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Air-gap Eccentricity Fault Diagnosis of Induction Motors Using EMD

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Abstract

The accuracy of fault diagnostic systems for induction motors relies on a comparison of the currently extracted sensory features with those captured during normal operation. To detect the timing of these impacts from vibration signals accurately, this paper presented an efficiency diagnosis method based on empirical mode decomposition (EMD), aimed to diagnose the air-gap eccentricity fault of induction motors. Analyses the Hilbert modulus spectrum of stator current in induction motors by EMD, to obtain the fault characteristics frequency f_r accurately, and distinguish the fault characteristics component from the fundamental wave in stator current. The simulation result demonstrated the high sensitivity and clarity of this proposed method, efficiently distinguish the fault frequency from the basic frequency in the stator current.

Keywords: *air-gap eccentricity, Hilbert modulus, empirical mode decomposition (EMD), fault diagnosis*

1. Introduction

As the backbone of modern industry, induction motors covers a broad range of mechanical equipment and plays an important role in industrial applications. With rapid development of science and technology, rotating machinery in modern industry is growing larger, more precise and more automatic. Its potential faults become more difficult to find. Fault diagnostics of induction motors are very important to ensure safe operation; timely maintenance can increase operation reliability and preventive rescue, especially in high power applications. The induction motor faults are generally classified as either mechanical or insulation system faults. Common mechanical faults include rotor bar breakage, rotor end ring cracking, static and/or dynamic air-gap irregularities, stator winding faults, bent shaft, misalignment, and bearing gearbox failures. Statistical data show that the mechanical faults are responsible for more than 95% of all failures [1-4].

Air-gap eccentricity is one of the main faults of induction motors. It is appearances in almost all the induction motors. When it happens, the motor generates imbalanced electromagnetic force and leads to the rotor vibration, thus the performance of the bearing is worsen. This makes several faults, such as stator core deformation, winding wore and insulated damage. And some faults even worse—stator rotor winding, core damage, even the “sweep boring”. Therefore, detecting and diagnosing the air-gap eccentricity fault is of significant value to the safety operating of the induction motors [5-7].

Conventional signal processing techniques include time-domain statistical analysis and Fourier transform, which have proved to be effective in fault diagnosis of rotating machinery. However, these techniques are based on the assumption that the process generating signals is stationary and linear. They usually result in false information when they are applied to the mechanical fault signals, because the mechanical faults by nature are non-stationary and transient events

The empirical mode decomposition (EMD) is a novel signal analysis tool, whereby the underlying notion of instantaneous frequency provides insight into the time-frequency signal features [1]. This technique has been first introduced in ocean research and has since become an established tool for the analysis of non-stationary and nonlinear data with a number of

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important applications in signal processing. Unlike other signal decomposition techniques, which map the signal space onto a space spanned by a predefined basis, the idea behind this method is to decompose a general data set into a number of “basis functions” termed intrinsic mode functions (IMFs), which are derived directly from the data, in a natural way [2,3]. In spite of the well-established and understood EMD-based analysis of real-valued processes, a major issue that prevents a wider application of EMD in signal processing is that this concept has been developed strictly for real-valued data. On the other hand, several important signal processing areas (telecommunications [4, 5], sonar [6-9], radar, machinery [10-13] to mention but a few) use complex-valued data structures. To analyze these within the EMD framework, it is necessary to develop an extension of the standard EMD suitable for dealing with complex-valued data. In addition, a strong motivation for the development of the EMD for complex-valued data comes from the concept of so-called instantaneous frequency, which gives EMD an edge over other established time-frequency analyzers [8-13].

The EMD method has attracted considerable attention and been widely applied to fault diagnosis of rotating machinery recently. This paper applied the EMD technique to the spectrum analysis of Hilbert modulus of stator current in induction motors, and obtained the fault characteristics frequency. This method can efficiently detect the air-gap eccentricity fault of induction motors, thus can hence the operating reliability of induction motors. It is shown that the proposed method based on EMD obtains a more precise diagnosis result.

2. EMD Technique and Basic Theory

EMD is a self-adaptive analysis method for nonlinear and non-stationary signals. It may decompose a complicated signal into a collection of intrinsic mode functions (IMFs) based on the local characteristic time scale of the signal. EMD technique was first proposed by Huang *et al.* as part of the Hilbert–Huang transform (HHT) in 1998, which has been proven to be an effective method in analyzing the non-stationary signals for fault detection. It aims to break up any signal into a sum of oscillating components extracted directly from this one in an adaptive way. These components (or IMF for “Intrinsic Functions Mode”) are interpreted like non-stationary forms of waves (i.e., modulated in amplitude and frequency) being able to be possibly associated nonlinear oscillations [14-15].

When HHT is applied to analyze the signals, the signals are first decomposed into several Intrinsic Mode Function (IMF) components by EMD, and then, Hilbert transform is applied to calculate the instant amplitudes and instant frequency of the IMFs to form the Hilbert spectrum. Unlike the wavelet transform, for which the user has to pre-determine a mother wavelet and then the level of decomposition manually, EMD is able to perform decomposition of the raw signal and automatically determine the level of decomposition based on the nature of that raw signal.

Any signal can be considered as the superposition of a slow component $a(t)$ (low frequency) and an approximation called fast component $d(t)$ (high frequency) called detail. These components are IMF (Intrinsic Modal Functions) interpreted as being non-stationary waves.

The steps of the EMD procedure are provided as follows.

Step 1) Find the local maxima and local minima of the signals.

Step 2) Construct the lower and upper envelopes of the signals by the cubic spline based on the local maxima and local minima, respectively.

Step 3) Calculate the mean values $m(t)$ by averaging the lower envelope and the upper envelope.

Step 4) Subtract the mean values from the original signals to produce the IMF candidate component $h_1(t) = f(t) - m(t)$. If it is the true IMF, go to the next step. In addition, the IMF component $C_i(t) = h_m(t)$ is saved. If it is not the IMF, repeat Steps 1) – 4).The stop condition for the iteration is given by

$$\sum_{t=0}^{T} \frac{\left[h_{m-1}(t) - h_m(t)\right]^2}{h_{m-1}^2(t)} \leq SD \tag{1}$$

where $h_{m-1}(t)$ and $h_m(t)$ denote the IMF candidates of the $m-1$ and m iterations, respectively, and, usually, SD is set between 0.2 and 0.3.

Step 5) Calculate the residual component by subtracting the IMF component obtained in Step 4) from the original signal $res_i(t) = f(t) - C_i(t)$. This residual component is treated as new data and is subjected to the same processes described previously to calculate the next IMF component.

Step 6) Repeat Steps 1) – 5) until the final residual component becomes a monotonic function and no more IMF component can be extracted or the envelopes become smaller than a predetermined value.

Through Steps 1)–6), the original signals $f(t)$ can be decomposed into N empirical modes $(C_1 - C_N)$.

3. Hilbert Modules Spectrum Analysis of Stator Current

The power supply of induction motors is supposed to be the ideal three phase sine AC power, and the structure of the motor is symmetrical. When the motor operates successfully, the phase current is ideal sine wave. Take phase A for example, define the phase current and the line current of the motor as [18]:

$$\begin{cases} u_{\mathrm{A}}(t) = U_{\mathrm{m}} \cos(\omega_1 t) \\ i_{\mathrm{A}}(t) = I_{\mathrm{m}} \cos(\omega_1 t - \varphi_f) \end{cases} \tag{2}$$

where U_m and I_m are the amplitude of phase fundamental wave voltage and current, respectively; φ_f is the power factor angle of the motor.

Air-gap eccentricity involves static eccentricity and dynamic eccentricity, when they happens at the same time, stator winding will generate induction characteristics frequency $f_1 \pm f_r$ and $f_1 \pm 2f_r$, in which $f_1 \pm f_r$ are the basic characteristics constituent. If we consider the fluctuation of torque and rotate speed generated by the current related to this frequency and the eccentricity magnetic field, we can calculate the fault characteristics frequency $f_1 \pm mf_r$, $f_{ecc} = f_1 \pm mf_r$, where f_{ecc} means frequency of the fault characteristics in the stator current when the eccentricity fault happens, f_1 is the frequency of the power supply, f_r is the rotation angle frequency of the rotor, which equals to $(1-s)\, f_1/p$, p means the pole number of the induction motor.

Define the current of phase A as:

$$i_{af} = I_m \cos(\omega_1 t - \varphi_f) + \sum_{n=1}^{\infty} \begin{Bmatrix} I_{ec1n} \cos[(\omega_1 - n\omega_r)t - \varphi_{1n}] \\ +I_{ec2n} \cos[(\omega_1 + n\omega_r)t - \varphi_{2n}] \end{Bmatrix} \tag{3}$$

where I_m, I_{ec1n}, I_{ec2n} respectively means the current amplitude of basic frequency component, $f_1 - nf_r$ component, $f_1 + nf_r$ component; φ_f, φ_{1n}, φ_{2n} respectively means the current's phase angle falls behind the voltage's of basic frequency component, $f_1 - nf_r$ component, $f_1 + nf_r$ component.

Analysis the current i_{af} by Hilbert transform:

$$\begin{cases} \hat{x}(t) = \dfrac{1}{\pi} \displaystyle\int_{-\infty}^{+\infty} \dfrac{x(\tau)}{t - \tau} d\tau = x(t) * \dfrac{1}{\pi t} \\ Z(t) = x(t) + j\hat{x}(t) \end{cases} \tag{4}$$

According to this equation, we can calculate the Hilbert modulus signal $I_s(t)$,

$$I_s(t)=\left|i_{af}+j\hat{i}_{af}\right|^2=\left(I_{mf}^2+I_{ec1n}^2+I_{ec2n}^2\right)+2I_{mf}I_{ec1n}\cos\left(\omega_r t-\varphi_f+\varphi_{1n}\right)$$
$$+2I_{mf}I_{ec2n}\cos\left(\omega_r t-\varphi_f+\varphi_{2n}\right)+2I_{ec1n}I_{ec2n}\cos\left(2\omega_r t-\varphi_{1n}+\varphi_{2n}\right) \quad (5)$$

After analyses the stator current by Hilbert transform, we convert the fundamental wave which disturb the fault component into AC component, thus can reduce the influence. And the related I_{ec1n} and I_{ec2n} was converted to $2sf$ and $4sf$, respectively. $4sf$ equals to I_{ec1n} multiply to I_{ec2n}, and its value is very small, which is hard to observe in the spectrum analysis. However, the AC component may easily submerge the $2sf$ frequency component, which leads to the difficulty to obtain the fault characteristics, so the AC component must be filtered. Once the filter was done, the analysis of the Hilbert modulus signals of the stator current is performed by EMD, thus can obtain the f_r component, which can be the criterion of the air-gap eccentricity fault.

4. Case Studies and Simulation Results

Take one certain induction motor of air-gap eccentricity fault for example, define s=0.015, $f_1=50HZ$, p=2, for phase A, the current signal is:

$$i_{Af}(t)=10\cos(2\pi f_1 t)+0.2\cos\left[\left(f_1-f_r\right)2\pi t\right]+0.2\cos\left[\left(f_1+f_r\right)2\pi t\right] \quad (6)$$

where $f_r=(1-s)f_1/p$.

The fault current and its Hilbert modulus of phase A shown as Figure 1.

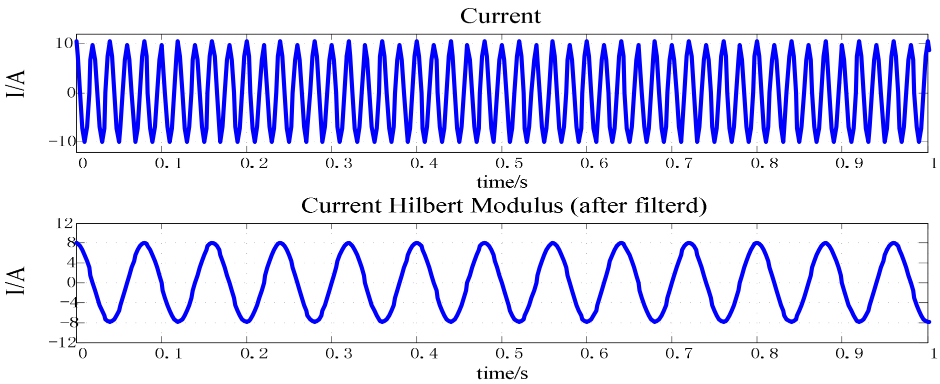

Figure 1 The fault current and its Hilbert modulus of phase A

Analysis the fault current by Hilbert transform according to EMD, once the AC components of the Hilbert modulus signals were filtered, then perform the decomposition by EMD. Figure 2 shows the simulation result.

By decomposition the stator current Hilbert modulus with EMD, four IMFs obtained, the first one is the f_r component. In Figure 3, the analysis is performed during 0~1s, the EMD can accurately decompose the f_r component, which frequency is 24.62Hz, and amplitude is 8. Which almost match the theory calculation, and the deco posited IMF1 component can be used as the criterion of fault. The simulation result demonstrates that: even the “sweep boring” happens to the induction motor; this proposed method can successfully obtain the fault characteristics component, so it has a high precision.

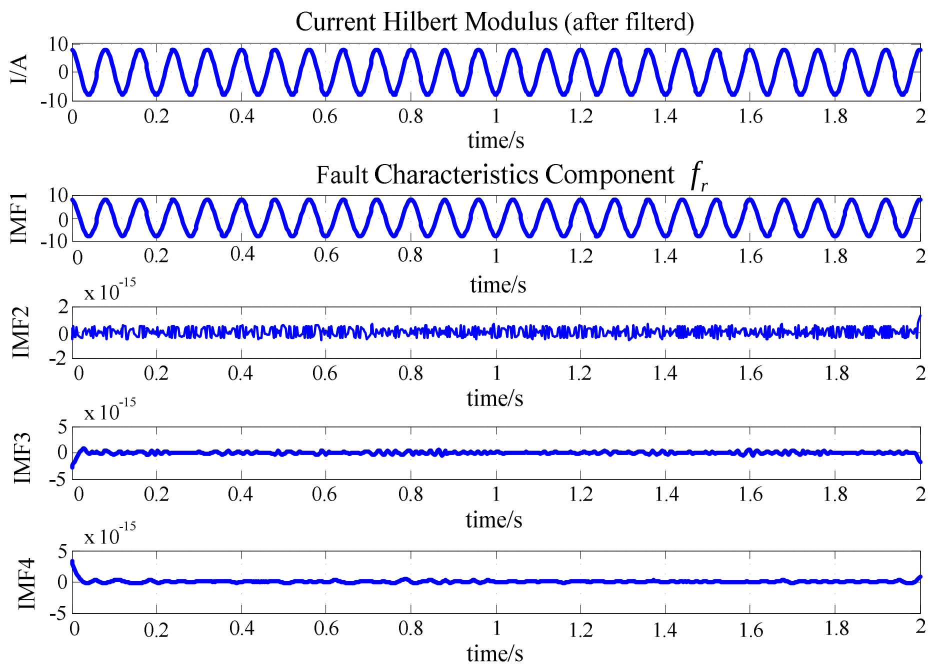

Figure 2. Decomposition of stator current Hilbert modulus

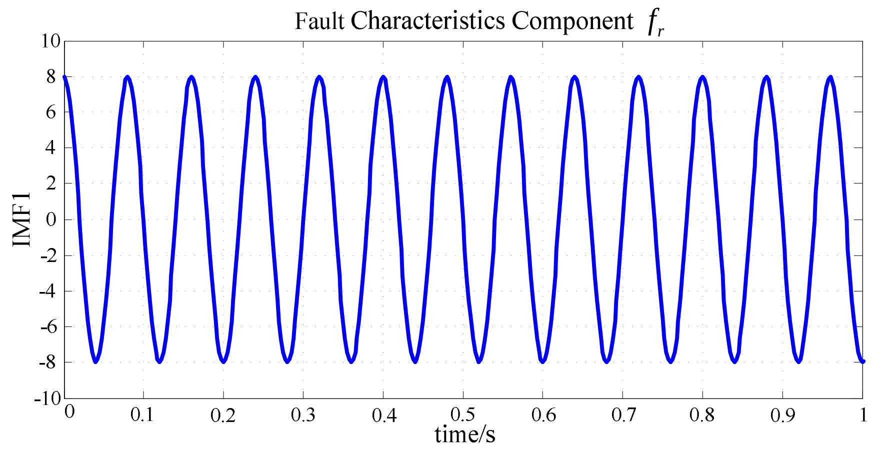

Figure 3 Fault characteristics component f_r

From the results of the simulation experiment, it can be seen that the EMD method is able to solve the problem of mode mixing and achieve better decomposition results than the conventional method. Thus, the proposed method based on EMD is a powerful tool for early rub-impact fault diagnosis in rotating machinery. It is also a promising diagnosis method for other faults occurring in rotating machinery. But, as some experts said, every method has its shortcomings. For the advanced signal processing techniques presently used in fault diagnosis, wavelet transform, spectral kurtosis, analysis, EMD, etc., it is difficult to find one technique is superior to the others in any cases. Generally, aiming at the specific diagnosis problem, the best one may be selected by comparison.

5. Conclusion

Conventional machine fault diagnostic methods use the increase in vibration energy at the broad frequency spectrum or at a selective high-frequency spectrum as a vital indicator in detecting the occurrence of the impacts caused by faulty components. However, it has the problem of mode mixing, so we propose a new method based on EMD to overcome this shortcoming in this paper. EMD is based on the local characteristic time scales of a signal and could decompose the complicated signal into a set of complete and almost orthogonal components named IMF. The IMFs represent the natural oscillatory mode embedded in the signal and work as the basis functions, which are determined by the signal itself, rather than pre-determined kernels. Thus, it is a self-adaptive signal processing method that can be applied to nonlinear and non-stationary process perfectly. The EMD method provides a powerful tool for nonlinear and non-stationary signal analysis.

When the air-gap eccentricity fault occurs, analysis the stator current with Hilbert transform, then the fault characteristics component can be achieved. And through the analysis of Hilbert modulus spectrum of stator current in induction motors by EMD, this proposed method can successfully obtain the fault characteristics component f_r, thus can distinguish the fault characteristics component from the fundamental wave in stator current. And the simulation result showed that the proposed method is able to extract the fault characteristic information and identify the faults effectively. At the same time, it is shown that the proposed method based on EMD obtains a more precise diagnosis result.

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