Autoregressive Modeling Based Bearing Fault Detection in Induction Motors

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Abstract— **This study investigates the performance of autoregressive (*AR*) modeling method to detect bearing fault in induction motor. For this purpose, *AR* models of current and vibration signals which are acquired during the load performance tests of healthy and faulty induction motor are established. The variation of *AR* model order with *AR* coefficients, the residuals computed as the difference between original signals and their *AR* representation, and the error computed as the difference between spectra of the original signals and their *AR* models are compared for healthy and faulty cases of the motor. It is obtained that variance of *AR* model coefficients for both current and vibration signals is increased in faulty case. Also *AR* modeling error is large for faulty vibration signal both in time domain and frequency domain.**

Keywords-Autoregressive modeling; Bearing fault; Feature extraction; Induction motor; Spectral analysis.

I. INTRODUCTION

Induction motors are one of the frequently used electrical drives in industrial processes and predictive maintenance of these motors is an important issue to ensure safe, reliable and economic operation of the industrial processes. The information related to fault features have to be known previously to take necessary and timely maintenance actions. The statistical studies on the distribution of failure causes of induction motors have shown that 41% of failures are caused from bearing related faults. This is the highest percentage among other type of faults such as stator related and rotor related faults [1-4].

For predictive maintenance studies it is necessary to know fault features. To extract bearing fault features, signal based methods such as statistical and spectral analysis techniques are used frequently. In these methods fault features are investigated on the acquired data and compared with their baseline values [2-8].

Autoregressive (*AR*) modeling is a parametric signal based method which models the signal using its previous values and an error term. In this study, *AR* models of the current and vibration signals are established using the data acquired from healthy and faulty induction motor. Variation of model coefficients, modeling errors and spectra of original and its *AR* model are compared to investigate effectiveness of *AR* modeling technique for detecting bearing fault.

II. AUTOREGRESSIVE MODELING

A wide sense *AR* process of order p may be generated by filtering unit variance white noise, $v(n)$ with an all-pole filter shown in Fig. 1 [9,10].

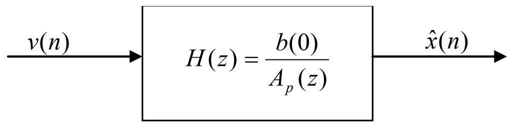

Figure 1. Modeling a random process.

The filter can be defined by a difference equation and transfer function as below

$$x(n)+\sum_{k=1}^{p} a_p(k)x(n-k)=b(0)v(n) \quad (1)$$

$$H(z)=\frac{b(0)}{A_p(z)}=\frac{b(0)}{1+\sum_{k=1}^{p} a_p(k)z^{-k}} \quad (2)$$

The filter coefficients that produce the best approximation $\hat{x}(n)$ to $x(n)$ are determined using the autocorrelation sequence of the *AR* process satisfying the Yule-Walker equations, which are

$$r_x(k)+\sum_{l=1}^{p} a_p(l)r_x(k-l)=\left|b(0)^2\right|\delta(k) \quad ; \quad k\geq 0 \quad (3)$$

Where $\delta(k)$ is the unit sample sequence. Therefore, given the autocorrelations $r_x(k)$ for $k = 0,1,\ldots, p$ these equations can be solved for the *AR* coefficients $a_p(k)$. This approach is referred to as Yule-Walker method. The coefficient $b(0)$ in the *AR* model is determined by

$$\left|b(0)^2\right|=r_x(0)+\sum_{k=1}^{p} a_p(k)r_x(k)\cdot \quad (4)$$

And $r_x(k)$ is a statistical autocorrelation which is unknown in most applications and estimated from a sample realization of the process. Given $x(n)$ for $0 \le n \le N$, where N is the number of samples, $r_x(k)$ is estimated using the sample autocorrelation

$$\hat{r}_x(k) = \frac{1}{N}\sum_{n=0}^{N-1} x(n)\, x(n-k)\,. \qquad (5)$$

III. Experimental Data

Bearing fault is formed artificially by the shaft current technique which includes running the motor for 30 minutes with the motor rotating at no load and externally applied shaft current of 27 A at 30 V alternating current. This form of damage is called as fluting damage, and bearing components get damaged caused by electrical sparking [3,4].

The current and vibration signals analyzed in this study are obtained by the experimental setup and data acquisition system shown in Fig. 2 in order to get fault characteristics. Here the test motor is put on a motor performance test platform and the measurements are taken. During this test procedure, the motor current and vibration data with a sampling frequency of 12 kHz is acquired at 100 % load condition for the healthy and faulty cases of the motor. Vibration measurement is taken by the accelerometer which is closer to the bearing at process-end side of the motor.

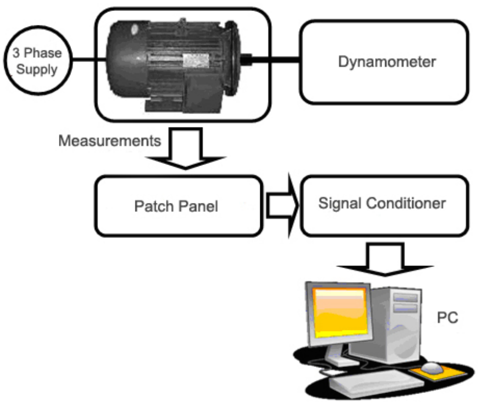

Figure 2. Motor load testing and data acquisition system.

IV. Extraction Of Bearing Fault Characteristics

In order to search fault characteristics related to bearing fault, *AR* modeling technique which represents the signal as a linear combination of its previous values and an error term is applied to the stator current signal and vibration signal which is acquired from the healthy and faulty cases of motor. *AR* model order is determined according to Akaike's Information Criteria (*AIC*) as follows.

$$AIC(p) = N\log(RSS/(N-p-1)) + 2p$$

where *RSS* is the residual sum of squares defines as

$$RSS = \sum_{n=0}^{N-1}\left[x(n) - \hat{x}(n)\right]^2 \,.$$

Here N denotes the number of samples and it is taken as 3000 samples which correspond to a measurement time of 0.25 s. Fig. 3 shows the variation of *AIC* values as a function of model order for current and vibration data for healthy and faulty cases of the motor. The model order which makes $AIC(p)$ minimum is given in the Table I.

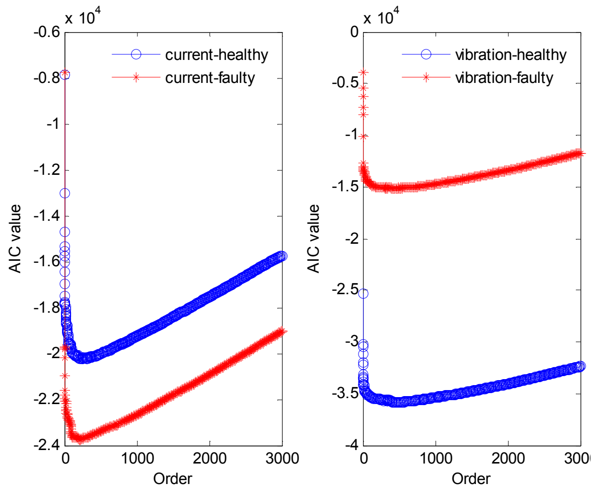

Figure 3. Variation of *AIC* values with *AR* model order.

TABLE I. Determination of Model Order

	Healthy	Faulty
Current	214	211
Vibration	459	414

Fig. 4 shows the variation of *AR* coefficients for the model orders given in Table I.

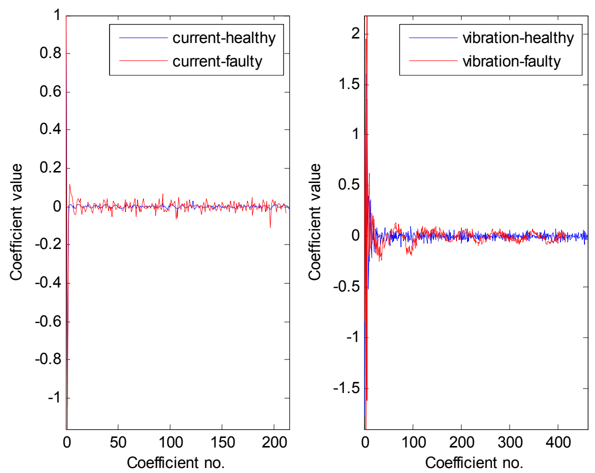

Figure 4. Variation of *AR* coefficients.

From Fig. 4 it is clearly noticeable that the variances of *AR* coefficients are increased from the healthy case to faulty case for both current and vibration data. These values are given in

Table II. From this table it can be concluded that variance of *AR* model parameters can be an indicator of the bearing fault.

TABLE II. VARIANCES OF *AR* COEFFICIENTS

	Healthy	Faulty
Current	0.0098	0.0118
Vibration	0.0244	0.0494

After the determination of model order and *AR* model coefficients, the signals are predicted. Fig. 5 shows original signal, its *AR* model and the error between them for the healthy and faulty motor current signals. The same values are shown for the vibration signals as seen in Fig. 6.

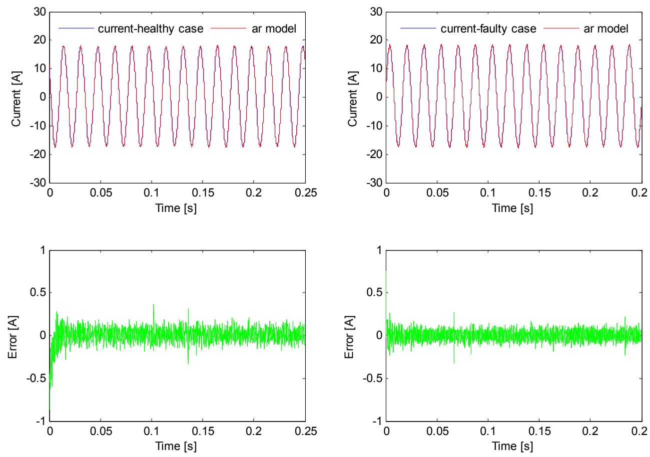

Figure 5. Original current signals and their predictions using *AR* method for healthy and faulty cases of motor (upper plots), and the residuals computed as the difference between them (lower plots).

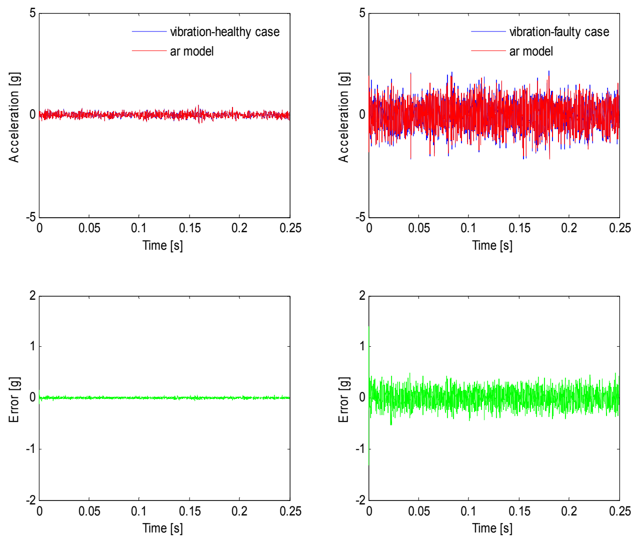

Figure 6. Original vibration signals and their predictions using *AR* method for healthy and faulty cases of motor (upper plots), and the residuals computed as the difference between them (lower plots).

From the time domain plots shown in Fig. 5 it is seen that the error range is same between healthy and faulty case of motor, however, from Fig. 6 it is seen that modeling error is increased in comparison to healthy case vibration data. This can be considered another fault indicator of bearing fault. The modeling error is bigger resulting from the damaged bearing.

Fig. 7 and Fig. 8 show the Power Spectral Density (*PSD*) variations of original current and vibration signals and their AR models. In the frequency domain plots the error which is computed as the absolute difference between *PSD* of original signal and *PSD* of its *AR* model is shown.

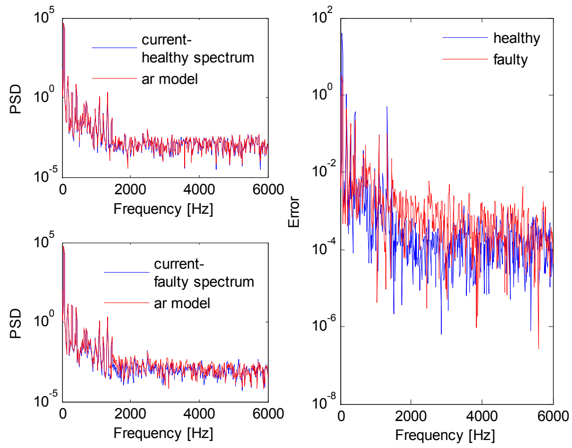

Figure 7. *PSD*s of original current signals and *PSD*s of their predictions using *AR* method for healthy and faulty cases of motor (left plots), and the error computed as the difference between them (right plot).

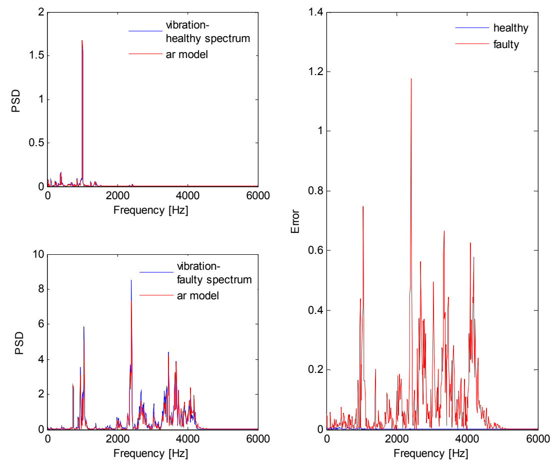

Figure 8. *PSD*s of original vibration signals and *PSD*s of their predictions using *AR* method for healthy and faulty cases of motor (left plots), and the error computed as the difference between them (right plot).

From Fig. 7 it is seen that there is a small difference between the errors in the spectrum of current signals. Therefore this small difference may not be sufficient enough to detect the fault. On the other hand from Fig. 8 it is seen that the error is very small for the healthy case, but for the faulty case the error is very large especially in higher frequency region of the spectrum. From the related literature it is known that bearing fluting damage shows itself in a frequency range of 1.5-4 kHz in the spectrum of vibration signal which is compatible with the results in this study.

V. CONCLUSIONS

In this study effectiveness of autoregressive (*AR*) modeling method is investigated for extracting bearing fault characteristics. *AR* models of motor stator current and vibration signals are determined for healthy and faulty cases of the induction motor which has bearing damage. The results can be given as follows:

- The variances of *AR* coefficients are increased in faulty case for both current and vibration signals.
- Time and frequency domain analysis of current signals does not give sufficient information to detect damage.
- Both time domain and frequency domain analysis of original vibration signals and their *AR* models give noticeable difference to detect bearing fault. To show this difference, the residuals are computed as the difference between original vibration signal and its prediction by AR method. It is seen that the residuals computed in time domain for the faulty case are much bigger than the healthy case. Also in the frequency domain, the error computed as the absolute difference between the spectrum of original vibration signal and the spectrum of its *AR* model for health and faulty case is much bigger in the higher frequency region of the spectrum. In other words, AR modeling of vibration signals for the faulty case is not as good as the one for the healthy case. Hence, it can be said that this difference are resulted from the bearing fault.

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