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Predictive Maintenance by Electrical Signature Analysis to Induction Motors

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Additional information is available at the end of the chapter

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1. Introduction

Industries always try to increase the reliability of their productive process. In this context, predictive maintenance performs a fundamental role in order to reach high availability and reliability concerning their pieces of equipment. Predictive maintenance can be understood as the action on the equipment, system or installations based on the previous knowledge about the operation condition or performance, obtained by means of parameters previously determined (Bonaldi et al, 2007).

Since the induction motors are the center of the vast majority of the industrial processes, this chapter gives total emphasis to the failure analysis and identification of this kind of electrical machine. Like all the rotating machines, the induction motors are exposed to many different adversities such as thermal and environmental stresses and mechanical damages, which demand maximum attention (Lambert-Torres et al., 2003). Usually, in industries, attention must be even larger since the downtime costs are very high. High and medium voltage induction motors are highly used in industrial processes. Many of them are strategic to the productive process and, because of that, looking for solutions that minimize the failure statistics is mandatory. In most cases, these motors are highly reliable and extremely expensive, forcing the company to operate without a stand-by.

Many predictive techniques are applied to these motors to reduce the number of unplanned outage. The most common techniques applied to fault detection in induction motors are: vibration analysis, acoustical analysis, speed oscillations, partial discharges, circuit analysis, etc. The analyses based on mechanical concepts are established, but the techniques based on electrical signature analysis are being introduced only now. Because of that status, the application of Electrical Signature Analysis (ESA) to industries is the concern of this chapter.

The industries currently look for products and outside services for predictive maintenance. In many cases, the outside service company or even the industrial plant predictive group make mistakes that can compromise the whole condition monitoring and failure diagnosis process.

In this increasing demand for prediction technology, a specific technique referred as Electrical Signature Analysis (ESA) is calling more and more attention of industries. Considering this context, this chapter intends to disseminate important concepts to guide companies that have their own predictive group or want to hire consultants or specialized service to obtain good results through general predictive maintenance practices and, especially through electrical signature analysis.

Figure 1 presents the comparative between vibration analysis and ESA (considering Motor Current Signature Analysis (MCSA), Extended Park’s Vector Approach (EPVA) and Instantaneous Power Signature Analysis (IPSA)), showing which technique is more recommended to a specific kind of problem in a determined part of the rotating drive train. One can say that those techniques are complementary.

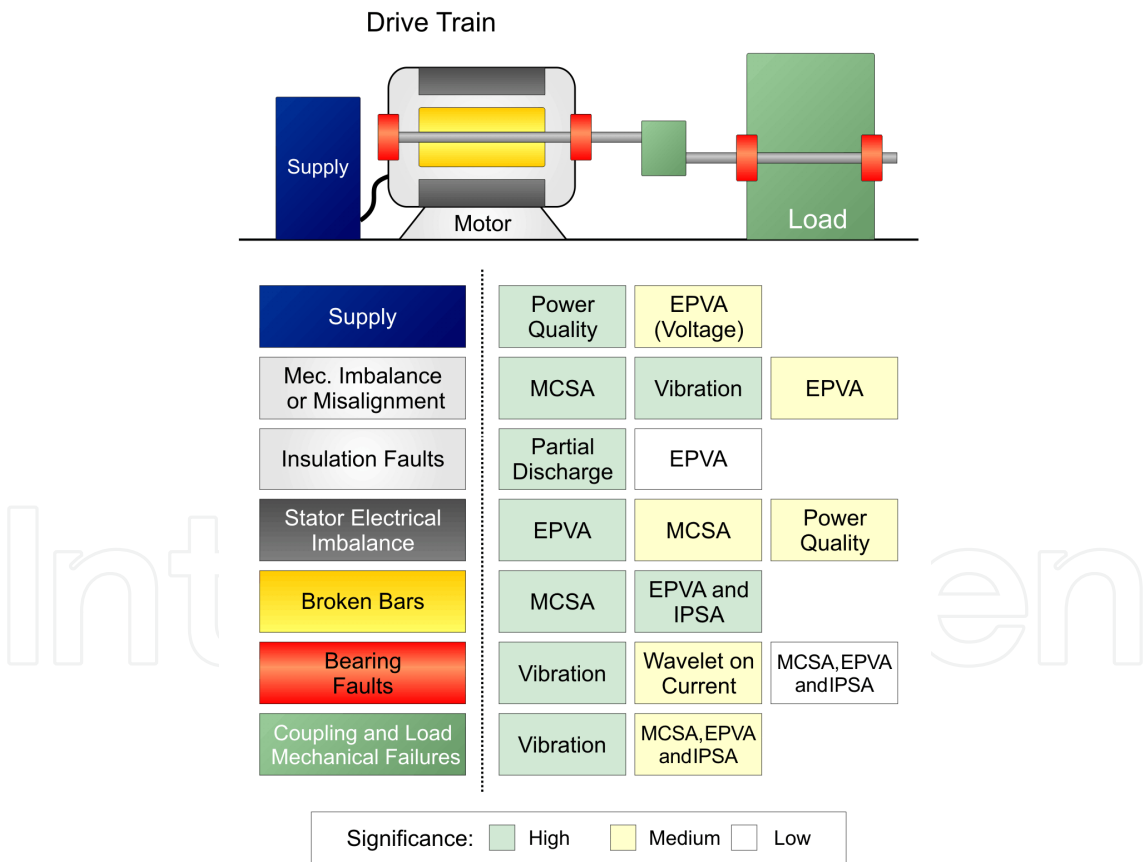


Figure 1. Comparison of predictive maintenance techniques

The main objective of this chapter is to present a procedure to acquire and analyze electrical signals for condition monitoring of electrical machines through motor current signature analysis in order to get the best possible results in an industrial environment. As secondary

contributions, the chapter intends to disseminate important concepts to guide companies that have their own predictive group or want to hire consultants or specialized service to obtain good results through general predictive maintenance practices and, especially through electrical signature analysis. For this purpose, the chapter presents a discussion between condition monitoring and troubleshooting, pointing the differences between both approaches and the main benefits and problems involved with each one.

The result of the proposed discussion in this chapter is a procedure of acquisition and analysis, which is presented at the end of the chapter and intends to be a reference to be used by industries that have a plan to have ESA as a monitoring condition tool for electrical machines.

2. Considerations about maintenance

The motors are the center of the majority of the industrial production processes. Therefore, these machines deserve concerns to increase the reliability of the productive process. In this sense, many techniques have been developed for an on-line motor monitoring of the behavior and performance.

Monitoring condition of electric machines is an evaluation continuous process of the health of equipment during all its useful life. The main function of a monitoring predictive system is to recognize the development of failures in an initial state. For the maintenance department, each failure must be detected as soon as possible in order to promote a programmed stop of the machine.

The process of continuous monitoring of the condition of vital electric machines for the production process brings significant benefits for the company. The main benefits are: bigger efficiency of the productive process, reduction of the losses for not-programmed stops, increase of the useful life of the equipment, and build a historical of failure (Legowski et al., 1996; Tavner et al., 1997; Thomson & Fenger, 2001).

A continuous monitoring system must observe parameters that give to the maintenance team trustworthy information for the decision-making. The more usual monitored parameters are: voltage and current of the stator; temperature of the nucleus; level of vibration; instantaneous power; level of contamination in the lubricant of the rolling; speed of rotation; flow of escape; and so on.

In such a way, it can be noticed that this area of the technology demands knowledge of the functioning of electric machines, instrumentation, microprocessors, processing of signal, analysis of materials, chemical analysis, analysis of vibrations, etc.

2.1. Classification of the maintenance activities

“Maintenance” can be understood as the action to repair or to execute services in equipment and systems. It can have its activities classified in four main groups:

- a. Corrective maintenance: this is the most primary form of maintenance. It occurs after a failure carried out. Usually, it becomes the unavailable equipment for use. Many disadvantages of this type of maintenance are clear. As examples, the systematic occurrence of not-programmed stops, lesser time of useful life for the machine, bigger consumption of energy (since with the presence of the failure the motor needs more current keeping the constant torque) can be cited.
- b. Preventive maintenance: this is the name that receives a set of actions developed with the intention of preventing the occurrence of unsatisfactory conditions, and consequently, reducing the number of corrective actions. When preventive maintenance plan is elaborated, a set of technical measurements must be created in order to increase the machine reliability and decrease the total cost of the maintenance. A preventive maintenance program can still choose for one of the three types of activities: continuous monitoring; periodic measurements; or predictive techniques.
- c. Predictive maintenance: as it can see previously, the predictive maintenance can be a sub-area of the preventive maintenance. However, the predictive maintenance presents some proper characteristics as:
 - Support in not invasive techniques, that is, it is not necessary to stop the operation of the machine for its application
 - Elimination of corrective maintenance;
 - Not consideration of information as the durability of components;
 - On-line or off-line can be effected through techniques.
- d. Systematic maintenance: characterized for the substitution of components of the equipment or for the substitution of the equipment as a whole (Bonaldi et al., 2007).

2.2. Status of predictive maintenance

Usually, industries have the vast majority of their condition monitoring programs based on the mechanical parameters analysis. The most common methods applied are: Vibration Analysis, Acoustical Analysis, Shock Pulse and Speed Fluctuations. Other techniques involving mechanical concepts are also applied such as temperature monitoring, oil and gases analysis, etc.

When involving electrical concepts, intrusive methods are more common used in industries such as surge test, polarization index, hipot tester, motor circuit analysis (MCA), etc. These techniques are more correctly classified as preventive maintenance, being performed at planned outages.

Concerning motor condition monitoring through non-intrusive electrical methods in Brazil, one can observe more often the RMS voltage and current monitoring. For example, broken bars produce current oscillations that can be observed through an ampere-meter installed in the electric panel. But, again, it is not possible to separate load oscillations from broken bars.

This way, a more reliable program to detect electrical and mechanical problems must consider the introduction of new condition monitoring tools, mainly those related to electrical signature that has been neglected until now. Since the petrochemical industry constantly aims to increase the process reliability and operational continuity, a very

interesting and little explored field surfaces, which is the introduction of predictive maintenance techniques based on electrical signature analysis.

3. Common failures in three-phase induction motors

Consider the following brief description of the most common failures that can be avoided through the adoption of condition monitoring methods:

- Bearings Faults:** can be caused by incorrect lubrication, mechanical stresses, incorrect assembling, misalignment, etc. They can affect all the bearing parts such as inner and outer races, cage and balls or rolls.
- Stator Winding Faults:** normally a consequence of overheating, contamination, project errors, etc., possibly causing shorted turns, shorted coils (same phase), phase to phase, phase or coil to ground and single phasing. Such failures cause stator electrical imbalance as well as variations in the current harmonic content. Mechanical problems can also occur in the stator such as loosen edges, but this is statistically less frequent.
- Rotor Faults:** usually caused by broken bars or broke end rings, rotor misalignment and imbalance.

Faults in the coupling (pulley, belt and gear mesh) and in the attached load also can be diagnosed. The failures are also related to the petrochemical process different characteristics. For example, at off-shore plants, the motors start directly from the mains. This demands high start currents and causes pulsating torques which contributes to the origin of rotor and stator faults. Furthermore, outdoors motors present more incidence of failure than indoor motors. The same statistic holds for high voltage motors and high speed motors when compared with low voltage motors and low speed motors.

3.1. Abnormalities in three-phase induction motors

The main focus of problems in three-phase induction motors are in the stator and the supports. The main causes of failures are: superheating, imperfections in the isolation, mechanical bearings and electric failures. Figure 2a presents a division of the failures in three-phase induction motors with squirrel steamer and power of 100 HP or higher (Bonnett & Soukup, 1992).

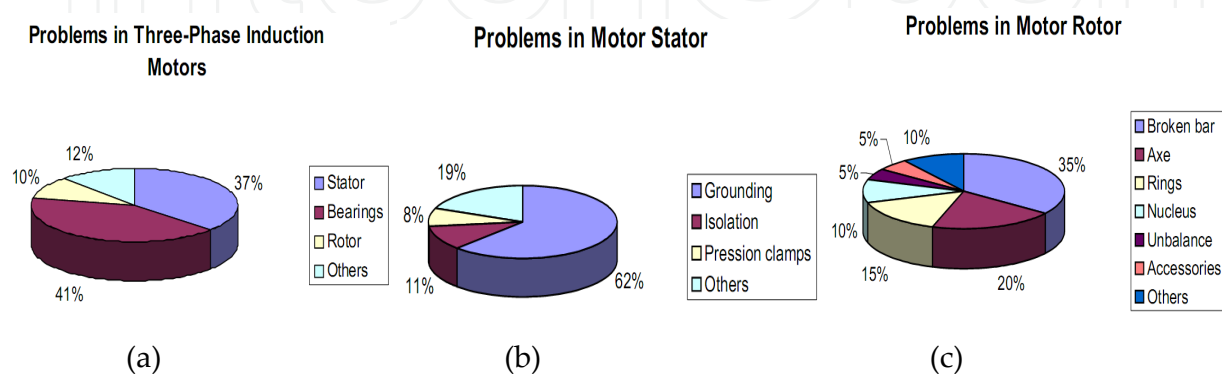


Figure 2. Problems in: (a) Three-Phase Induction Motors, (b) Motor Stator, and (c) Motor Rotor.

In one hand, the main source of electrical problems in induction motor is in stator that totalizes 37% of the total of failures. Figure 2b details different type of problems in the motor stators. In the other hand, problems in the motor rotor totalize 10% of the total of motor failures, and they are shown in Figure 2c.

3.2. Relation between motor specification and failure mechanism

Many failures can be deriving of incorrect specifications. The specification of a motor must consider the mechanical and electric conditions, and the environment in which the machine goes to work. The monitored parameters are affected by these operational conditions. In terms of the mechanical conditions, the failures appear as resulted of the behavior of the load. Amongst the main problems they are distinguished:

- Successive overloads that can cause superheating and/or damages to the bearing;
- Pulsing load that can cause damages to the bearing;
- Repeated departures that can damage the machine bearing;
- Vibration that can be transmitted to the machine causing damages to the bearing.

In terms of the electric conditions, the failures can result of the electrical power system characteristics or the load feeder by the motor. Amongst the main problems they are distinguished:

- Slow fluctuations of voltage being able to cause loss of stop power and of the machine.
- Brusque fluctuations of voltage being able to cause failure in the isolation.

In terms of the environment conditions, the failures can result of the characteristics of the process in which the machine is being used. Amongst the main problems they are distinguished:

- High temperatures that can cause the deterioration of isolation.
- Humidity and pollution that can respectively cause imperfections and contamination of the isolation.

Thus, it is clear that the failures that occur in electric machines depend on the type of machine and the environment where it is working. What it is really important to observe it is that the failure mechanism happens in gradual way, from an initial defect up to real failure. The time of propagation of the failure depends on some factors. However, the major parts of the failures present initial pointers of its presences and are exactly in these initial indications that the predictive maintenance must act (Bonaldi et al., 2003).

4. Electrical signature analysis overview

Electrical Signature Analysis (ESA) is the general term for a set of electrical machine condition monitoring techniques through the analysis of electrical signals such as current and voltage. These techniques are: Current Signature Analysis (CSA), Voltage Signature Analysis (VSA), Extended Park's Vector Approach (EPVA), Instantaneous Power Signature

Analysis (IPSA), among others. The electrical motor of the rotating system under analysis is analyzed for the failure diagnosis purposes, acting as a transducer in this process. Variations in the voltage and current signals are analyzed in relation to some failure patterns.

The industrial application of ESA techniques aims to improve the equipment reliability once those techniques imply greater robustness to the diagnosis. The expected results are: downtime reduction, increase in the machine availability, maintenance costs reduction, better management and planning of maintenance, etc.

The inherent benefits in ESA are: non-intrusive; it does not demand sensors installed in the rotating drive train; it is not necessary to be suited for classified areas (the sensors can be installed in the motor control centre (MCC) free of explosive mixtures); it presents high capability of remote monitoring, reducing the human exposure to risks; it can be applied to any induction motor without power restriction; it presents sensitivity to detect mechanical failures in the motor and load, electrical failures in the stator and problems in the mains, etc.

For these reasons, one recommends the application of these techniques (together with the mechanical approaches) in order to prevent catastrophic failures; improve the safety and the reliability of the productive process; reduce the downtime, improve the condition monitoring of motors installed in places of difficult access and improve the motor management in the maintenance context for reliability purposes.

Among the several ESA techniques, two of them are considered in this chapter: MCSA and EPVA.

The stator line current spectral analysis has been widely used recently for the purpose of diagnosing problems in induction machines. This technique is known as Motor Current Signature Analysis (MCSA) and the current signal can be easily acquired from one phase of the motor supply without interruption of the machine operation. In MCSA the current signal is processed in order to obtain the frequency spectrum usually referred to as current signature. By means of the motor signature, one can identify the magnitude and frequency of each individual component that constitutes the signal of the motor. This characteristic permits identifying patterns in the signature in order to differentiate healthy motors from unhealthy ones and point where the failures happen. Although it is important to say that the diagnosis is something extremely complicated, e.g., the decision of stopping or not the productive process based on the current spectrum indications is always not elementary and demands experience and knowledge of the process.

4.1. Current and voltage signature analysis

CSA – Current Signature Analysis or VSA – Voltage Signature Analysis techniques are used to generate analyses and trend of electric machines dynamically. They aim to detect predictive problems in a rotating electric machine, such as: problems in the stator winding, rotor problems, problems on the engagement, problems in bound load, efficiency and system load; problems in the bearing, among others. It may initially cause a certain

astonishment that the electrical signals contain information in addition to the electrical characteristics of the machine under supervision, but they work for mechanical defects as a transducer, allowing the electrical signals (voltage and/or current) can carry information of electrical and mechanical problems until the power panel of the machine.

The signs of current and/or voltage of one or three phases of the machine produce, after analyzed, the *signature of machine*, i.e., its operating pattern. This signature is composed of magnitudes of frequencies of each individual component extracted from their signals of current or voltage. This isolated fact itself is an advantage, as it allows the monitoring of the evolution of the magnitudes of the frequencies, which can denote some sort of evolution of operating conditions of the machinery. The response that the user of such a system needs to know is whether your machine is "healthy" or not, and that part of the machine the failure might occur.

This analysis (diagnosis) is not something easy to be done, because it involves a set of comparisons with previously stored patterns and own "history" of the machine under analysis. In this instant, normally a specialist is called to produce the final diagnosis, generating the command when stopping the machine.

4.2. Motor Current Signature Analysis (MCSA)

MCSA is the technique used to analyze and monitor the trend of dynamic energized systems. The appropriate analysis of the results of applying predictive technique helps in identifying problems in stator winding, rotor problems, problems in the coupling, problems in attached load, efficiency and system load, problems in the bearing, among others.

This technique uses the induction motor as a transducer, allowing the user to evaluate the electrical and mechanical condition from the panel and consists primarily in monitoring of one of the three phases of the supply current of the motor. A simple and sufficient system for the implementation of the technique is presented in the Figure 3a.

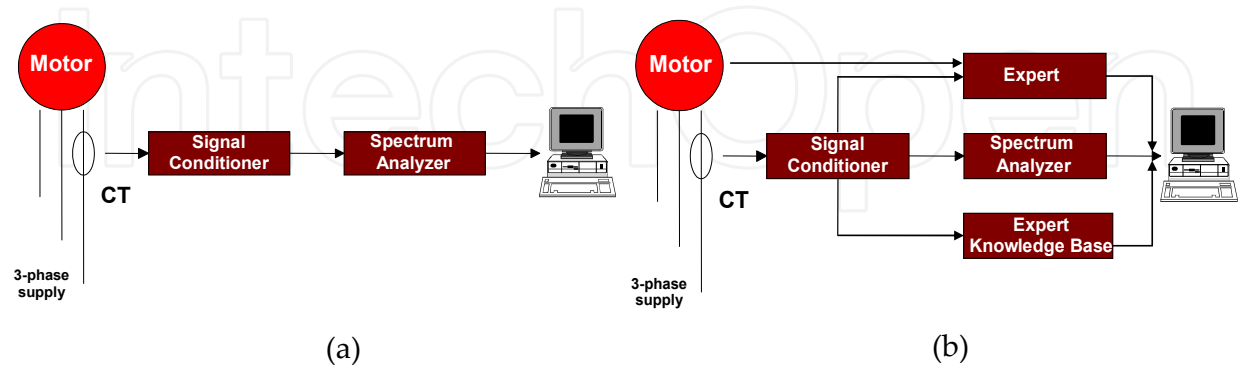


Figure 3. Basic System for Spectral Analysis of the Current

Thus, the current signal of one of the phases of the motor is analyzed to produce the power spectrum, usually referred to as motor signature. The goal is to get this signature to identify the magnitude and frequency of each individual component that integrates the motor

current signal. This allows that patterns in current signature be identified to differentiate "healthy" motors from "unhealthy" ones and even detect in which part of machine failure should occur.

However, it is important to note that the diagnosis is something extremely complicated, i.e. the definition of stopping or not the production process in view of the indications of the power spectrum is always difficult and requires experience and knowledge of the process. This time, it is important to consider the expert knowledge and the data history of the behavior of the set (motor, transmission system and load). For this reason, an automatic diagnostic system that combines the data history of the motor to the attention of specialist is a niche market quite promising. This way, the automatic diagnosis and analysis system is no longer as simple as the model shown in Figure 3a and can be represented by the new elements in Figure 3b.

The Fast Fourier Transform (FFT) is the main tool employed, however some systems employ in conjunction with other techniques to increase the ability of fault detection since signal acquisition, through processing, up to the diagnostic step. Among the most important issues related to acquisition of signals and the FFT include:

- a. **Frequency range:** the frequency response is typically required in MCSA 5 kHz. This way, the bandwidth of the transducers used must be at least 10 kHz.
- b. **Nyquist theorem:** this theorem states that for any signal to be reconstructed without significant losses must be removed samples with twice the maximum frequency of the signal. In practice it uses 10 times the maximum frequency and ensures excellent accuracy.
- c. **Resolution:** spectral lines resolution, i.e. the distance between two spectral is given by (1):

$$\Delta f = \frac{f_s}{N} \quad (1)$$

Where Δf is the spectral resolution, f_s is the sampling frequency used, and N is the number of samples.

Other important issues are related to the own operation of induction motors. The first one is the induction motor synchronous speed that is given by (2):

$$N_s = \frac{f_1}{p} \quad (2)$$

Where f_1 represents the power frequency, N_s is the velocity of the rotating field, and p is the number of motor pole pairs.

From the synchronous speed, two important concepts for the current signature analysis can be presented: the slip speed and the slip. In MCSA is important to note that the rotor speed is always less than the synchronous speed. The frequency of the induced currents in the rotor is a function of frequency and power slip. When operating without load, the rotor rotates at a speed close to the synchronous speed. In this case, torque should be just

sufficient to overcome friction and ventilation. The difference between the rotor speed (N_r) and the synchronous speed (N_s) is named as slip speed (N_{slip}):

$$N_{slip} = N_s - N_r \quad (3)$$

When mechanical load is attached to the rotor demanding torque the rotor speed decreases. In this turn, the slip speed increases and also the current in the rotor to provide more torque. As the load increases, the rotor continues having reduced its speed relative to synchronous speed. This phenomenon is known as motor slip, denoted by s .

$$s = \frac{(N_s - N_r)}{N_s} \quad (4)$$

Another important definition refers to slip frequency. The frequency induced in the rotor is correctly set to slip frequency and is given by:

$$f_2 = (N_s - N_r) \cdot p \quad (5)$$

As noted, the rotor frequency is directly proportional to the slip speed and the number of pair of poles. Thus:

$$s \cdot N_s = N_s - N_r \text{ and } p \cdot N_s = f_1 \text{ then } f_2 = s \cdot f_1 \quad (6)$$

This is a very important result for MCSA once the current frequency is rotor slip function. The characteristic frequencies are well known. The patterns of these failures are presented below.

The stator line current spectral analysis has been widely used recently for the purpose of diagnosing problems in induction machine. This technique is known as MCSA and the current signal can be easily acquired from one phase of the motor supply without interruption of the machine operation. In MCSA the current signal is processed in order to obtain the frequency spectrum usually referred to current signature. By means of the motor signature, one can identify the magnitude and frequency of each individual component that constitutes the signal of the motor. This characteristic allows identifying patterns in the signature in order to differentiate healthy motors from unhealthy ones. Mechanical failures such as rotor imbalance, shaft misalignment, broken bars and bearing problems are common in induction machines applications and commonly discussed or presented when talking about MCSA. Another very important cause of poor functioning of induction motor is load mechanical failure. When a mechanical failure is present either in the motor, or in the transmission system or in the attached load, the frequency spectrum of the line current, in other words, the motor signature, becomes different from that of a non-faulted machine.

When a mechanical failure occurs in the attached load of an induction motor, multiples rotational frequencies appear in the stator current due to the load torque oscillation (Benbouzid, 2000). These frequencies are related to the constructive characteristics of the load and the transmission system, and an abnormal value of a given frequency expresses a

specific failure, and more, the severity of this failure. The frequency component that appears in the stator current spectrum can be expressed by:

$$f_{lf} = f_1 \pm \kappa f_r \quad (7)$$

Where f_{lf} is the characteristic frequency of the load fault, f_1 is the supply frequency, κ is the constant resulting from the drive train constructive characteristics and f_r is the motor rotational frequency.

It is known that when a mechanical failure has developed in the load, it generates an additional torque (T_{lf}). Thus, the overall load torque (T_{load}) can be represented by an invariable component (T_{const}) plus this additional variable component which varies periodically at a characteristic frequency ω_f in (8)

$$T_{load}(t) = T_{const} + T_{lf} \cos(\omega_f t) \quad (8)$$

Where T_{lf} is the amplitude of the load torque oscillation caused by the load mechanical failure and $\omega_f = 2\pi f_{lf}$. Also, the torque relates to the rotational frequency (ω) can be expressed by:

$$T(t) = T_{motor}(t) - T_{load}(t) = J \frac{d\omega_r(t)}{dt} \quad (9)$$

Where J is the total inertia of machine and load. Thus:

$$J \frac{d\omega_r(t)}{dt} = T_{motor}(t) - T_{const} - T_{lf} \cos(\omega_f t) \quad (10)$$

In steady state, $T_{motor} = T_{const}$ and:

$$\frac{d\omega_r(t)}{dt} = -\frac{1}{J} (T_{lf} \cos(\omega_f t)) \text{ and } \omega_r(t) = -\frac{T_{lf}}{J} \int \cos(\omega_f t) dt + Const. \quad (11)$$

Then

$$\omega_r(t) = -\frac{T_{lf}}{J\omega_f} \sin(\omega_f t) + \omega_{r0} \quad (12)$$

Observing (12), the mechanical speed consists of a constant component ω_{r0} and a component which varies according to a sinusoidal signal. Then, the integration of mechanical speed results in the mechanical rotor position $\theta(t)$:

$$\theta_r(t) = \frac{T_{lf}}{J\omega_f^2} \cos(\omega_f t) + \omega_{r0} t \quad (13)$$

The rotor position oscillations act on the magneto motive force (MMF). In normal conditions, the MMF referred to as the rotor ($F_r^{(R)}$) can be expressed by (14).

$$F_r^{(R)}(\theta', t) = F_r \cos(p\theta' - s\omega_1 t) \quad (14)$$

Where θ' is the mechanical angle in the rotor reference frame, p is the number of pole pairs, ω_1 is the synchronous speed, s is the motor slip, and F_r is the rotor MMF.

Figure 4 shows a phasorial diagram for the rotor MMF (R axes) referred to the stator frame (S axes), the difference can be expressed by the angle θ' .

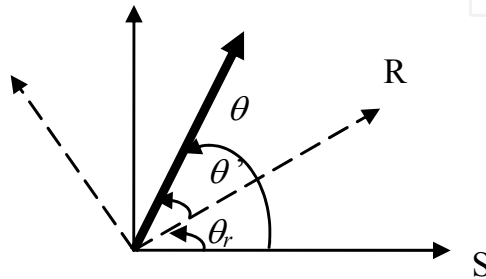


Figure 4. Phasorial diagram of the rotor MMF referred to the stator frame

According the Figure 4 and Equation (14) and replacing (13) in (15), it results in:

$$\theta = \theta' + \theta_r \text{ and } F_r(\theta, t) = F_r \cos[p(\theta - \theta_r) - s\omega_1 t] \quad (15)$$

$$F_r(\theta, t) = F_r \cos\left(p\theta - p\omega_{r0}t - \frac{pT_{lf}}{J\omega_{lf}^2} \cos(\omega_{lf}t) - s\omega_1 t\right) \quad (16)$$

Doing $\beta = pT_{lf}/J\omega_{lf}^2$ and using the relation $\omega_{r0} = (1-s)\omega_1/p$, it produces:

$$F_r(\theta, t) = F_r \cos\left(p\theta - \omega_1 t - \beta \cos(\omega_{lf}t)\right) \quad (17)$$

Where β is the modulation index and generally $\beta < 1$.

At this point, it is important to notice that the term $\beta \cos(\omega_{lf}t)$ means a phase modulation. The failure does not have direct effect on stator MMF which can be expressed by:

$$F_s(\theta, t) = F_s \cos(p\theta - \omega_1 t - \varphi_s) \quad (18)$$

Where φ_s is the initial phase between rotor and stator MMFs.

Supposing for the sake of simplicity the value of the air gap permeance Λ constant (because slotting effects and eccentricity were neglected), the air gap flux density B can be expressed by the product of total MMF and Λ :

$$B(\theta, t) = [F_s(\theta, t) + F_r(\theta, t)]\Lambda \text{ and}$$

$$B(\theta, t) = B_s \cos(p\theta - \omega_1 t - \varphi_s) + B_r \cos(p\theta - \omega_1 t - \beta \cos(\omega_{lf} t)) \quad (19)$$

As the flux $\varphi(t)$ is obtained by the integration of the flux density $B(\theta, t)$, then all phase modulation existing in the flux density also exists in the flux $\varphi(t)$. It is important to explain that the winding structure affects only the flux amplitude and not its frequencies. Thus:

$$\varphi(t) = \varphi_s \cos(\omega_1 t - \varphi_s) + \varphi_r \cos(\omega_1 t - \beta \cos(\omega_{lf} t)) \quad (20)$$

The relationship between the flux and the current is given by the equation (21).

$$V(t) = R_s I(t) + \frac{d\varphi(t)}{dt} \quad (21)$$

Where R_s is the stator resistance. Thus,

$$I(t) = \frac{V(t)}{R_s} - \frac{1}{R_s} \frac{d\varphi(t)}{dt} \quad (22)$$

And as:

$$\begin{aligned} \frac{d\varphi(t)}{dt} = & -\omega_1 \varphi_s \sin(\omega_1 t + \varphi_s) - \omega_1 \varphi_r \sin(\omega_1 t + \beta \cos(\omega_{lf} t)) \\ & + \omega_{lf} \beta \varphi_r \sin(\omega_1 t + \beta \cos(\omega_{lf} t)) \sin(\omega_{lf} t) \end{aligned} \quad (23)$$

With the last term being neglected once $\beta \ll 1$. Finally:

$$I(t) = \underbrace{\frac{V(t)}{R_s} + \frac{1}{R_s} \omega_1 \varphi_s \sin(\omega_1 t + \varphi_s)}_{\text{Stator}} + \underbrace{\frac{1}{R_s} \omega_1 \varphi_r \sin(\omega_1 t + \beta \cos(\omega_{lf} t))}_{\text{Rotor}} \quad (24)$$

$$I(t) = \underbrace{I_{st} \sin(\omega_1 t + \varphi_s)}_{i_{st}} + \underbrace{I_{rt} \sin(\omega_1 t + \beta \cos(\omega_{lf} t))}_{i_{rt}} \quad (25)$$

Notice that the term i_{st} results from stator MMF and it is not influenced by the torque oscillation, and the term i_{rt} results from the rotor MMF and presents phase modulation due to torque oscillations. And also, when the motor is healthy β is null.

Considering the component i_{rt} with phase modulation in (14) given in its complex form:

$$i_{rt}(t) = I_{rt} e^{j(\omega_1 t + \beta \cos(\omega_{lf} t))} \quad (26)$$

Applying a Discrete Fourier Transform (DFT) in (26), as well known from communications theory, it can be expressed by (27).

$$I_{rt}(f) = I_{rt} \sum_{n=-\infty}^{\infty} j^n J_n(\beta) \delta(f - (f_1 + nf_{lf})) \quad (27)$$

Where J_n denotes the n th-order Bessel function of first kind and $\delta(f)$ is the Dirac delta function. Since β is so small, the Bessel functions of order $n \geq 2$ can be neglected.

Finally, the Power Spectral Density (PSD) of the stator current, considering the approximations used, is given by:

$$|I(f)| = (I_{st} + I_{rt} J_0(\beta)) \delta(f - f_1) + I_{rt} J_1(\beta) \delta(f - (f_1 \pm f_{lf})) \quad (28)$$

It is clear that the phase modulation leads to sideband components of the fundamental at $f_1 \pm f_{lf}$ as it happens in an amplitude modulation. Considering all the development accomplished in this section and the result in (28), the load failure patterns can be presented.

4.3. Voltage Signature Analysis (VSA)

The technique of Voltage Signature Analysis follows the same strategy of analysis of the current signature; however the signal is analyzed from the voltage supply of the motor. This technique is most often used in analysis of generating units. In the case of motors, it can be usefully employed in cases of problems from the motor power and the analysis of electric stator imbalance in conjunction with the analysis of the current signature. It can be used also to know the origin of certain components in the power spectrum, that is, it can be used to infer if the source of the component comes from the mains or has its origin in the array itself.

4.4. Instantaneous Power Signature Analysis (IPSA)

The analysis of the instantaneous power is another failure analysis technique based on spectral analysis. The big difference between this technique and MCSA and VSA is that it considers the information present in voltage and current signals of a motor phase concurrently and demodulated fault component appears under the name of Characteristic Frequency. Considering an ideal three phase system, instant power $p(t)$ is given by:

$$p(t) = v_{LL}(t) i_L(t) \quad (29)$$

Where v_{LL} is the voltage between two terminals of the motor and i_L is the current entering one of these terminals. And, a motor under normal conditions, i.e. without breakdowns, and constant velocity, one has:

$$v_{LL}(t) = \sqrt{2} V_{LL} \cos(\omega t) \quad (30)$$

$$i_{L,0}(t) = \sqrt{2}I_L \cos\left(\omega t - \varphi - \frac{\pi}{6}\right) \quad (31)$$

$$p_0 = v_{LL}(t)i_{L,0}(t) = V_{LL}I_L \left[\cos\left(2\omega t - \varphi - \frac{\pi}{6}\right) + \cos\left(\varphi + \frac{\pi}{6}\right) \right] \quad (32)$$

Where V_{LL} and I_L are the RMS values of voltage and current line, ω is the angular frequency and φ is the phase angle of the motor load.

Let's consider now the presence of a mechanical fault in the drive train, resulting in the appearance of motor torque oscillations accompanied by surges of speed and slip, which in turn result in modulations in the current spectrum.

For simplicity, it is considered that the failure cause only an amplitude modulation on the stream of the stator by deleting the effect on stage. It could also prove that phase modulations, in function of torque oscillations, appear in current as amplitude modulations by processed result from similar functions to the Bessel functions. The modulated current i_L can be expressed by:

$$\begin{aligned} i_L &= i_{L,0}(t) \left[1 + M \cos(\omega_f t) \right] \\ &= i_{L,0}(t) + \frac{MI_L}{\sqrt{2}} \left\{ \cos\left[\left(\omega + \omega_f\right)t - \varphi - \frac{\pi}{6}\right] + \cos\left[\left(\omega - \omega_f\right)t - \varphi - \frac{\pi}{6}\right] \right\} \end{aligned} \quad (33)$$

Where M is the index modulation and ω_f is the angular frequency of the failure.

The expression of instant power results in:

$$\begin{aligned} p(t) &= p_0(t) + \frac{MV_{LL}I_L}{2} \left\{ \cos\left[\left(2\omega + \omega_f\right)t - \varphi - \frac{\pi}{6}\right] + \cos\left[\left(2\omega - \omega_f\right)t - \varphi - \frac{\pi}{6}\right] + \right. \\ &\quad \left. + 2\cos\left(\varphi + \frac{\varphi}{6}\right)\cos(\omega_f t) \right\} \end{aligned} \quad (34)$$

Besides the fundamental component $2\omega/2\pi$ and the lateral bands in $(2\omega \pm \omega_f)/2\pi$, the spectrum of instantaneous power contains an additional component directly related to the modulation caused by failure. This component is named as **Characteristic Component** and can be used as information for the diagnosis of the condition of the machine.

The following simulation which considers a motor current modulation originated by an alleged mechanical failure whose frequency characteristic is of 15 Hz. Note the Figure 5 that the spectrum of voltage does not have any type of modulation, since the current spectrum has lateral bands apart from 15 Hz fundamental's (located at 60 Hz). The instantaneous power spectrum has the fundamental frequency in 120 Hz with modulations of 15 Hz at 105 and 135 Hz, besides presenting the fault feature component in isolated 15 Hz.

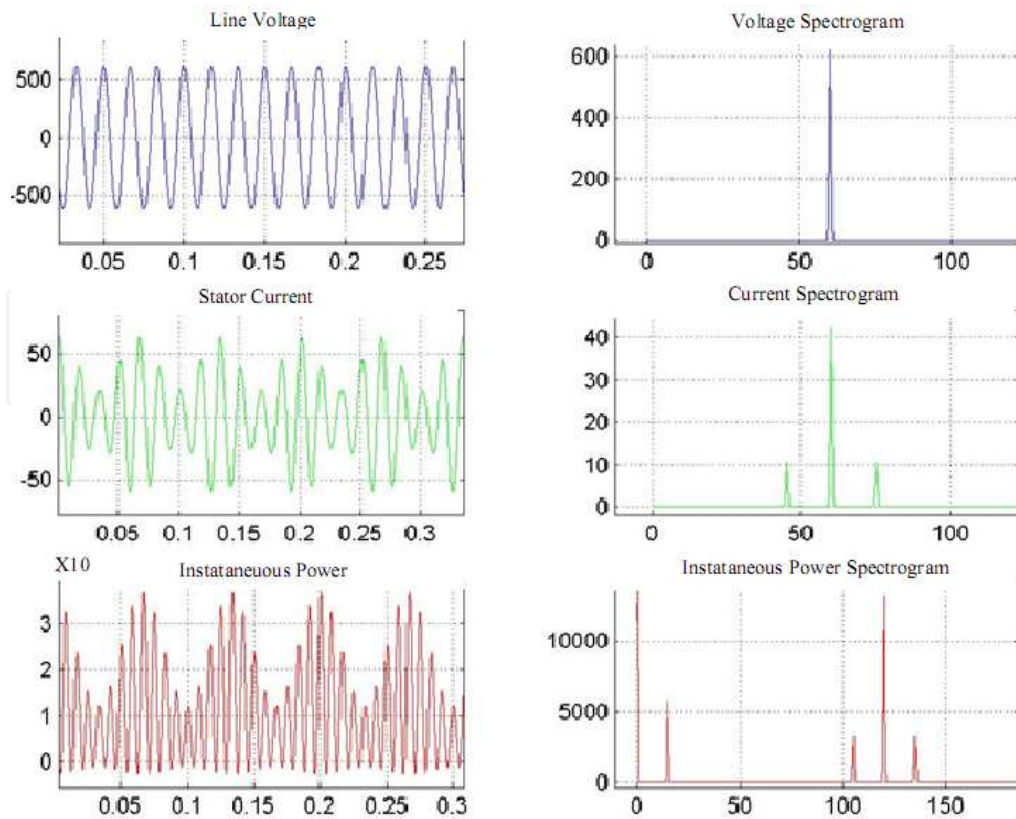


Figure 5. Fault Simulation in 15 Hz and the respective spectra of voltage, current and instant power

4.5. Enhanced Park's Vector Approach (EPVA)

The first research involving the use of Park's vector method for the diagnosis of failures in motors such as short circuit between turns, airgap eccentricity and broken bars, etc. (Cardoso & Saraiva, 1993). At first, the proposed damage detection was based only on the distortion suffered by circle of Park on the emergence and on the aggravation of the damage. More recently, the technique has been improved (now named EPVA) and may be described as following steps. The three phases of currents in a motor can be described by:

$$i_A = i_M \cos(\omega t - \alpha) \quad (35)$$

$$i_B = i_M \cos\left(\omega t - \alpha - \frac{2\pi}{3}\right) \quad (36)$$

$$i_C = i_M \cos\left(\omega t - \alpha + \frac{2\pi}{3}\right) \quad (37)$$

Where i_M is the peak value of the supply current, ω is the angular frequency in rad/s, α is the initial phase angle in rad, t is the time variable; and i_A , i_B and i_C are respectively the currents in the phases A, B and C. The current components of the Park's vector are given by:

$$i_D = \left(\frac{\sqrt{2}}{\sqrt{3}}\right)i_A - \left(\frac{1}{\sqrt{6}}\right)i_B - \left(\frac{1}{\sqrt{6}}\right)i_C \text{ and } i_Q = \left(\frac{1}{\sqrt{2}}\right)i_B - \left(\frac{1}{\sqrt{2}}\right)i_C \quad (38)$$

Ideally:

$$i_D = \left(\frac{\sqrt{6}}{2}\right)i_M \cos(\omega t - \alpha) \text{ and } i_Q = \left(\frac{\sqrt{6}}{2}\right)i_M \sin(\omega t - \alpha) \quad (39)$$

Graphically, ideal conditions generate a perfect Park circle centered at the origin of coordinates, as shown in Figure 6.

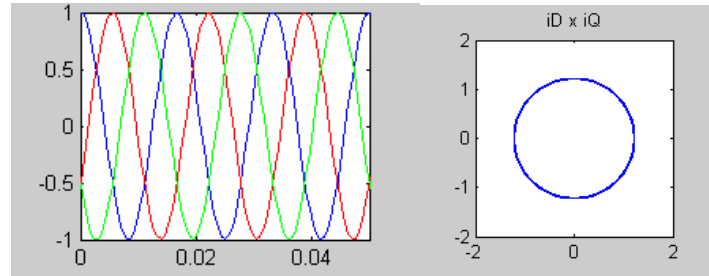


Figure 6. Signals in time and Park circle

Under abnormal conditions of operation, i.e. when the emergence of mechanical or electrical failure, the previous equations are no longer valid and the circle of Park passes to suffer distortions. As these changes in the circle of Park are difficult to be measured, was proposed by EPVA method of observation of spectrum of Park's vector module. The advantage of EPVA technique combines the simplicity of the previous method (analysis of the Park's circle) with spectral analysis capability. In addition, the fundamental component of the motor power is automatically subtracted from the spectrum by Park transformation, causing the failure characteristics components appear prominently. The most important point is the fact that the technique considers the three phases of current, generating a more significant spectrum by encompass information from three phases. This feature is extremely useful in cases where failure can only be detected if considered the three phases. This is the case of unbalanced electric motor fuelled in open loop.

When there is an unbalanced voltage supply, the motor currents can be represented by:

$$i_A = i_d \cos(\omega t - \alpha_d) + i_i \cos(\omega t - \beta_i) \quad (40)$$

$$i_B = i_d \cos\left(\omega t - \alpha_d - \frac{2\pi}{3}\right) + i_i \cos\left(\omega t - \beta_i + \frac{2\pi}{3}\right) \quad (41)$$

$$i_C = i_d \cos\left(\omega t - \alpha_d + \frac{2\pi}{3}\right) + i_i \cos\left(\omega t - \beta_i - \frac{2\pi}{3}\right) \quad (42)$$

Where i_d is the maximum value of the current direct sequence, i_i is the maximum value of reverse sequence current, α_d is the current initial phase angle direct sequence in rad, and β_i is the initial phase angle reverse sequence current in rad. In the Park's vector:

$$i_D = \left(\frac{\sqrt{3}}{\sqrt{2}} \right) (i_d \cos(\omega t - \alpha_d) + i_i \cos(\omega t - \beta_i)) \text{ and } i_Q = \left(\frac{\sqrt{3}}{\sqrt{2}} \right) (i_d \sin(\omega t - \alpha_d) - i_i \sin(\omega t - \beta_i)) \quad (43)$$

And the square of the Park's vector module is given by:

$$|i_D + ji_Q|^2 = \left(\frac{3}{2} \right) (i_d^2 + i_i^2) + 3i_d i_i \cos(2\omega t - \alpha_d - \beta_i) \quad (44)$$

Now, just applying the FFT to the square of the Park's vector module and observe that this is composed by a DC level plus one additional term located at twice the supply frequency. It is exactly this additional term that indicates the emergence and intensification of stator electrical asymmetries. Let's the example shown in Figure 7a which is considered an unbalanced feed; and also, the Park circle passes to resemble an ellipse and arises in the spectrum the component located at twice the supply frequency, as shown in Figure 7b and c. Thus, the whole process can be represented by the elements of Figure 8.

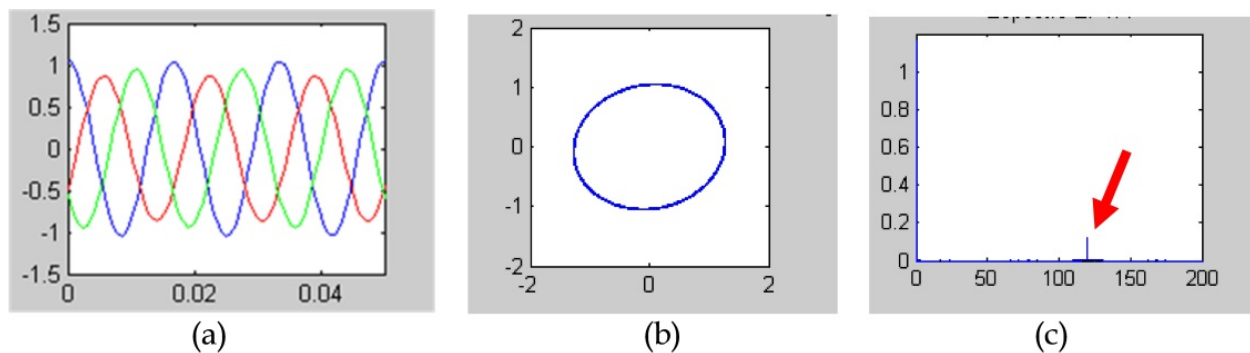


Figure 7. Imbalance between the phases, Park circle distorted and presence of the component at twice the supply frequency

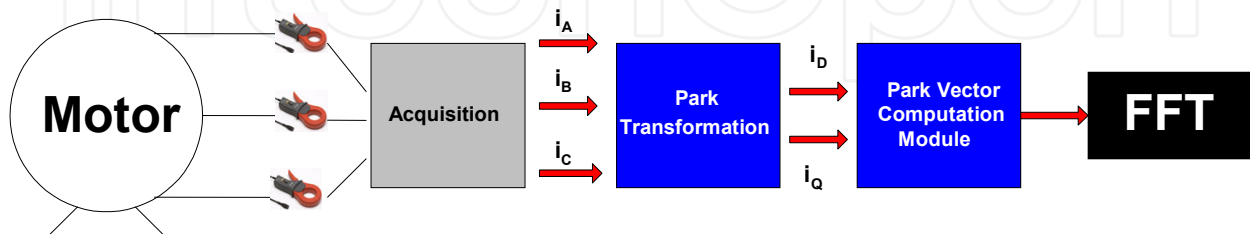


Figure 8. Block Diagram of the EPVA technique

This demonstrates the effectiveness of the component located at twice the supply frequency (in this case 120 Hz) of the EPVA monitoring to diagnosis short circuit between turns. The test procedure was the following: used the Marathon motor failures Simulator Spectra Quest

in which *taps* was inserted to the gradual introduction of imbalance in power depending on the insertion of short. Figure 9a presents the characteristics of the motor and the *taps* as to the short are introduced.

Tests have been made in the conditions of non-faulted motor (no imbalance) and five severities of short circuit generating imbalances of 1.2 V, 1.8 V, V, V 5.4 6.7 and 8.5 V. Figure 9b shows the overlap of the spectra of the motor in normal condition (in red) and motor in the worst condition of imbalance (8.5 V) highlighting the component twice the power frequency in the spectrum of Park vector module.

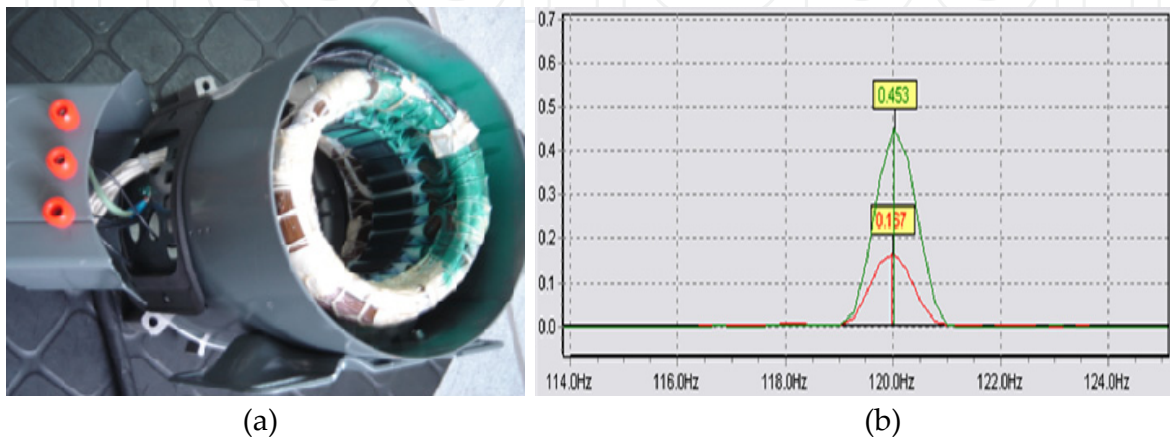


Figure 9. Featured for the inserted short-circuit and spectrum of Park vector module

The current trend curve (shown in Figure 10) demonstrates a general growth of electric unbalance component EPVA with increasing the short circuit. Each three points of the curve represent a condition of normal severity, starting and advancing to severity 1 (1.2 V), 2 (1.8 V), 3 (5.4 V), 4 (6.7 v) and 5 (V 8.5). Severity 4 presents amplitude less than Severity 3 due to a change in the equilibrium condition of input voltage shown in the trend curve in tension (shown in Figure 10), being thus possible to separate the effects of those supply imbalances caused by short circuits and other anomalies.

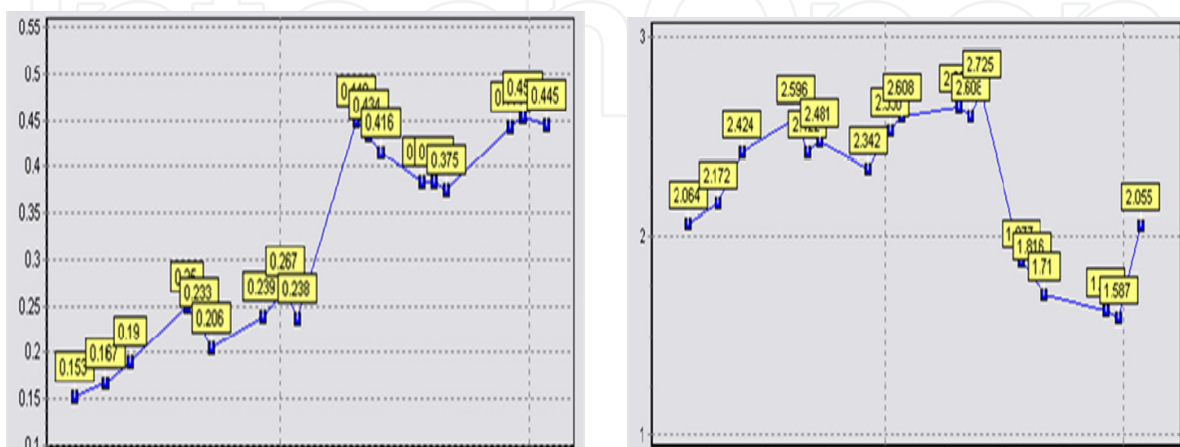


Figure 10. Trend curve to the imbalance component: (a) for current and (b) for voltage

5. Patterns of failures

A fault in any part of the machine is a decrease in this part performance when compared with the minimum requirements specified. Thus the fault results from natural wear, project errors, incorrect installation, poor use or a combination of all of them. If the fault is not identified in time and increases, failure may ensue (Thorsen & Dalva, 1999). Therefore, failure is the reason why the machine breaks down. This way, one tries to identify the fault before it becomes a failure, even when it is incipient.

5.1. Rotor failure patterns

This section shows the failure patterns for rotor problems.

1. Broken Bar: it is the rotor most common problem and the better known pattern. Figure 11 presents this failure pattern, where f is the supply fundamental frequency and s is the motor slip.

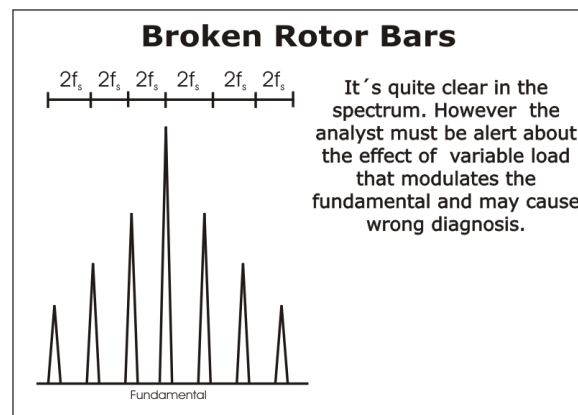


Figure 11. Broken bar pattern

2. Air gap Eccentricity: it is the condition in which the air gap doesn't present a uniform distance between the rotor and stator, resulting in a region of maximum air gap and another region of minimum air gap. There are two kinds of air gap eccentricity: static and dynamic. Figure 12 shows the patterns for both kinds, where f_1 is the supply fundamental frequency, R is number of rotor bars, and CF is the center frequency.
 - a. Static Eccentricity: the minimal radial air gap position is fixed in the space. The stator core is bowed or there is an incorrect positioning between the rotor and the stator generated as a consequence of misalignment. Besides those possibilities, constructive aspects permit an inherent level of eccentricity due to the tolerances of the manufacturing process.
 - b. Dynamic Eccentricity: the minimum air gap turns with the rotor. The main causes are: rotor outer diameter is not concentric, rotor thermal bent, bearing problems, rotor or load imbalance.

Mechanical problems such as rotor misalignment and imbalance can be also inferred in the low spectrum through the analysis of the rotational frequency sidebands. Figure 13 shows this pattern, where f_r is rotational frequency.

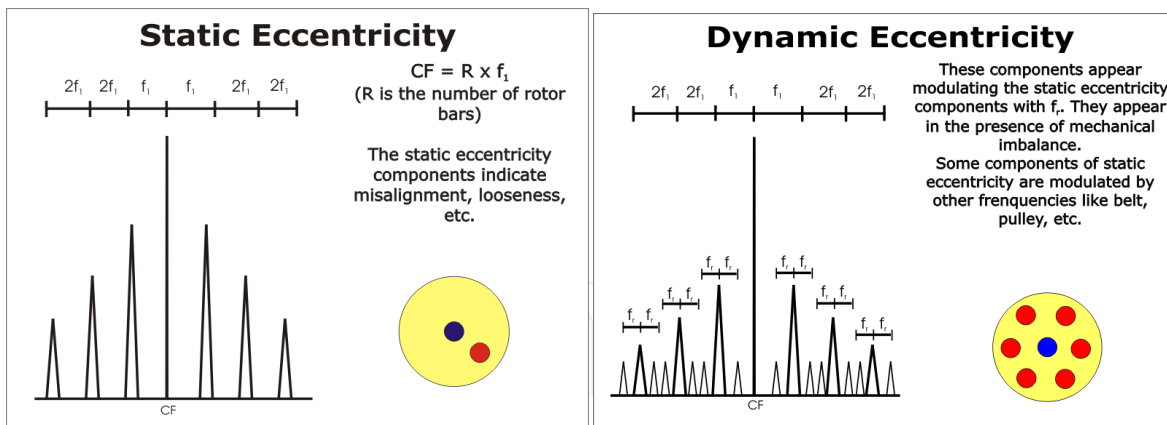


Figure 12. Static and Dynamic Eccentricities patterns

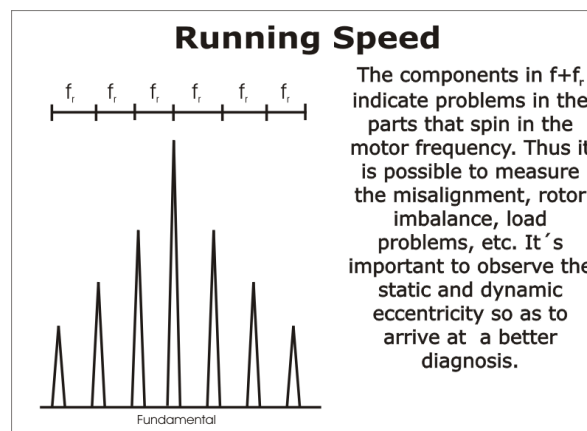


Figure 13. Rotational frequency pattern

5.2. Stator failure patterns

Most induction motor stator failures are related to the windings. The occurrence of failures in the stator core is less frequent. In spite of being rare, this last problem can cause considerable damages to the machine (Borges da Silva et al., 2009).

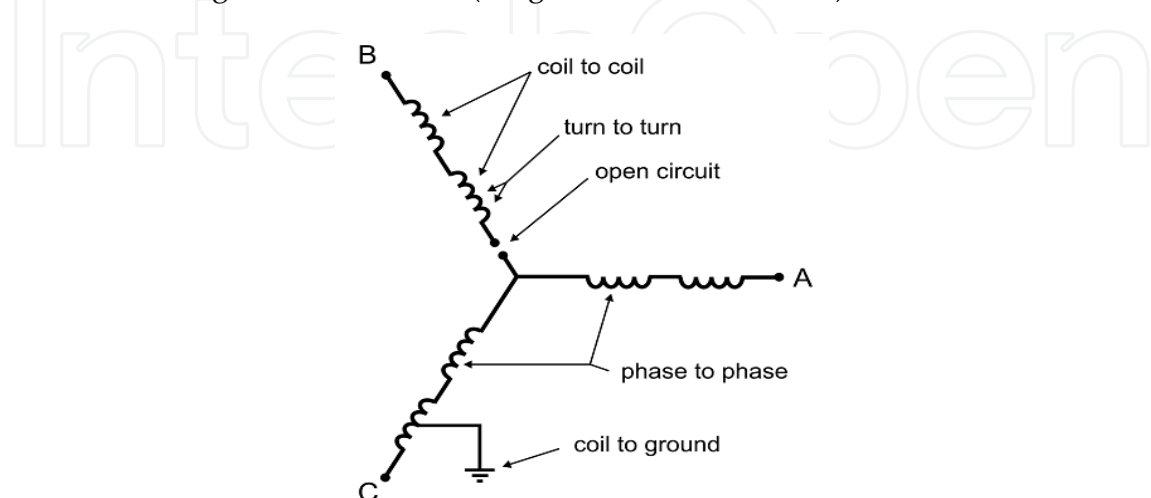


Figure 14. Stator winding failure modes

The failures related to the stator windings present a diversified set of possible manifestations according to the Figure 14. It is possible to notice their simultaneous occurrence. There are MCSA patterns for the detection of these failures, but EPVA is the most recommended technique to detect electrical imbalance in motors without direct torque control.

5.3. Bearing failure patterns

The monitoring of bearing damages is very important in predictive maintenance program since these problems account for 40% of the total amount of failures in an induction motor (Schoen et al., 1995). Many papers have recommended current signature analysis for the diagnosis of bearing faults, although it is important to register that this is an area that can be more explored and improved, tracking earlier fault detection.

There are several causes for bearing damages. Since this is not the objective of this work, the chapter presents just the characteristic components of failure in the outer and inner races, and rolling elements. The pattern is given by the Figure 15; where FBPFO is the rolling element characteristic frequency, FBPFI is the inner race characteristic frequency, FBSF is the outer race characteristic frequency, FFTF is the cage characteristic frequency, PD is the bearing pitch diameter, BD is the ball bearing diameter, β is the contact angle, n is the number of rolling elements, and F_r is the rotational speed.

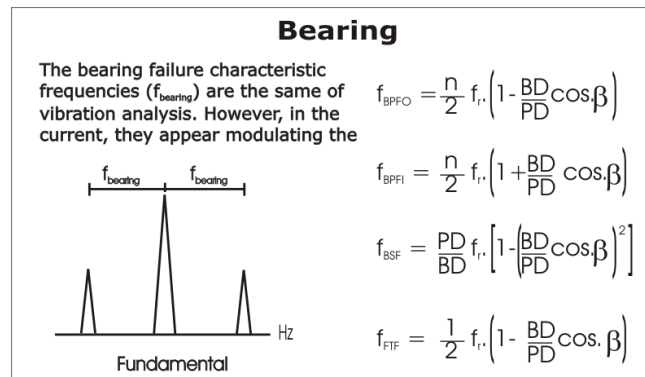


Figure 15. Bearing failure modes

5.4. Load failure patterns

The vast majority of the published papers about failure monitoring via current spectrum analysis presents the failure patterns related to broken bars and air gap eccentricity. This chapter presents a very meaningful contribution to the previous works since it adds new patterns related to the attached load. All the patterns have been tested, first through controlled laboratory tests and later through industrial cases. The failure patterns can be divided in three groups: motor failure, transmission system failure and attached load failure. By using the induction motor as a transducer, one can monitor the complete drive train, i.e., motor, transmission system and attached load, so as to increase the reliability of productive system.

5.4.1. Transmission System Failure

The MCSA monitors the frequency components related to pulleys (motor pulley and load pulley), belts and gear mesh. It has been observed that load problems can reflect in the transmission system frequency components. This characteristic is one more way of detecting mechanical load failures to be used in addition to the load characteristic frequency components.

1. **Pulleys:** by analyzing the rotational frequency one can detect problems related to the motor pulley. When there is no change in the speed, it is not possible to distinguish the damaged pulley from the healthy one since they have the same rotational frequency. But when a speed transformation is present, one can monitor the load pulley and the attached load through the pattern presented in Figure 16. In this case, f_{lf} is equal to f_{pulley} , and f_{pulley} is the load pulley characteristic frequency given by (45).

$$f_{pulley} = \frac{D_{motor_pulley} \times f_r}{D_{load_pulley}} \quad (45)$$

Where f_r is the rotational frequency, D_{motor_pulley} is the diameter of the motor pulley and D_{load_pulley} is the diameter of the load pulley. The sideband components of the fundamental are at $f_1 \pm f_p$.

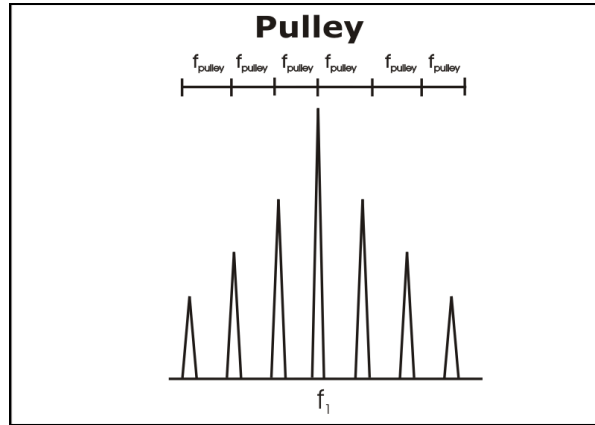


Figure 16. Load Pulley Pattern

The most common problems are eccentric pulley, pulley with mechanical looseness and unbalanced pulley. Problems related to the load can also reflect in the same frequencies. When this happens, the analyst himself must cross pieces of information from other spectrum regions so as to arrive at a reliable conclusion.

2. **Belts:** the first step when monitoring the belt characteristic frequency components is to calculate the belt frequency (f_b). In this case, f_{lf} is equal to f_b , and f_b is the belt characteristic frequency given by (46).

$$f_b = \frac{D_{motor_pulley} \times \pi \times f_r}{L_{belt}} \quad (46)$$

Where L_{belt} is the belt length

This way the sideband components of the fundamental are at $f_1 \pm f_b$. After calculating this frequency, it is enough to follow the pattern presented in Figure 17 and follow up the tendency curve in order to diagnose problems in this transmission system element.

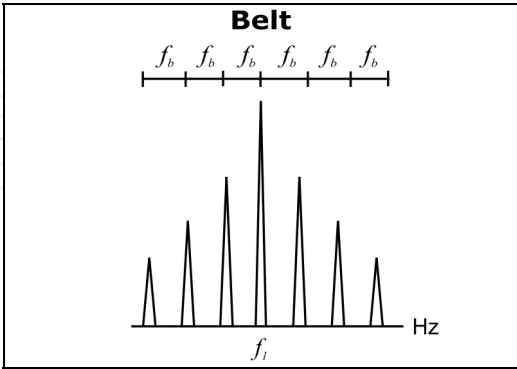


Figure 17. Belt Failure Pattern

Besides diagnosing problems such as loosen belt, broken belt or too taut belt, one can analyze problems originating in the load. In case of load failure, the vibration levels in the belts increase considerably and result in higher amplitudes for the belt characteristic frequencies.

3. **Gear Mesh:** in this case, two spectrum regions must be monitored. The first one, in a lower frequency band, shows punctual failure in the gear (for instance, a broken tooth). These frequencies are related to the rotational frequencies before and after the speed transformation. This way the sideband components of the fundamental are at $f_1 \pm f_{r1}$ and $f_1 \pm f_{r2}$ respectively. Where f_{r1} is the rotational frequency before the speed transformation and f_{r2} is the rotational frequency after the speed transformation. The second spectrum region of interest shows distributed failures in the gear. They are known as gear mesh frequency (f_g) and can be calculated by multiplying the rotational shaft speed by the gear teeth number Figure 18a illustrates this situation, and Figure 18b shows the sideband components of the fundamental are at $f_1 \pm f_g$.

$$f_g = n \cdot f_{r1} = N \cdot f_{r2} \tag{47}$$

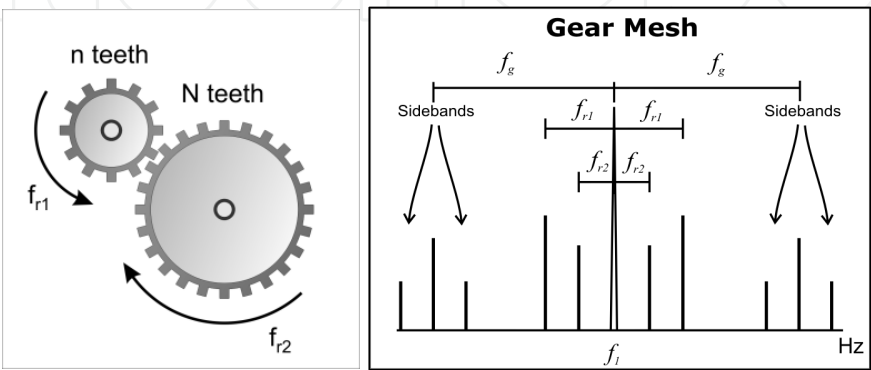


Figure 18. Gear features: (a) gear mesh, and (b) gear mesh failure pattern

5.4.2. Attached load failure

As seen previously, a load fault reflects in the motor stator current by means of torque oscillations. This chapter presents in this section three different kinds of loads and their respective patterns. Other load types result in different patterns but the fundamental sequence is always the same: define the characteristic frequencies from the constructive data, find their presence in the motor current signature due to torque oscillations from load faults, analyze the tendency curve and diagnose the fault.

1. **Centrifugal Pumps:** for the analysis of centrifugal pumps one has to consider the pump rotational frequency (f_{r_pump}) and the vane pass frequency (f_{vp}) that is given by:

$$f_{vp} = n \cdot f_{r_pump} \quad (48)$$

Where n is the number of pump vanes.

The analysis of the pump rotational frequency (f_{r_pump}) indicates problems related to misalignment or pump imbalance. In this case, f_{lf} is equal to f_{r_pump} and the sideband components of the fundamental are at $f_1 \pm f_{r_pump}$. On the other hand, the increase of the amplitudes of vane passing frequency indicates problems inside the pump, such as vane deterioration. Now the sideband components of the fundamental are at $f_1 \pm f_{vp}$. Figure 19 shows the pattern for these frequencies.

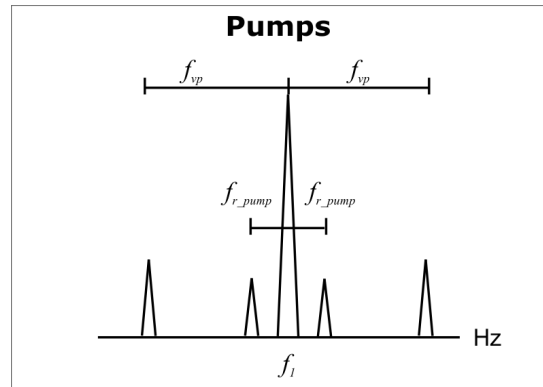


Figure 19. Centrifugal pump failure pattern

In addition to those frequencies one has to monitor the increase of saliencies close to the supply frequency. These frequencies are characteristic of pump signature and also can indicate pump problems.

2. **Screw Compressor:** the complete set motor, gear mesh and screw compressor can be monitored by means of MCSA satisfactorily. The motor and the gear mesh can be analyzed according to the patterns presented previously. Figure 20a shows the scheme of a screw compressor. Where N is the motor gear teeth number, n is the compressor gear teeth number, L_m is the male screw lobules number, L_f is the female screw lobules number, F_r is the motor rotational frequency, F_{r1} is the male screw rotational frequency, F_{r2} is the female screw rotational frequency and F_p is the pulsation frequency. The screw compressor failure spectral pattern is presented in Figure 20b.

The screw compressor analysis takes into consideration three characteristic frequencies:

- a. Male screw rotational frequency: in this case, $f_{rf} = f_{r1}$ and f_{r1} is the male screw rotational frequency given by (51). The sideband components of the fundamental are at $f_1 \pm f_{r1}$.

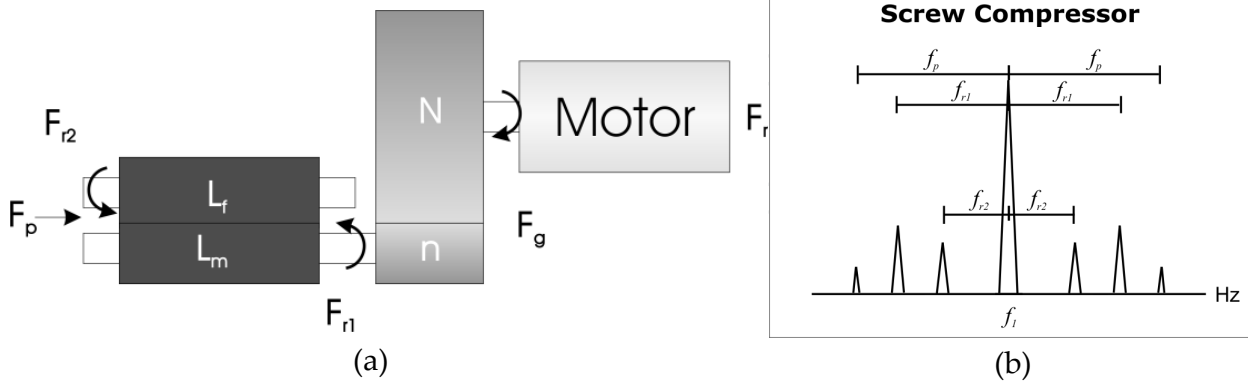


Figure 20. Screw compressor: (a) schematic and (b) failure spectral pattern

$$f_{r1} = \frac{N}{n} \cdot f_r \quad (49)$$

- b. Female screw rotational frequency: in this case, f_{rf} is equal to f_{r2} and f_{r2} is the female screw rotational frequency given by (50). The sideband components of the fundamental are at $f_1 \pm f_{r2}$.

$$f_{r2} = \frac{L_m}{L_f} \cdot f_{r1} \quad (50)$$

- c. Pulsation frequency: in this case, f_{rf} is equal to f_p and f_p is the pulsation frequency given by (51). The sideband components of the fundamental are at $f_1 \pm f_p$.

$$f_p = L_m \cdot f_{r1} = L_f \cdot f_{r2} \quad (51)$$

When the screw compressor has two stages, it is enough to apply the same reasoning for the second stage of compression. Since the speed transformations are different, the characteristic component of each stage can be separated in the spectrum.

3. **Fans:** in the same way of pumps, fan failure analysis considers the fan rotational frequency and the blade passing frequency (f_{bp}):

$$f_{bp} = N_b \times f_{r_fan} \quad (52)$$

Where N_b is the number of blades and f_{r_fan} is the fan rotational frequency.

Analyzing the rotational frequency (f_{r_fan}), problems related to misalignment or fan imbalance can be detected. When, f_{rf} is equal to f_{r_fan} and the sideband components of the fundamental are at $f_1 \pm f_{r_fan}$. Also, the increase of the amplitudes of blade passing frequency

indicates problems like blade deterioration or break. The sideband components of the fundamental are given by $f_1 \pm f_{bp}$. Figure 21 shows the fan failure patterns.

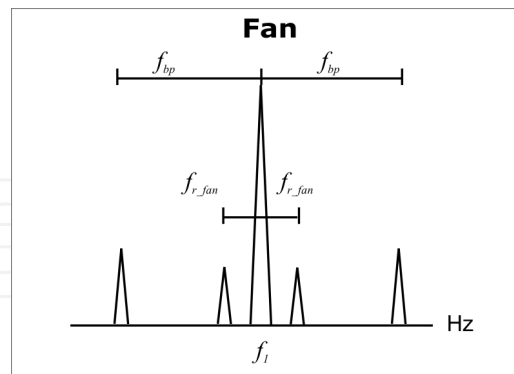


Figure 21. Fan failure pattern

6. Elements of a monitoring system for predictive maintenance

A sophisticated monitoring system can read the entrances of hundreds of sensors and execute mathematical operations and process a diagnosis. Currently, the diagnosis is gotten, most of the time, using artificial intelligence techniques (Lambert-Torres et al. 2009).

Considering the previous statements, a monitoring system can be divided in four main stages: (a) transduction of the interest signals; (b) acquisition of the data; (c) processing of the acquired data; and (d) diagnosis. Figure 22 presents a pictorial form of this process.

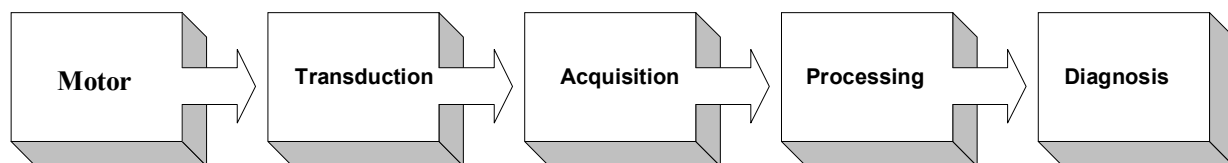


Figure 22. Steps of the Monitoring Process

6.1. Transduction

A transducer is a piece of equipment that has in its entrance an input value to be monitored (current, voltage, acceleration, temperature, etc), whereas in its output it has a signal that is conditioned and envoy to the acquisition system and processing. The main transducers used in the monitoring processing of electric machines are:

- For measurement of temperature: they are the three main methods of measurement of temperature: thermocouple, thermister, and RTD (Resistance Temperature Detection).
- For the measurement of vibration: two types of transducers for the vibration analysis exist: the absolute transducers or with contact and the relative ones or without contact. The absolute transducers measure the real movement of the machine, whereas the relative ones measure the movement of an element of the machine in relation to the other element. The accelerometer is the main and more used existing absolute sensor in the market.

- For measurement of force: the most common is the strain gauge, that it is a device that understands a resistance that has its modified size and transversal area in function of the application of a force. Then, the force can be measured through the variation of the resistance.
- For measurement of electric and magnetic values: the electric values are measured from transforming of voltage and current those always are presented as part of the protection system. However, it can still have the necessity an extra measure, the density of magnetic flow in the machine, using itself a hall-effect device.

6.2. Data acquisition

The data acquisition is a stage with fundamental importance; because it needs to guarantee the integrity and precision of the collected data. The precision of the data demanded of the acquisition is determined by the future mathematical manipulations that are applied to the data set. The collection and the transmission of the data must be made in order to minimize to the maximum the effect of the noise, being become the sufficiently consistent data. In complex systems with many entrances, it is oriented that the processing system is remote, that is, located to a certain distance of the inspected process. Figure 23 presents an example where some motors are being monitored. A group of adjacent machines is connected to a point of collection of data that digitalize the signal and sends for the remote central office of processing and diagnosis.

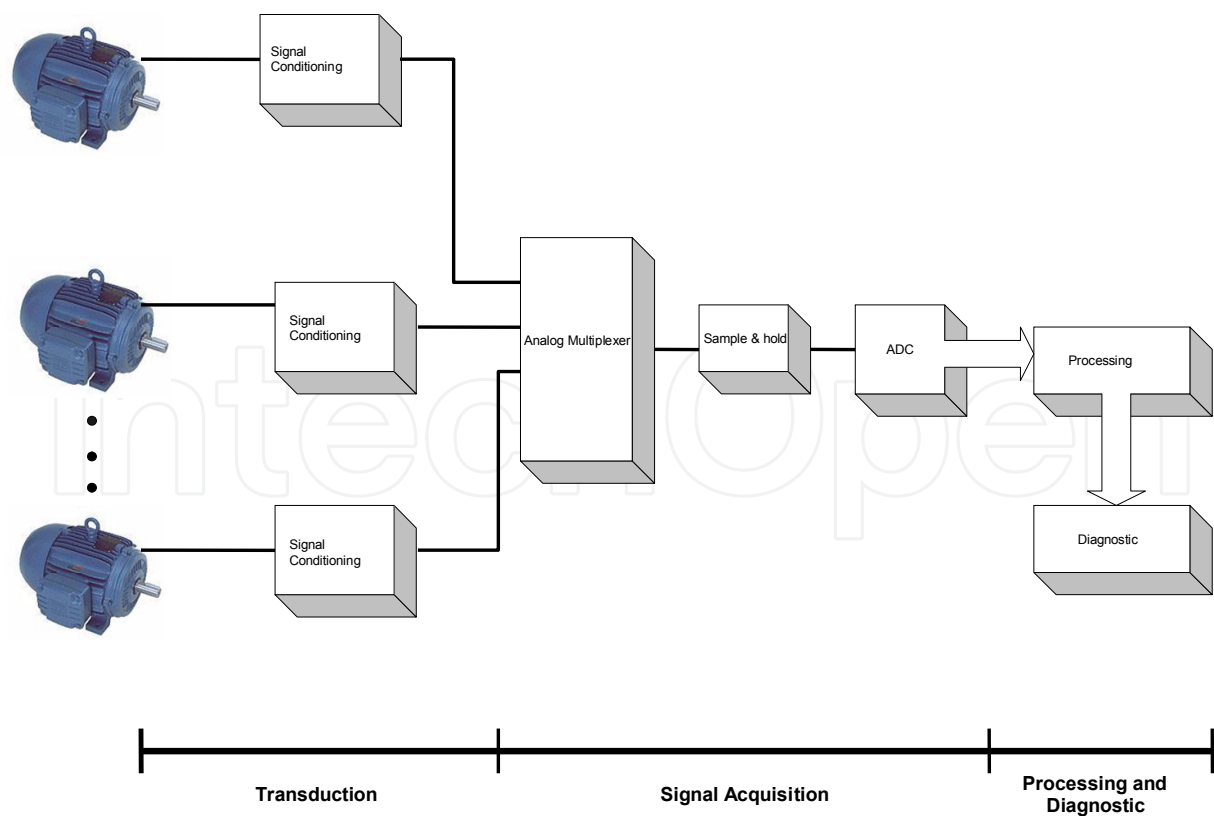


Figure 23. Example of a Monitoring System

The multiplexer is essential when a great number of channels must be monitored. Moreover, it also is recommended for a small number of channels, since it allows the use of only one converter A/D. Already converter A/D is the heart of the acquisition system and must be specified in function of the time of conversion and precision.

6.3. Processing

The task of the processing must be to catch the collected data and to manipulate them and/or to transform them, aiming at the agreement of these for the system of diagnosis in a faster and easier form. The processing can be done on-line or off-line. The choice depends on the process that are being monitored and on the speed with that the characteristics of interest of this process modify themselves.

There are different techniques of processing to monitor electric machines. One of the simplest of them, it examines the amplitude of the signal of entrance of the function in the time, and compares it with a predetermined value. Elaborated techniques are currently possible due to the new computers, such as: spectral analysis, correlation, averages, cepstral, envelope analysis, etc.

6.4. Diagnosis

Diagnosis is the part most critical of the system, because it involves decisions and consequently money. Currently, many techniques of artificial intelligence as expert systems and neural nets are being used (Lambert-Torres et al., 2009).

7. Implementation in a real-case predictive maintenance

A Brazilian petroleum company has decided to implement electrical signature analysis through a remote condition monitoring system named Preditor (PS Solutions, 2011). The communication is based on Ethernet network. Each hardware has been plugged in this network has an IP address and through the motor configuration the software knows exactly where each signal comes from. This way it is possible to monitor the motor condition from a remote office with a group of expert analysts or to count on the automatic support of the software.

Among the induction motors monitored, an example of electrical imbalance was chosen. Motor nameplate features are 250 CV, 2400 V, 70 A, 505 RPM, 14 poles, and attached to a reciprocating compressor. The remote system software has indicated electrical imbalance based on EPVA signature. Figure 24 presents the stator electrical imbalance signature and tendency curve for this motor.

One can observe from the figure above that the electrical imbalance was around 5.7%. For an idea of magnitude, all the other motors presented an electrical imbalance around 1%. The motor history was tracked and the maintenance department detected a set of defective coils in one phase. These coils were by-passed, which caused the imbalance, as shown in Figure 25.

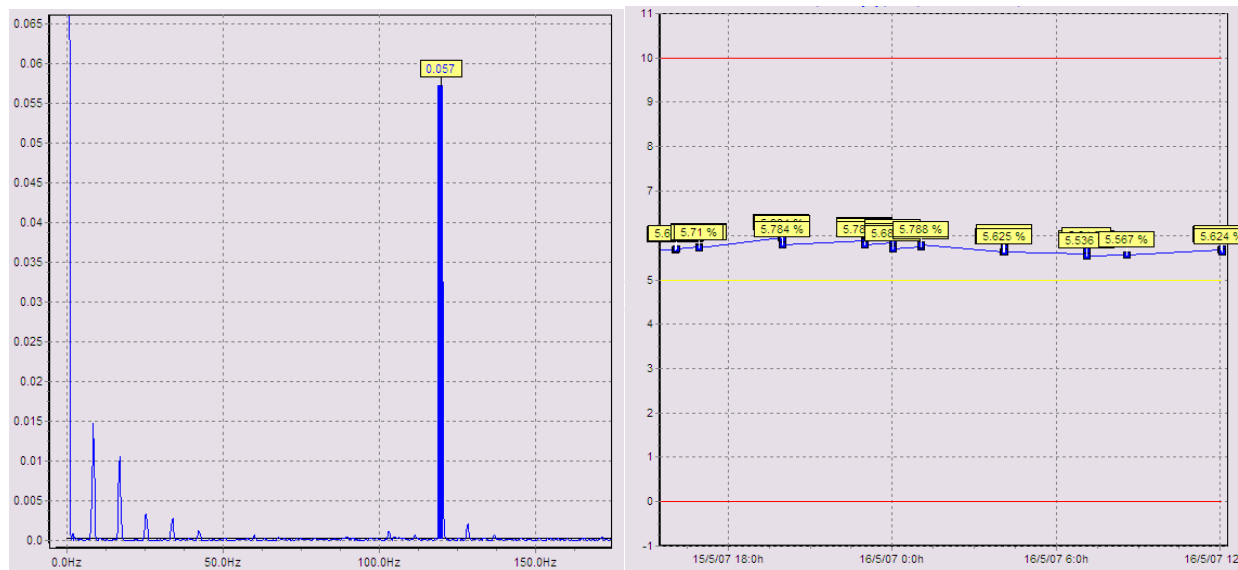


Figure 24. Stator electrical imbalance signature and tendency curve

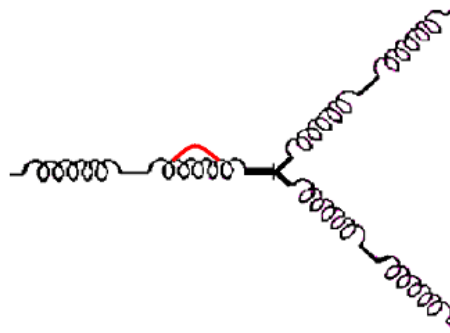


Figure 25. Set of defective coils by-passed

After all the implementing job, one can say that the remote system based on electrical signature analysis is an effective alternative for rotating machines monitoring since the system fits the refineries safety rules. It still allows the non-intrusive monitoring, avoiding exposing the workers to electrical shock and arcs, confined spaces and eliminating the necessity of job permissions and risk analysis for signal acquiring (which implies in cost reduction). The electrical failure dynamic monitoring presents a good potential to increase the industries process reliability. Besides, the techniques also allow the tracking of mechanical components, which is an interesting tool to detect mechanical faults in machines located in places of difficult access.

In 2006, a petroleum refinery experienced an unplanned outage in its Coker Unit caused by the breakage of some rotor bars in the induction motor of the decoking pump which damaged the rotor and the stator of the motor as can be seen in the picture below. The damaged motor had the following features: Poles – 4, Rated Power – 1700 kW, Rated Voltage – 13.8 kV, Shaft Height – 500 mm, and Hazardous Area – Free zone. Although it is not possible to operate without the decoking pump, there is not a standby motor because of its high reliability and cost. Figure 26 shows the stator and rotor damages.



Figure 26. Stator and Rotor Damages

After the event, the motor was sent to be repaired, but the first information was that it would take 70 days to be fixed. Since this deadline would compromise the refinery production plan, the refinery's maintenance team started looking for a similar motor. In normal conditions, it was not possible to find a better solution, than to wait for 70 days (considering the purchase of a new motor it would take, at least, 6 months). Luckily, a motor was found in a factory with the following features: Poles – 4, Rated Power – 1656 kW, and Rated Voltage – 4.16 kV, Shaft Height – 450 mm, and Hazardous Area – Free zone.

Considering that the refining process is based on pumps and compressors, the engineers noticed that the unique parameter that should be exactly the same was the number of poles. To the others, the following analysis was done:

- Rated Power – Since the original motor does not operate at its rated power, it was possible to use the similar motor;
- Rated Voltage – the refinery had a voltage transformer in stock (4.16/13.8 kV), that could be used to supply the rated voltage to the similar motor;
- Shaft Height – the original motor shaft was higher than the similar one, but this could be solved easily by adapting the skid.

Besides, considering that the decoking pump had been installed in a non hazardous area, the similar motor completely met the requirement to be installed. Then, after a short negotiation, an agreement was made between the oil company and the motor manufacturer, where the similar motor was rented to be adapted, while the manufacturer made another motor to replace the original one. While the similar motor was in its way to the refinery, all possible and necessary electrical and mechanical work to fit this motor to the site was in process. When the similar motor arrived, the maintenance team spent only one day to replace the motor. Six days after the outage, the Coker Unit started over.

8. Cost analysis

Based on the Brazilian Petroleum Company experience reported above, in terms of costs, it is very easy to demonstrate the benefits of having an ESA system installed together with a motor management.

Considering that 1 day without production means losses of US\$ 300,000.00, we would have US\$ 21,000,000.00 in 70 days. However, as we found a motor to be adapted, we had just 6 days of losses (US\$ 1,800,000.00). If we had an ESA System installed monitoring this motor, we could realize in advance that the motor was developing a failure. As we said before, some refineries have similar motors that could be adapted. So, in that case, it would be possible to plan the replacement, sending the motor, and making the adaptations and stopping the production for only 1 day, i.e. losses of US\$ 300,000.00.

9. Conclusions

The industries currently look for products and outside services for predictive maintenance. In many cases, the outside service company or even the industrial plant predictive group make mistakes that can compromise the whole condition monitoring and failure diagnosis process. In this increasing demand for prediction technology, a specific technique referred as Electrical Signature Analysis (ESA) is calling more and more attention of industries.

Considering this context, the presented chapter intends to disseminate important concepts to guide companies that have their own predictive group or want to hire consultants or specialized service to obtain good results through general predictive maintenance practices and, especially through electrical signature analysis.

The result of the proposed discussion in this chapter is a procedure of acquisition and analysis, which is presented at the end of the chapter and intends to be a reference to be used by industries that have a plan to have MCSA as a monitoring condition tool for electrical machines.

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10. References

Benbouzid, M.H. (2000). A Review of Induction Motors Signature Analysis as a Medium for Faults Detection, *IEEE Transactions on Industrial Electronics*, Vol.47, No.5, (October 2000), pp. 984-993, ISSN 0278-0046.

- Bonaldi, E.L., Borges da Silva, L.E., Lambert-Torres, G. de Oliveira, L.E.L. (2003). A Rough Sets Based Classifier for Induction Motors Fault Diagnosis, *WSEAS Transactions on Systems*, Vol.2, No.2, (April 2003), pp. 320-327, ISSN 109-2777.
- Bonaldi, E.L., de Oliveira, L.E.L., Lambert-Torres, G. & Borges da Silva, L.E. (2007). Proposing a Procedure for the Application of Motor Current Signature Analysis on Predictive Maintenance of Induction Motors, *Proceedings of the 20th International Congress & Exhibition on Condition Monitoring and Diagnosis Monitoring Management - COMADEM 2007*, Faro, Portugal, Jun. 13-15, 2007.
- Bonnett, A.H., & Soukup, G.C. (1992). Cause and Analysis of Stator and Rotor Failures in Three-Phase Squirrel-Cage Induction Motors, *IEEE Transactions on Industrial Electronics*, Vol.28, No.4, (July/August 1992), pp. 921-937, ISSN 0278-0046.
- Borges da Silva, L.E., Lambert-Torres, G., Santos, D.E., Bonaldi, E.L., de Oliveira, L.E.L. & Borges da Silva, J.G. (2009). An Application of MSCA on Predictive Maintenance of TermoPE's Induction Motors, *Revista Ciências Exatas*, Vol. 15, No. 2, (July 2009), pp. 100-108, ISSN 1516-2893.
- Cardoso, A.J.M. & Saraiva, E.S. (1993). Computer-Aided Detection of Airgap Eccentricity in Operating Three-Phase Induction Motors by Park's Vectors Approach, *IEEE Transactions on Industry Applications*, Vol.29, No.5, (Sept/Oct 1993), ISSN 0093-9994.
- Lambert-Torres, G., Bonaldi, E.L., Borges da Silva, L.E. & de Oliveira, L.E.L. (2003). An Intelligent Classifier for Induction Motors Fault Diagnosis, *Proceedings of the International Conference on Intelligent System Applications to Power Systems - ISAP'2003*, Paper 084, Lemnos, Greece, Aug. 31 – Sept. 3, 2003.
- Lambert-Torres, G., Abe, J.M., da Silva Filho, J.I. & Martins, H.G. (2009). *Advances in Technological Applications of Logical and Intelligent Systems*, IOS Press, ISBN 978-1-58603-963-3, Amsterdam, The Netherlands.
- Legowski, S.F., Sadrul Ula, A.H.M., & Trzynadlowski, A.M. (1996). Instantaneous Power as a Medium for the Signature Analysis of Induction Motors. *IEEE Transactions on Industry Applications*, Vol.32, No.4, (July/August 1996), pp. 904-909, ISSN 0093-9994.
- PS Solutions. (October 2011). Predictor, Available from www.pssolucoes.com.br, visited on 22/10/2011.
- Schoen, R.R., Habetler, T.G., Kamram, F. & Bartheld, R.G. (1995). Motor Bearing Damage Detection Using Stator Current Monitoring, *IEEE Transactions on Industrial Electronics*, Vol.31, No.6, (Nov/Dec 1995), pp. 1274-1279, ISSN 0278-0046.
- Tavner, P.J., Ran, L., Penman, J. & Sedding, H. (1987). *Condition Monitoring of Rotating Electrical Machines*, The Institution of Engineering and Technology – IET, 2nd Edition, ISBN 978-0863417412, London, UK.
- Thomson, W.T., & Fenger, M. (2001). Current Signature Analysis to Detect Induction Motor Faults, *IEEE Industry Applications Magazine*, Vol.7, No.4, (July 2001), pp. 26-34, ISSN 1077-2618.

Thorsen, O.V. & Dalva, M. (1999). Failure Identification and Analysis for High-Voltage Induction Motors in the Petrochemical Industry, *IEEE Transactions on Industry Applications*, Vol.35, No.4, (July/August 1999), pp. 810-817, ISSN 0093-9994.

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