis indicated that the frequency of the cyclic loading resulting from kiln crank was consistent with the rotation frequency of the rotary kiln's cylinder. Therefore, it can be found from the results of Fourier spectrum analysis of the IMF components that the frequencies of IMF8 and IMF9 components are consistent with the rotation frequencies of the rotary kiln's cylinder, which is 0.067HZ, as shown in Figure 14(b). Therefore, it can be deemed can IMF8 and IMF9 components contain the feature information of cyclic loading. Therefore, the new signals were reconstructed on the basis of the time-domain characteristics of IMF8 and IMF9 components. The new signals could effectively reflect the features of cyclic loading. The time-domain characteristics of the vibration signals of the right supporting rollers at the three supporting station were shown in Fig. 15. To further extract the features of the restructured signals, we calculated the energy of the new signals, with the formula as follows:

$$E_i=\int_{-\infty}^{+\infty}|c_i(t)|^2\,dt \qquad (18)$$

Where $c_i(t)$ denotes the local energy of the reconstructed signal with different scales.

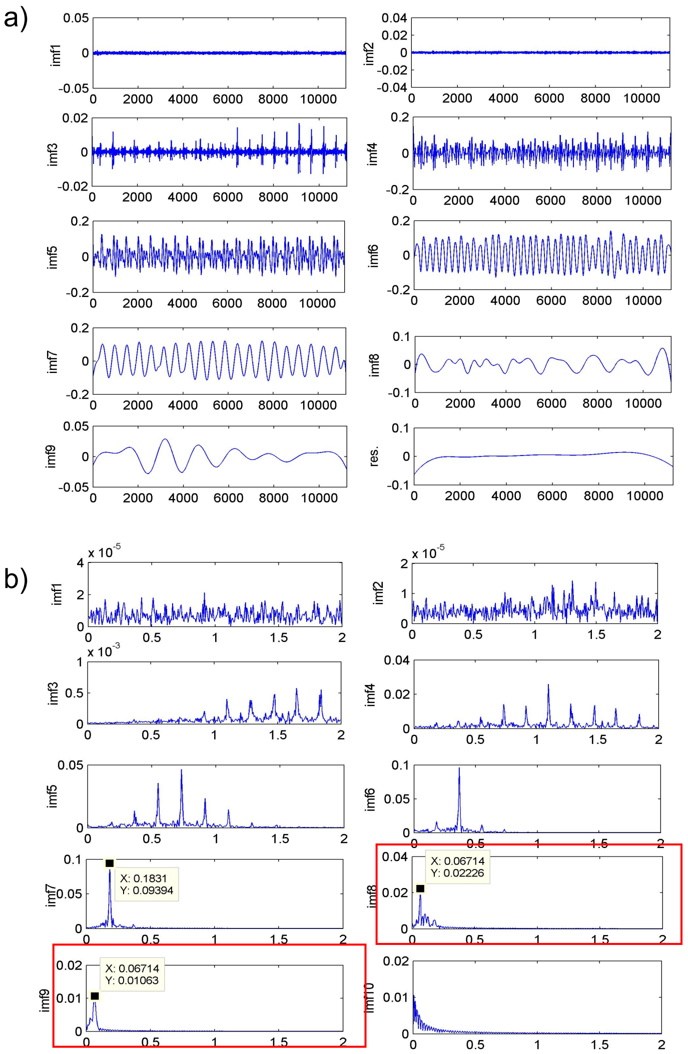


Fig. 14. The WTD-EEMD result of the vibration signal of in time domain and frequency domain.

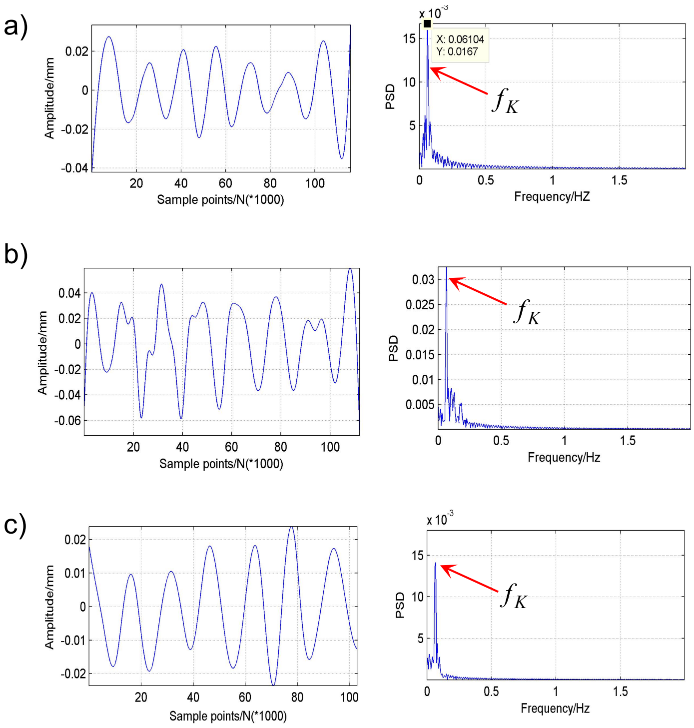


Fig. 15.The reconstructed signal in time domain and frequency domain of the left supporting roller in the first(a), second(b) and third(c) station

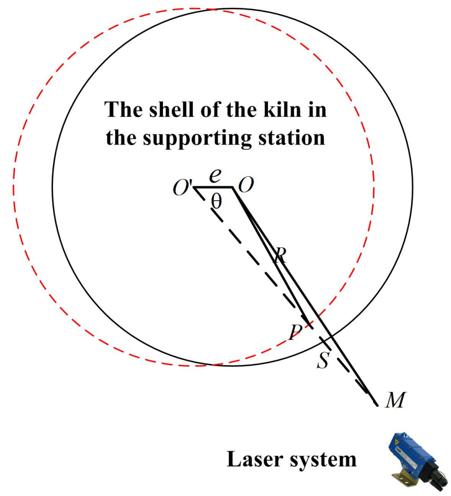


Fig.16. The eccentricity measurement of the cross section near the supporting station

Based on the above analysis, the energy of the new signals can be calculated by formula (18). In order to verify the relationship between the energy of the new signals and the kiln crank near the supporting station, the eccentricities of the cross sections of the kiln cylinder near the supporting stations were measured. The layout of the laser system was shown in Fig.16. The eccentricity of the cross section can be calculated [30] by the formula (18), (19) and (20):

$$a = (2/n)\sum_{i=1}^{n} \Delta r_i \cos\theta_i \tag{19}$$

$$b = (2/n)\sum_{i=1}^{n} \Delta r_i \sin\theta_i \tag{20}$$

$$e = \sqrt{a^2 + b^2} \tag{21}$$

Where (a,b) is the geometric center of the cross section and Δr_i is the deviation value of radius of each section which can be measured by the laser sensor; n is the number of points collected by the laser and $\theta_i (\theta_i = 2\pi / n \cdot i)$; e is the eccentricity of the cross section. And the eccentricity of the cross section of the kiln cylinder in the were station was shown in Fig.17, the specific values of the a, b and e are shown in **Table.3.**

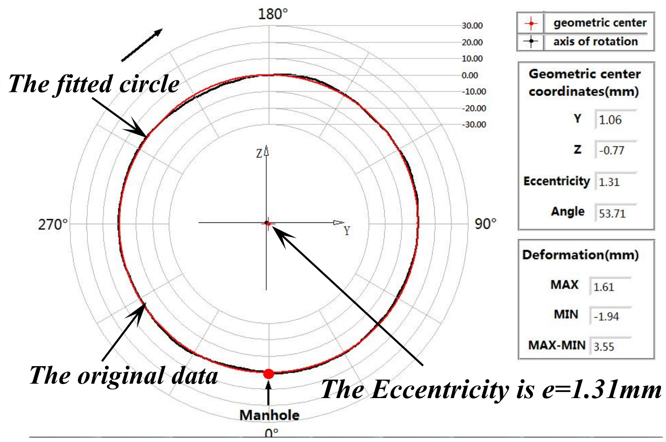


Fig. 17 .The eccentricity of all cross section of the kiln cylinder based on the measurement and calculation method in literature [30]

Table.3. The value of the parameter a , b and e .

Parameter	Value(mm)
a	1.06
b	-0.77
e	1.31

To verify the effectiveness of the proposed method, the results of the energy of the new signal of the three supporting rollers and the eccentricity of the cross sections near the three supporting station were listed in Table 3. Also, the relationship between the eccentricity of the kiln cylinder in the supporting stations and the energy of the kiln harmonic (KH) of the supporting rollers can be indicated in Fig.18. From Table 4 and Fig.18, it can be found that energy value has positive correlation with the eccentricity value. It means that when the value of eccentricity of the cross section near the supporting station increased (the degree of the kiln crank enhanced), the energy value of the reconstructed signal get increased, which agreed well with numerical analysis results. And we can tell that the energy value of the reconstructed signal is an excellent indicator to reflect the degree of the kiln crank in the supporting station. Also, the analysis result indicated the proposed method is effective to identify the kiln crank by using the vibration monitoring of the supporting rollers. Therefore, the crank of the rotary kiln can be identified by the proposed method, which provide an effective and practical technique for evaluate the operation state of the large low-speed rotary kiln.

Table.4. The eccentricity of the kiln cylinder in the supporting stations obtained by the laser system and the energy of the kiln harmonic (KH) of the supporting rollers obtained by the proposed WTD-EEMD method.

	Eccentricity	Energy
Supporting station #1	1.31mm	2.5533
Supporting station #2	3.03mm	6.4387
Supporting station #3	2.28mm	4.4920

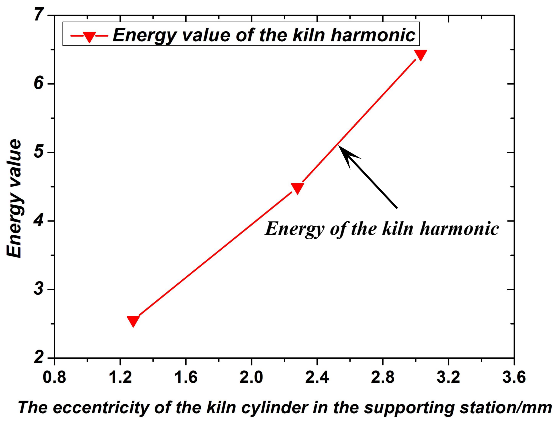


Fig.18. Relationship between the eccentricity of the kiln cylinder in the supporting stations and the energy of the kiln harmonic (KH) of the supporting rollers

V. CONCLUSIONS

In this paper, a novel strategy for kiln crank identification based on WTD-EEMD method by using the vibration monitoring of the supporting rollers was proposed. The main contributions and conclusions of this paper are:

(1) The kiln crank effect to the supporting rollers was analyzed and the vibration model of the supporting rollers was put forward. The numerical analysis result indicated that the characteristic frequency of the cyclic load caused by the kiln crank was consistent with the kiln harmonic (KH). Also the energy of kiln harmonics (KH) will increase when the kiln crank enhanced.

(2) A method for identifying kiln crank based on WTD-EEMD was proposed. Compared with the EMD and EEMD method, it has the maximum SNR and the minimum RMSE value for feature extraction, which indicated that the proposed WTD-EEMD method can effectively suppress the noise of the signals and can be applied for analyze the vibration signals of the supporting rollers.

(3) With the numerical analysis, the sensitive IMF components decomposed by the EEMD method which contain rich cyclic load information can be selected. And the new signal reflects the kiln crank information can be constructed by the selected IMF components.

(4) The effectiveness of the proposed WTD-EEMD method has been verified in the in the industry field. The experiment result showed that the degree of the kiln crank has positive correlation the energy intensity of the new signals, which agrees well with the numerical analysis result. Therefore, the proposed can be used for the kiln crank identification. Also, the energy of the reconstructed signal was a good indicator to reflect the degree of the kiln crank.

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