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Liu, Dehong; Inoue, Hiroshi; Kanemaru, Makoto

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Abstract

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Mitsubishi Electric Research Laboratories, Inc.
201 Broadway, Cambridge, Massachusetts 02139

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Dehong Liu
Mitsubishi Electric Research Laboratories
Cambridge, MA
liudh@merl.com

Hiroshi Inoue, Makoto Kanemaru
Mitsubishi Electric Corporation
Amagasaki, Japan
{Inoue.Hiroshi, Kanemaru.Makoto}@cw.MitsubishiElectric.co.jp

***Abstract*—Motor current signature analysis (MCSA) has been widely used in motor fault detection including bearing fault, broken-bar, and eccentricity, etc. When a motor's fault is in its early stage or a faulty motor is operating in varying load conditions, fault signature may be submerged in the background noise and interference, making fault detection a very challenging problem. In this paper, we address the problem of extracting small fault signature of frequency components under a varying load condition and a noisy background. To this end, we segment the time-domain stator current into overlapped sequences, and treat each sequence as an independent measurement of an imaginary sensor. A minimum variance beam-forming method is then employed to generate the current frequency spectrum with robust performance under varying-load operations. Our method is validated with experimental data collected on a motor with a minor eccentricity fault operating in varying conditions.**

***Index Terms*—Current spectrum analysis, fault detection, varying operation, minimum variance beam forming**

I. Introduction

Motor current signature analysis (MCSA) has been a prevailing method during the past decades for detecting motor faults such as bearing fault, eccentricity, and broken-bar fault, *etc* [1]. When any kind of these motor faults occurs, the rotating flux in the air gap becomes asymmetric, and consequently induces extra frequency components in the stator current. MCSA-based fault detection methods aim to extract fault signatures in the frequency domain by analyzing the stator current.

In practice, the extraction of fault frequency components can be very challenging due to the following reasons. First, motor fault frequency components are generally much weaker than the operating frequency component, especially at the early stage of motor fault development. Second, the weak fault signature can be easily submerged in the background noise or interference. For example, when the motor is driven by an inverter, its fault signature may be interfered by harmonics of the power electronic devices due to their switching operations. Third, motors are generally operating in varying load and varying speed conditions. The non-periodic time varying factor will inevitably introduce spectrum distortion in MCSA. Therefore, it is desirable to develop a robust fault signature extraction method for motors under varying operating conditions to effectively extract fault signatures from noisy measurements.

Frequency spectral analysis is a classic signal processing problem and widely used in all kinds of applications [2]. The most common spectral analysis method in MCSA-based fault detection is the Fourier transform for its simplicity. This method works well in most cases when the motor under test is operating at a steady status, but not very satisfactory for varying-load operations. For varying-load operations, a straightforward way is to measure multiple time sequences and take the average such that the influence of noise and varying operations can be averaged down [3]–[5]. This method however requires longer time measurements and may not work effectively for extracting small fault signatures. Other advanced signal-processing methods such as ESPRIT [6], MUSIC [7], and compressive sensing (CS) [8], *etc*., are introduced by researchers to the motor fault detection community to achieve high-resolved spectrum. However, these methods are either sensitive to noise or heavily relying on the signal model. A low noise level or a small load fluctuation that occurred during the measurement period could interfere the accuracy of fault detection.

Motivated by array signal processing methodologies, we propose to use the minimum-variance beam-forming method [9] to perform motor current spectral analysis. The detailed idea is described as follows. We first segment the time-domain stator current under test into multiple overlapped time sequences with a fixed time shift. Each sequence is treated as an independent measurement of an imaginary current sensor. Since the time difference between adjacent sequences is identical, these imaginary sensors form a linear imaginary sensor array. The spectrum analysis problem is then converted to a beam-forming problem of a linear array in the frequency domain. We borrow the idea of the minimum-variance(MV) beam forming method from array signal processing techniques to improve the detection performance under noisy measurements. Due to the variation of motor operating conditions, each sensor has a different and unknown frequency-dependent gain factor. MV-based spectrum analysis aims to achieve a robust spectrum by using a weighted sum of spectrum of each time sequence, where the weights are frequency-dependent and optimized by minimizing the noise variance of the output spectrum.

To validate our proposed method, we take the motor eccentricity issue as an example to perform MCSA-based fault detection. In particular, a motor with a minor eccentricity fault is considered in our experiments and a magnet powder brake is mounted with the motor as its load. The motor stator current is then measured under various load conditions by changing the input current of the magnet powder brake. By comparing MCSA results on the experimental data using different methods, we demonstrate that our method can effectively extract fault frequency components under varying load conditions even under strong noise interference.

The rest of the paper is organized as follows. Section II introduces motor signatures for different kinds of motor faults. Section III describes frequency spectrum analysis methods, including classic Fourier transform based methods as well as our proposed robust minimum variance based method. Section IV describes our experiment setup and presents our results of MCSA using different methods, with conclusion drawn in Section V.

II. Motor current signature analysis

Motor current signature analysis (MCSA) has been widely used in motor fault detection for decades because of its effectiveness and noninvasive property. Based on the stator current frequency spectrum, MCSA methods aim to extract characteristic frequency components for different types of faults [10].

For example, when there exists a broken bar fault in a squirrel-cage induction motor, a set of new frequency components besides the operating frequency component appear in the spectrum of stator currents [11],

$$f_{bar} = (1 \pm 2ks) f_s, \tag{1}$$

where $k = 1, 2, \ldots$; s is the slip; and f_s is the fundamental supply frequency. MSCA-based broken-bar fault detection techniques focus on detecting the dominant frequency component in the stator current, which is $f_{b1} = (1 - 2s) f_s$.

For bearing fault, depending on the fault location or fault type in the bearing, some periodic vibration pulses are generated as a result of the impact, and consequently a characteristic frequency f_c is induced in the stator current. For different types of bearing fault mentioned above, f_c is listed as follows [12].

Cage defect hits outer race:

$$f_{co} = \frac{f_r}{2}(1 - \frac{d}{D} cos\theta), \tag{2}$$

Cage defect hits inner race:

$$f_{ci} = \frac{f_r}{2}(1 + \frac{d}{D} cos\theta), \tag{3}$$

Outer race defect hits balls:

$$f_o = N_b \frac{f_r}{2}(1 - \frac{d}{D} cos\theta), \tag{4}$$

Inner race defect hits balls:

$$f_i = N_b \frac{f_r}{2}(1 + \frac{d}{D} cos\theta), \tag{5}$$

Ball defect hits both races:

$$f_b = \frac{D}{d} f_r (1 - \frac{d^2}{D^2} cos^2\theta), \tag{6}$$

where f_r is the mechanical frequency of the rotor, d is the ball diameter, D is the pitch or cage diameter, N_b denotes the number of balls, and θ is the contact angle characterizing the point of contact between the ball and the raceway.

For eccentricity fault in most induction machines, the fault signature frequency in the current signal is [13]

$$f_{ecc} = ((kR \pm n_d) \frac{1-s}{p} \pm \nu) f_s, \tag{7}$$

where R is the number of rotor slots, p is number of pole pairs, k is any positive integer, n_d is the eccentricity order ($n_d = 0$ in case of static eccentricity and $n_d = 1, 2, 3, ...$, in case of dynamic eccentricity), and ν is the order of stator time harmonics. Without the number of rotor slots, a simplified version is given by [14], [15]

$$f'_{ecc} = [1 \pm m(\frac{1-s}{p})] f_s = f_s \pm m f_r, \tag{8}$$

where $f_r = \frac{1-s}{p} f_s$ is the rotor frequency related to the rotational speed.

Therefore, for most motor fault detection problems, the objective of MCSA-based methods is to extract the corresponding fault signature components via effectively frequency spectral analysis. Once a fault frequency component over a certain threshold is detected, it is claimed that there exists a corresponding fault. The fault severity level can be further estimated depending on the magnitude of the fault frequency component as well as other operating conditions.

III. Frequency spectrum analysis

A. *Classic frequency spectrum analysis*

Frequency spectrum analysis is a classic problem in signal processing. Let $i_s(t)$ represent the time-domain stator current of a motor in an ideal steady-state operation. Note that the current could be a single phase current or a combination of three phase current after proper phase alignment such as Park transform. For the healthy motor, the time-domain stator current can be represented as

$$i_{sh}(t) = I_s \cos(2\pi f_s t + \phi_s), \tag{9}$$

where I_s is the stator current amplitude related to the motor load condition, f_s is the operating frequency, and ϕ_s is the initial phase of the operating frequency component.

When there exists a motor fault, the motor current signal includes extract frequency components

$$i_{sf}(t) = i_{sh}(t) + \sum_k I_{f,k} \cos(2\pi f_{f,k} t + \phi_{f,k}), \tag{10}$$

where $I_{f,k}$ represents the magnitude of the k^{th} fault frequency component $f_{f,k}$, as mentioned in Sec. II , and $\phi_{f,k}$ is the initial phase of the k^{th} fault frequency component.

The frequency spectrum of the stator current i_s ($= i_{sh}$ or i_{sf} depending on the health condition) can be achieved by the Fourier transform as

$$I_s(\omega) = \int i_s(t)e^{-j\omega t}dt. \tag{11}$$

For periodic signals in motor operations, a discrete Fourier transform (DFT) is typically used to compute the Fourier spectrum based on discrete time samplings $i_s(n)$. We ignore the detailed correspondence between the frequency and the sampling rate, and simplify the expression of Fourier spectrum as

$$\hat{S}_F(\omega) = DFT[i_s(n)]. \tag{12}$$

B. Spectrum analysis under varying conditions

Note that the fault signature component is typically very weak compare to the operating signal, and the value of $I_{f,k}$ could be $40dB$ to $60dB$ lower than that of I_s, depending on the fault type and the fault severity. Therefore, it is very common that the fault signature component is interfered by the operating signal or other noise, especially under varying operating conditions.

Under varying load conditions, the stator current amplitude I_s is not a constant any more, but varying with the load condition. In such situations, the performance of fault detection via simple DFT will be degraded since the small fault component could be submerged into the background noise. To effectively analyze the stator current spectrum, we introduce a parameter $\alpha(t)$ to reflect the impact of varying load, and express the practical measurement of time-domain stator current as

$$i(t) = \alpha(t) \otimes i_s(t) + \nu(t), \tag{13}$$

where $\alpha(t)$ is a time-domain function showing the impact of varying load, $\nu(t)$ is measured noise, and $\otimes$ is the convolution operation. In the frequency domain, we have

$$I(\omega) = A(\omega)S(\omega) + V(\omega), \tag{14}$$

where $I(\omega)$ and $S(\omega)$ stand for the Fourier spectrum of $i(t)$ and $i_s(t)$ respectively. Our objective is then to estimate $S(\omega)$ from measurement $i(t)$ such that the fault signature in $S(\omega)$, if there is any, can be extracted effectively.

A straightforward way to estimate $S(\omega)$ is to average multiple spectra to reduce the impact varying load. Assume that we have a serial of N equal-length time sequences $\{i_1(t), i_2(t), ..., i_n(t), ..., i_N(t)\}$. The frequency spectrum of each sequence can be represented by

$$\begin{aligned} I_n(\omega) = & \int i_n(t)e^{-j\omega t}dt \\ \approx & A_n(\omega)S_n(\omega) + V_n(\omega). \end{aligned} \tag{15}$$

Note that $A_n(\omega)$ is the Fourier spectrum of $\alpha_n(t)$ due to varying loads as mentioned before. Specially, when the motor is operating at steady status with a constant load and a constant speed, $A_n(\omega)$ is a constant. Otherwise, $A_n(\omega)$ varies due to the varying operation. The averaged spectrum is given by

$$\hat{S}_{avg}(\omega) = \frac{1}{N}\sum_n |I_n(\omega)| = \frac{1}{N}\sum_n |A_n(\omega)S_n(\omega) + V_n(\omega)|. \tag{16}$$

C. Robust spectrum estimation

To make use of array signal processing techniques, we generate N time sequences $\{i_1(\tau), i_2(\tau), ..., i_n(\tau), ..., i_N(\tau)\}$ by putting a sliding time window on the measured current $i(t)$, where the n^{th} time sequence $i_n(\tau)$ can be expressed as

$$i_n(\tau) = i(\tau + (n-1)t_s), \quad \text{for} \quad \tau \in [0, t_w], \ n = 1, ..., N. \tag{17}$$

Here t_w is the window size in time, and t_s is the time step between two consecutive time windows. The frequency spectrum of each segment can be represented by the spectrum of the first sequence with proper phase shift as

$$\begin{aligned} I_n(\omega) = & \int i_n(\tau)e^{-j\omega\tau}d\tau \\ \approx & A_n(\omega)S_n(\omega) + V_n(\omega) \\ = & A_n(\omega)e^{j\omega(n-1)t_s}S_1(\omega) + V_n(\omega). \end{aligned} \tag{18}$$

With proper phase compensation, we combine all N spectra to form the stator current spectrum in the frequency domain as

$$\hat{S}_{MV}(\omega) = \sum_{n=1}^{N} \beta_n(\omega)I_n(\omega)e^{-j\omega(n-1)t_s}, \tag{19}$$

where the weight β_n is optimized by minimizing the noise variance of spectrum at each frequency ω

$$\min_{\beta_n} \sum_n |\beta_n(\omega)I_n(\omega)e^{-j\omega(n-1)t_s}|^2, \quad s.t. \quad \sum_n \beta_n(\omega) = 1. \tag{20}$$

Let $\mathbf{w} = [\beta_1(\omega), ..., \beta_n(\omega), ..., \beta_N(\omega)] \in \mathcal{R}^{N\times 1}$, $\mathbf{R} = diag\{I_1^2(\omega), ..., I_n^2(\omega), ..., I_N^2(\omega)\} \in \mathcal{R}^{N\times N}$, and $\mathbf{a} = [1, ..., 1, ..., 1]^T \in \mathcal{R}^{N\times 1}$. Then the optimization problem in (20) is reformulated as a standard minimum-variance beamforming problem [9]

$$\min_{\mathbf{w}} \mathbf{w}^T\mathbf{R}\mathbf{w} \quad s.t. \quad \mathbf{w}^T\mathbf{a} = 1. \tag{21}$$

The closed-form solution of (21) is given by

$$\mathbf{w} = \frac{\mathbf{R}^{-1}\mathbf{a}}{\mathbf{a}^T\mathbf{R}^{-1}\mathbf{a}}. \tag{22}$$

Note that $\mathbf{w}$ is frequency dependent, meaning for each frequency we solve (22) to get a different $\mathbf{w}$.

IV. Experiments

A. Setup

To validate our proposed method, eccentricity fault is considered as an example for MCSA-based analysis. Experiments are carried out in lab using a motor with eccentricity fault. In order to generate eccentricity of the rotor, two bearings that support the rotor are taken out and replaced by two external ones fixed outside the motor such that the air gap can be manually adjusted within a certain range. Four gap sensors are placed in the stator part to monitor the horizontal and vertical air gaps at both ends to make sure the accuracy of adjustment. A magnetic powder brake is used as the load whose torque can be tuned by changing its input operating current. A picture of our experiment setup is shown in Fig. 1. The whole motor drive system is enclosed in a clear cage for safety purpose. During operation, the three-phase time-domain stator current is recorded for further analysis.

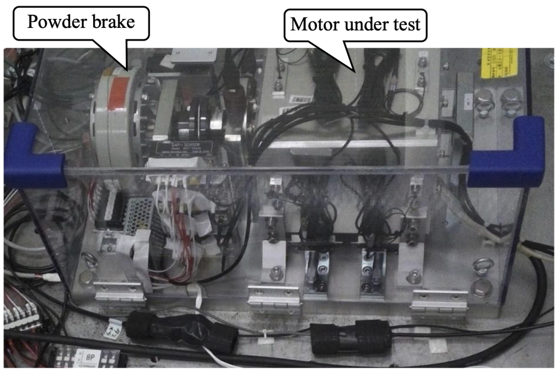


Fig. 1. Experiment setup

To simulate early stage eccentricity fault, we set the eccentricity level to 3%, where the eccentricity level is defined by

$$y_j = \frac{d_j}{\delta_0} \times 100\%, \tag{23}$$

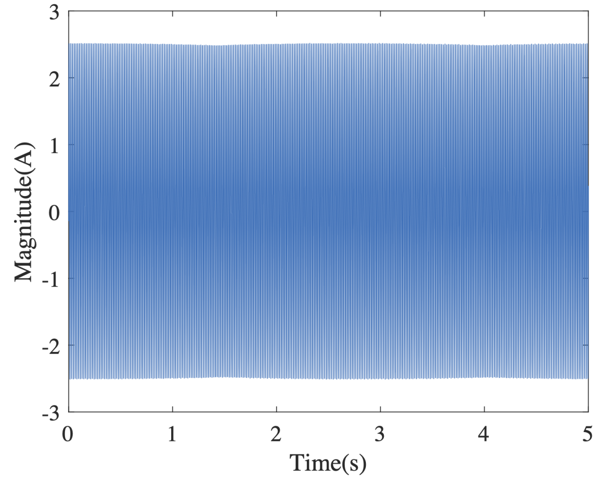
where d_j is the distance between the actual rotor axis and the ideal rotor axis, and δ_0 is the average air gap length in the corresponding healthy motor.

Experiments are conducted under various load conditions by adjusting the input operating current of the magnetic powder brake.

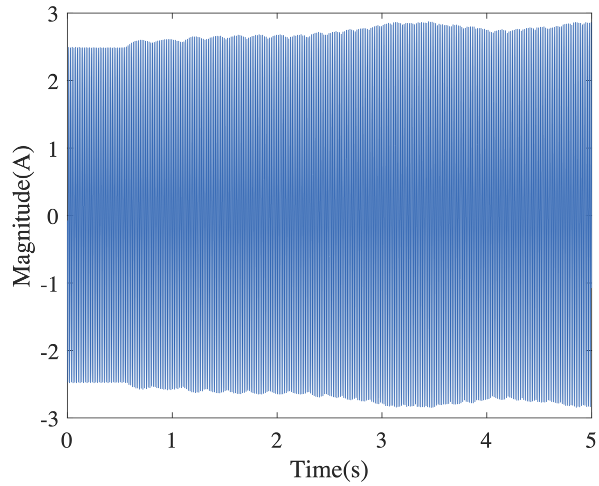
B. Results

We collect stator current of 60s with sampling rate $f_{sa} =$ 10kHz for different load conditions. Fig. 2 plots two examples of collected time-domain stator current data when we have a constant load and a varying load respectively. We observe that the amplitude of the current under the constant load condition is relatively flat, while varies greatly in varying load conditions. It is of great interest but challenging to extract the fault signature from the stator current with varying amplitude.

To extract the fault frequency components, we consider multiple spectral analysis methods mentioned in Sec. III. To achieve multi-sequence data, we segment the 60s time sequence data into $t_w = 4$s sequences with time step $t_s = 0.02s$. For comparison, we show in Fig. 3 the Fourier transform(FT) spectrum $\hat{S}_F(\omega)$, the averaged spectrum $\hat{S}_{avg}(\omega)$, and the minimum variance (MV) spectrum $\hat{S}_{MV}(\omega)$ for different load conditions. We can observed that the FM spectrum failed to detect the fault signature under varying load conditions. While the averaged spectrum reduces noise to some extent and works well in some cases but not consistently, the MV spectrum achieved by our proposed method consistently detects the fault signature components successfully for different varying loads, which in our case are 30Hz and 90Hz frequency components for eccentricity.



(a) constant load

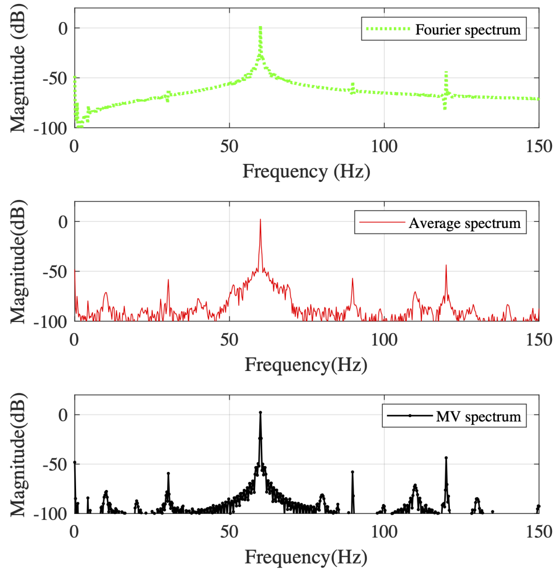


(b) varying load

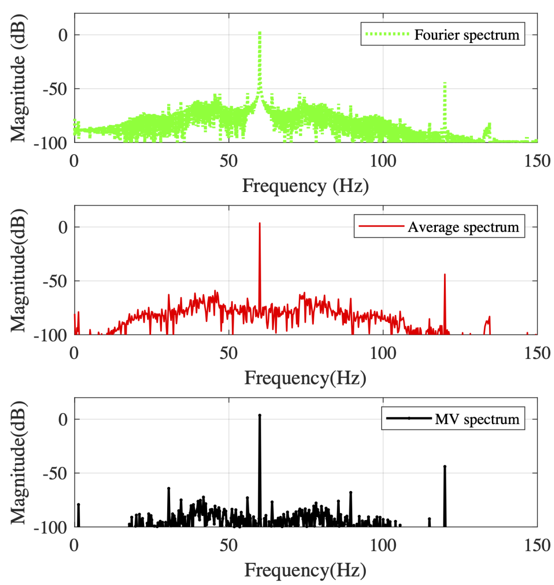
Fig. 2. Stator current time series.

V. Conclusion

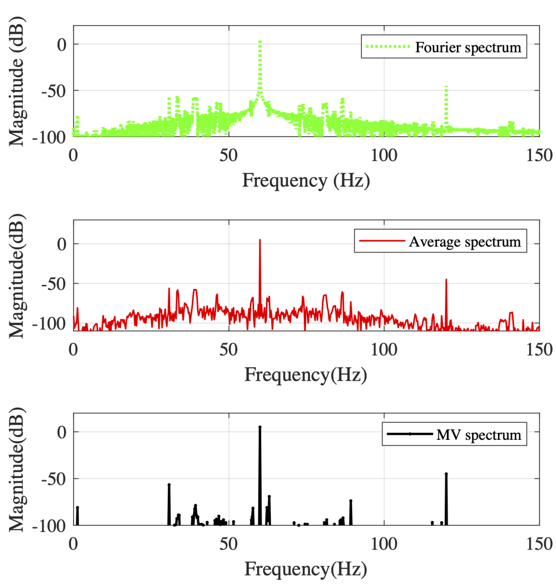
In this paper, we proposed a minimum variance based method to analyze the frequency spectrum of the stator current for detecting faults of motors under varying operation conditions. Experimental results demonstrate that our method can effectively extract fault signatures of the early stage eccentricity fault from noisy stator current measurements even for the motor operating in varying load conditions. Our method can be applied to other MCSA-based methods and to extract other fault signatures in the frequency domain.



(a) Random varying load



(b) Load with 0.3A powder brake current



(c) Load with 0.35A powder brake current

Fig. 3. Comparison of motor current spectra under varying load operations.

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