OFF-LINE METHODS FOR FAULT DIAGNOSIS AND INSPECTION

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Contents

Summary

Fault diagnosis is a mean to detect and isolate faults of a technical system. The off-line method provides the advantage that the excitation of the system can be chosen freely and is not limited to the normal working conditions of the system. The off-line fault diagnosis is usually applied to the quality control and inspection. Two methods of fault diagnosis are presented: The parameter estimation and the pattern recognition.

The efficient excitation of the system and its optimal modeling are the most important tasks for parameter estimation. The feature selection is very important for the pattern recognition. The feature extraction process reduces the information content of the measured signals to a necessary amount. A feature extraction with bad features destroys the information, which cannot be recovered.

Simulation helps to understand the behavior of a system. The simulation provides a quality measure for the model, which is useful for the parameter estimation. In case of faults in bearings the simulation provides the spectrum of the vibrations produced by the fault. That helps to select the right frequency lines (i.e., features) for the fault classification. The simulation of the current ripple shows the dependence of features on

the fault and its severity. Simulation is also most important for the design of a fault diagnosis system. Powerful methods are necessary, especially for an automatic design, because it becomes more and more difficult to get qualified test personal that are able to adjust a sophisticated test bench properly.

1. Introduction

The objective of the fault diagnosis is a fast and reliable test that includes the detection of faults and their kind and location in all parts of a technical system. The fault diagnosis is made on-line and off-line. The method of the fault diagnosis will be called on-line if the system is running under working conditions at its area of service (see *Industrial Applications of Fault Diagnosis*).

The fault diagnosis will be called off-line if the system is tested or diagnosed during maintenance hours in its area of service (see *Fault Diagnosis of Linear systems*) or it is tested in a special test bench. The latter is also called testing for quality control or inspection. In the case of quality control of electric motors in a production line, for instance, it is not necessary to connect the motor to any load. The motor is only connected to a power supply.

The voltage can be an arbitrary function, which is freely chosen, taking care of the motors physical limits, only. The necessary signal analysis and calculations on a computer are not made in real-time. During the time the next motor is fed into the test bench and is measured, the signals of the previously measured motor are analysed. This is an important advantage of the off-line methods for fault diagnosis. The test bench for the diagnosis of such a system under test (s.u.t.) should have the following properties:

- no external mechanical load
- easily measurable signals
- simple sensors
- efficient signal processing
- low power consumption
- fast signal processing
- short test time

Off-line methods for the fault diagnosis will be explained in detail. Electric motors are used as s.u.t., but it is possible to apply these methods to the fault diagnosis of other technical systems, too.

Electric fractional horsepower motors are used in automobiles, household appliances and other equipment. They are DC motors with permanent magnets, universal motors and 1-phase induction motors. Motors of higher power are 3-phase induction motors. The inspection of these motors is an important part of the quality control in a production line.

The goal is a fast and reliable test that includes the detection of faults and their location in all parts of the motor. Two test procedures are common: the parameter estimation and the acoustic or vibration test.

- The parameter estimation provides the nominal values of resistance, inductance and flux, as well as friction, speed and power. The test can either be carried out in a conventional test bench with a mechanical brake or with no load using the parameter estimation approach.

- The acoustic or vibration test gives evidence whether the acoustic noise of the motor is acceptable. Although the coupling of the accelerometer to the motor or the acoustic noise of the environment reaching the microphones still make it difficult to get reproducible diagnostic results, the processing of vibration and acoustic signals are widely used in quality assurance of the mass produced motors. The measurement of the current ripple of d.c. and a.c. motors provides also information whether the motor has a fault or not. Fault diagnosis uses all three types of signals. The signal processing includes methods like the pattern recognition, too. Features are extracted from the measured signals and the features are classified into the no-fault class and several fault classes.

A very successful approach to fault diagnosis is the parity space analysis. The parity space analysis (residual analysis) is nearly similar to the parameter estimation approach to fault diagnosis. Instead of parameters, state estimates are used: a set of measured variables y(k) of the actual system is compared with the corresponding signals of the nominal model, $\hat{\mathbf{y}}$(k). The difference $y(k) - \hat{y}(k) = \varepsilon(k)$ is the residual vector and is an element of the parity space. (see *Fault diagnosis for Linear Systems*, *Design Methods for Robust Fault Diagnosis*). The method will be beyond the scope of this article.

An important task is the modeling of the s.u.t. It is essential for parameter estimation because the s.u.t. is described by a mathematical model. In case of pattern recognition, modeling helps to understand the development of signals like noise or current ripple.

2. Parameter Estimation

The parameter estimation is accomplished with the least squares algorithm. This algorithm can be applied to continuous time or discrete time models. The advantage of parameter estimation based on continuous time models, in contrast to the time discrete ones, is that the physical significance of the parameters is given. Technical processes are described by linear systems, non-linear systems and linear-in-parameter (l.-i.-p.) models. Optimization is used to solve models that are not linear in parameters. The direct least squares algorithm can be applied to l-i-p systems. This approach is easily implemented and of minor computational expense. It will be preferred here.

Suppose a differential equation with constant coefficients. The input- and output-signals are measured and their derivatives exist. If an error $\varepsilon(t)$ is introduced, the equation of the model will be

$$y(t) = \mathbf{M}^{'}(t) \cdot \hat{\mathbf{a}} + \varepsilon(t) \tag{1}$$

with the measurement matrix $\mathbf{M}^{'}(t)$ also containing the derivatives of the input- and output-signals

$$\mathbf{M}^{'}(t) = \left[-y^{(1)}(t) .... -y^{(n)}(t) \vdots u(t) .... u^{(m)}(t) \right] \tag{2}$$

The parameter vector is

$$\hat{\mathbf{a}} = [\hat{a}_1 ... \hat{a}_n \vdots \hat{b}_0 ... \hat{b}_m]' . \tag{3}$$

Sampling of the signals and their derivatives at times t=kT with k=0,1,2...N leads to N+1 equations that can be written in matrix notations

$$\mathbf{y} = \mathbf{M} \cdot \hat{\mathbf{a}} + \mathbf{e} \tag{4}$$

Minimization of

$$S = \mathbf{e}^{\mathbf{T}} \cdot \mathbf{e} = \sum_{k=0}^{N} e^2(k) \tag{5}$$

provides the parameter vector

$$\hat{\mathbf{a}} = (\mathbf{M}^{'} \cdot \mathbf{M})^{-1} \cdot \mathbf{M}^{'} \cdot \mathbf{y} \tag{6}$$

$\mathbf{M}^{'}$ contains derivatives of the measured signals. These derivatives must be calculated from the signals. A numerical differentiation causes problems as it increases the noise at higher frequencies. The “modulating function” was successfully applied in practice. The modulating function and its derivatives are orthogonal functions within an interval t $\in$[0,T].

$$\begin{aligned} \mathbf{m(t)} &= \left[m_0(t), m_1(t), ..., m_n(t) \right]' \\ &= \left[m_0(t), -m_0^{(1)}(t), ..., (-1)^n m_0^{(n)}(t) \right] \end{aligned} \tag{7}$$

The model equation

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathbf{u}, \mathbf{a}) \tag{8}$$

with the state vector **x**, the input vector **u** and the parameter vector **a** is still valid when the modulating functions and their derivatives are convolved with the related signals and derivatives, respectively

$$\mathbf{m} * \dot{\mathbf{x}} = \mathbf{m} * \mathbf{f(x,u,a)} \tag{9}$$

As **m** $\neq$ 0 only within [0,T]

$$\dot{\mathbf{m}} * \mathbf{x} = \mathbf{m} * \mathbf{f(x,u,a)}$$

or

$$\dot{\mathbf{m}} * \mathbf{x} = \mathbf{m} * \dot{\mathbf{x}} \tag{10}$$

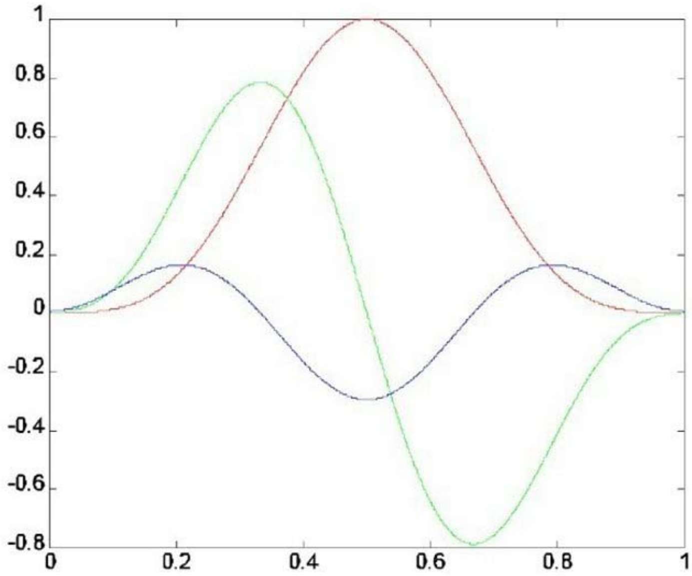

Figure 1. Modulating Functions

The modulating function, which contains no noise, is differentiated instead of the measured signals. This approach provides parameters of smaller bias than a numerical differentiation would deliver. Figure 1 shows a modulating function (Blackman-window) and its first and second derivatives.

Another interesting approach to the parameter estimation uses the least squares algorithm in the frequency domain instead of the time domain. The type of the excitation signal is quite free for off-line fault diagnosis. Therefore the excitation can be a periodic signal as well. A periodic signal can be easily transformed into the frequency domain without leakage effects if its frequency is known.

The starting point for the least squares solution in the frequency domain is again the model description added with an error signal e(t)

$$y(t) = \sum_{i=1}^{n} a_i x_i(t) + e(t) \tag{11}$$

If the signals are periodical, as mentioned before, they can be developed into Fourier series:

$$y = \sum_{k=0}^{\infty} \left[y_{ks} \sin(k\omega_0 t) + y_{kc} \cos(k\omega_0 t) \right]$$

$$x_j = \sum_{k=0}^{\infty} \left[x_{jks} \sin(k\omega_0 t) + x_{jkc} \cos(k\omega_0 t) \right] \tag{12}$$

where y_{ks}, y_{kc}, x_{jks}, x_{jkc} are Fourier coefficients. Substitution of the Fourier series (12) into normal equations with respect to the orthogonality principle gives

$$\frac{1}{2}\sum_{k=1}^{\infty} y_{ks} x_{iks} + \frac{1}{2}\sum_{k=1}^{\infty} y_{kc} x_{ikc} + y_0 x_{ioc} - \sum_{j=i}^{M} \alpha_i \left(\frac{1}{2}\sum_{k=i}^{\infty} x_{jks} x_{iks} + \frac{1}{2}\sum_{k=1}^{\infty} x_{jkc} x_{ikc} + x_{j0c} x_{i0c} \right) = 0$$

The next step is to simplify the normal equation for the determination of the coefficients by a complex notation

$$y_k = \frac{1}{\sqrt{2}} y_{kc} - j\frac{1}{\sqrt{2}} y_{ks} \quad for\ k \geq 1; \quad y_0 = y_{0c}$$

$$x_{ik}^* = \frac{1}{\sqrt{2}} x_{ikc} + j\frac{1}{\sqrt{2}} x_{iks} \quad for\ k \geq 1; \quad x_{i0} = x_{i0c}$$

$$x_{ik} = \frac{1}{\sqrt{2}} x_{ikc} - j\frac{1}{\sqrt{2}} x_{iks} \quad for\ k \geq 1; \quad x_{i0} = x_{i0c} \tag{13}$$

According to the complex notation, the normal equation becomes

$$\sum_{k=0}^{\infty} \left[\mathrm{Re}\left[y_k x_{i\,k}^* \right] - \sum_{j=1}^{M} a_j \,\mathrm{Re}\left[x_{jk} x_{i\,k}^* \right] \right] = 0 \tag{14}$$

In matrix notation it is

$$\mathrm{Re}\left[\underline{x}' \underline{y}^* \right] - \mathrm{Re}\left[\underline{x}' \underline{x}^* \right] \cdot \underline{a} = 0 \tag{15}$$

Note that the matrices X, X* and Y contain complex notations of spectral lines. Equation (15) can be expressed as

$$\underline{\hat{a}} = \left[\mathrm{Re}\left(\underline{x}' \underline{x}^* \right) \right]^{-1} \cdot \left[\mathrm{Re}\left(\underline{x}' \underline{y}^* \right) \right] \tag{16}$$

X^{-1} means the inverse of X, X‘ is the transpose. X* is the conjugate complex and Re( ) the real part of the elements. This algorithm is very similar to the least squares solution in the time domain. The necessary differentiation is a simple operation. According to the Fourier series equation (12) one obtains

$$\frac{dx}{dt}(t) = \sum_{k=0}^{\infty} - k\omega_0 x_{kc} \sin(k\omega_0 t) + k\omega_0 x_{ks} \cos(k\omega_0 t) \tag{17}$$

This operation in which cosine and sine terms were derived is very easy. Thus, differentiation in the frequency domain is achieved with the following simple operations

$$\frac{dx_{ks}}{dt} = -k\omega_0 x_{kc} \qquad \frac{dx_{kc}}{dt} = -k\omega_0 x_{ks} \tag{18}$$

The calculation of non-linearity, like the product of state variables, produces spectral lines at the sum and the difference of the frequencies of the original variables frequencies. Thus, the calculation is a multiplication of amplitudes only. It is noted here that these operations have to be carried out for all relevant complex spectral lines.

2.1. Modeling the System under Test

The models that are used for the parameter estimation are parametric models. Due to simple mathematics, there is the assumption that the models are linear in the parameters and time invariant. For the parameter estimation, the models must describe the technical process very precisely. If the description is not perfect a serial correlation can exist in the residuals, in addition to a correlation of the residuals with the excitation. These model errors make the fault isolation difficult.

The modeling will be demonstrated on the example of a low power DC motor. A first approach to developing appropriate models for the respective process (motor) is to describe the physical relations of the process. For a low power DC motor with permanent magnets, two equations are usually given.

Model A:

$$v = R \cdot i + c_1 \cdot \omega \qquad (19)$$

$$\frac{d\omega}{dt} = \frac{c_2}{J} \cdot i - \frac{c_3}{J} \cdot \omega \qquad (20)$$

The first equation describes the voltage balance where v represents the voltage, R the resistance, i the current, c_1 the flux, and ω the angular velocity of rotation. Normally the voltage drop of the brushes and voltage drop across the inductance of the coil are taken into account. But in a small power motor these terms are very small or can be made small by low frequency excitation, and they are omitted for first approximation. The torque balance with internal losses proportional to the speed is described by equation (20).

The parameter J represents the moment of inertia, c_2 the flux parameter and c_3 the friction parameter. These equations describe an ideal motor, but the behavior of real motors is different. Hence there must be a second step where the models have to be improved for the specific type of motor.

For the development of accurate models, the analysis of the residuals (model error) is one of the best methods. As a model will never be exact, the residuals contain portions of the state variables. Test criteria for the residuals are:

- small rms value of the residuals
- low serial correlation in the residuals
- low correlation between residuals and excitation

One can deduce the missing or wrong terms in the model equations from the deterministic structures in the residuals

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Bibliography

Beilharz J., Filbert D. (1997) *Using the Functionality of PWM Inverters for Fault Diagnosis of Induction Motors*. IFAC Symposium on Fault Detection Supervision and Safety for Technical Processes, 246 pp. Kingston Upon Hull, U.K.

Eykhoff P. (1979) *System Identification – Parameter and State Estimation*. John Wiley & Sons, New York.[A very good overlook of parameter estimation methods].

Frank P.M., Ding S.X., Köppen-Seliger B. (2000) *Current Developments in the Theory of FDI*. 4th IFAC Symposium on Fault Detection Supervision and Safety for Technical Processes, 16 pp. Budapest, Hungary. [The paper provides methods of the parity space analysis].

Fukunaga K. (1972) *Introduction to Statistical Pattern Recognition*. Academic Press, New York, London. [The book provides methods of feature evaluation].

Gertler J.J. (1999) *Fault Detection and Diagnosis in Engineering Systems*. Marcel Dekker, New York. [This presents an excellent overview on actual methods].

Ljung L. (1987) *System Identification – Theory for the User*. Prentice Hall, New York.

Parsons T. (1987) *Voice and Speech Processing*. McGraw-Hill, Inc., New York. [The book includes chapters on feature evaluation and transformations of the feature space].

Biographical Sketch

Prof. Dr.-Ing. Dieter Filbert (1938), VDE, studied Electrical Engineering at the Technical University (TU) of Berlin/Germany. After having finished his Doctoral Thesis in 1970, he worked in the industry. Since 1973, he has been a Professor for Measurement Science at the TU Berlin. His main interests are technical diagnosis, model-based measurement and digital test systems.