BRIEF REVIEW OF MOTOR CURRENT SIGNATURE ANALYSIS

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ABSTRACT - *Motor electrical current signature analysis (MCSA) is sensing an electrical signal containing current components that are direct by-product of unique rotating flux components. Anomalies in operation of the motor modify harmonic content of motor supply current. This paper presents brief introductory review of the method including fundamentals, fault detection techniques and current signatures of various faults.*

Keywords: *induction motor, current, signature analysis, MCSA, fault detection, condition monitoring*

1. INTRODUCTION

Induction motors are widely used in industrial drives because they are rugged, reliable and economical, [1]. They became an industry workhorse and play a pivotal role in industry for conversion of electrical into mechanical energy, [2]. Motor Current Signature Analysis (MCSA) is a condition monitoring technique used to diagnose problems in induction motors, [3-12]. Concept originates from early 1970s and was first proposed for use in nuclear power plants for inaccessible motors and motors placed in hazardous areas, [13]. It is rapidly gaining acceptance in industry today. Tests are performed online without interrupting production with motor running under the load at normal operating conditions, [4,13]. MCSA can be used as predictive maintenance tool for detecting common motor faults at early stage and as such prevent expensive catastrophic failures, production outages and extend motor lifetime. It can be used as a diagnostic tool and powerful addition to vibration and thermal monitoring (verifying a fault with more than one technology), [14-16]. MCSA is method from wider field of Electrical Signature Analysis (ESA), [17], useful for analyzing not only electrical induction motors, but also generators, power transformers as well as other electric equipment. Most popular of these techniques are: Current Signature Analysis (CSA), Voltage Signature Analysis (VSA), Extended Park's Vector Approach (EPVA) and Instantaneous Power Signature Analysis (IPSA), [11]. ESA also includes Motor Circuit Analysis, [18], involving analysis of resistance, impedance, inductance, phase angle, current/frequency response and insulation to ground faults, [19].

2. MOTOR CURRENT SIGNATURE ANALYSIS BASICS

Motor Current Signature Analysis is the technique used to analyze and monitor the trend of dynamic energized systems, [11].

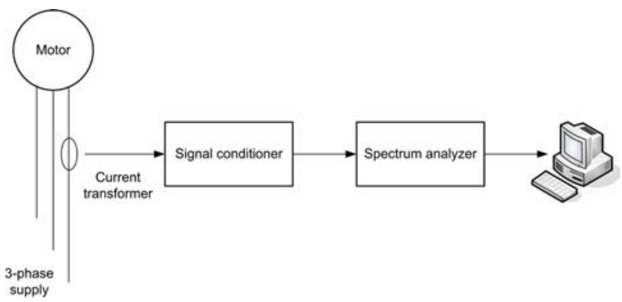


Figure 1 *Stator current monitoring system*

MCSA is monitoring stator current (more precisely supply current) of the motor, [7]. Typical stator current monitoring system is illustrated in Figure 1. Single stator current monitoring system is commonly used (monitoring only one of the three phases of the motor supply current). Motor stator windings are used as transducer in MCSA, picking the signals (induced currents) from the rotor (but also revealing information about the state of the stator).

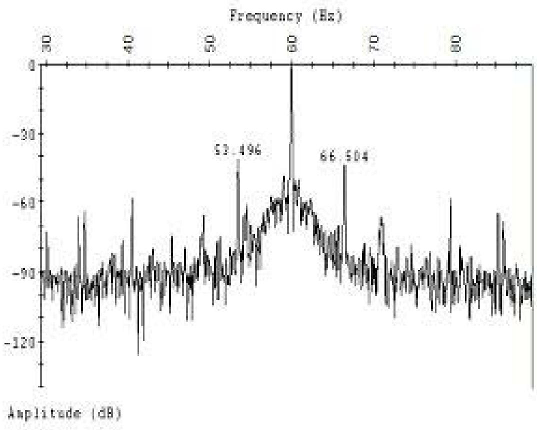


Figure 2 *Current spectrum of induction motor, [20]*

Motor current is sensed by a Current Sensor (clamp probe, current transformer) with resistive shunt across its output, [21], and recorded in time domain. Picked current signal is then led to a spectrum analyzer or specialized MCSA instrument. In ideal case motor current should be pure sinusoidal wave. In reality in motor current many harmonics are present. Current spectrum of a typical induction motor is illustrated in Figure 2. Various electrical and mechanical fault conditions present in the motor further modulate motor current signal and contributes to additional sideband harmonics. Faults in motor components produce corresponding anomalies in magnetic field and change the mutual and selfinductance of motor that appear in motor supply current spectrum as sidebands around line (supply, grid) frequency, [22]. Based on fault signatures motor faults can be identified and its severity accessed. Frequency range of interest in MCSA is typically 0-5 kHz, [11]. This, according to a Nyquist theorem, requires sample rate of at least 10000 samples per second. During the test motor should be run at loading greater then 70%. It should be noted that fault signals detected in motor supply current may also be influenced by operation of neighboring motors and system's environmental noise.

3. FAULTS THAT CAN BE DETECTED WITH MCSA

The major faults of electrical machines can broadly be classified by the following [3,13,23]:

a. Static and/or dynamic air-gap irregularities.
b. Broken rotor bar or cracked rotor end-rings.
c. Stator faults (opening or shorting of one coil or more of a stator phase winding)
d Abnormal connection of the stator windings.
e. Bent shaft (akin to dynamic eccentricity) which can result in a rub between the rotor and stator, causing serious damage to stator core and windings.
f. Bearing and gearbox failures

The most common faults are bearing faults, stator faults, rotor faults and eccentricity or any combination of these faults. When analyzed statistically, about 40% of the faults correspond to bearing faults, 30-40% to stator faults, 10% to rotors faults, while remaining 10% belong to a variety of other faults, [11,24]. Frequencies induced by each fault depend on the particular characteristic data of the motor (like synchronous speed, slip frequency and pole-pass frequency) as well as operating conditions, [2,18,25]. Main classes of faults that can be detected with MCSA are listed bellow.

3.1. AIR-GAP ECCENTRICITY

Air-gap eccentricity represents a condition when air gap distance between the rotor and the stator is not uniform. Two types of abnormal air-gap eccentricity exist: static and dynamic. In case of static eccentricity the position of minimal radial air gap is fixed, while in case of dynamic eccentricity position of

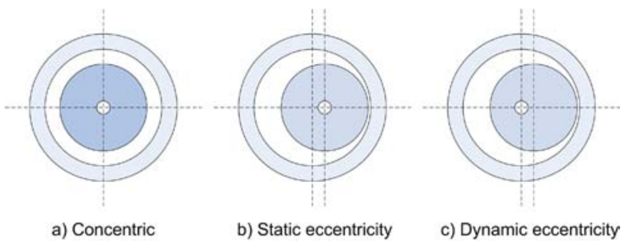


Figure 3 *Air gap: a) normal (concentric), b) static eccentricity and c) dynamic eccentricity*

minimal air gap follows turning of the rotor. Normal (concentric) state, static and dynamic eccentricity are illustrated in Figure 3, [26]. As the rotor bars recede or approach the stator magnetic fields, they cause a change to the current in the stator. In case of static eccentricity sideband components appear at frequencies determined by (1), [3] and shown in Figure 4, [3-5,8,11,18,25].

$$f_{ec} = f_g\left\{(R \pm n_d)\left(\frac{1-s}{p}\right) \pm n_{ws}\right\} \qquad (1)$$

where

f_{ec} is eccenticity frequency
f_g is electrical supply (grid) frequency
R is the number of rotor bars
s = slip
p = pole-pairs
$n_d = \pm 1$
n_{ws} = 1, 3, 5, 7 …

The slip is determined from (2)

$$s = \frac{N_s - N_r}{N_r} \qquad (2)$$

where

s is per unit slip
N_r is rotor speed
N_s is synchronous speed

Central frequency f_c on Figures 4 and 5 is determined by (3):

$$f_c = Rf_g \qquad (3)$$

where R is the number of rotor bars.

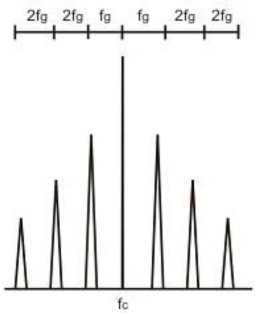


***Figure 4** Air gap – static eccentricity [11]*

When dynamic eccentricity is present, frequency components from static eccentricity are further modulated with the rotational frequency f_r, as shown in Figure 5.

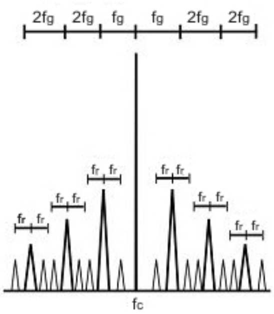


***Figure 5** Air gap- dynamic eccentricity [11]*

3.2. BROKEN ROTOR BARS

Primary causes of broken bars are direct online starting duty cycles (with fivefold the full load bar currents) and pulsating mechanics loads (like reciprocating machinery). They can cause sparking and overheating in a motor, [4]. By examining the frequency spectrum of the stator currents, early stages of rotor bar failures can be detected, [5,18,25,27-29]. When broken rotor bars are present, current components in stator windings can be detected at frequencies given by (4), [5]:

$$f_{brb} = f_g\left[k\left(\frac{1-s}{p}\right) \pm s\right] \qquad (4)$$

where

f_{brb} is broken rotor bar frequency
f_g is electrical supply (grid) frequency
p is number of pole pairs
s is per unit slip
k = 1, 2, 3, …

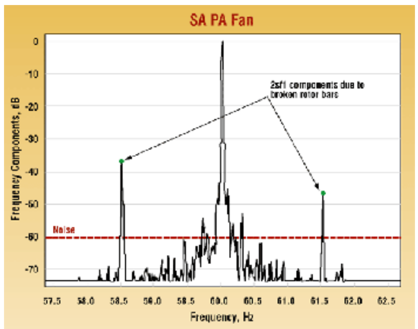


***Figure 6** Frequency spectrum from motor with broken rotor bars, [29]*

Upper and lower sidebands around supply component separated by twice the slip frequency are shown in Figure 6. The slip frequency is determined from (5):

$$f_{slip} = sf_g \qquad (5)$$

where

f_{slip} is slip frequency
f_g is electrical supply (grid) frequency
s is per unit slip

As a simple rule, if the difference between the main and sideband components is greater than 50 dB rotor has no faults, when difference is in range between 40 and 50 dB there is probably one bar broken and with difference less than 40 dB there are several broken bars or broken end ring, [23].

3.3. BEARINGS DAMAGE

Motor bearings faults are more difficult to detect then rotor cage problems, [5,7]. Four types of bearing misalignments exist, as is described in [5]. Such misalignments are common result of defective bearing installation. MCSA can detect bearing faults by detection of frequency components f_0 and f_1 that are for most bearings with between six and twelve balls determined by (6) and (7), [5, 25]:

$$f_0 = 0.4nf_{rm} \tag{6}$$

$$f_1 = 0.6nf_{rm} \tag{7}$$

where

f_0 is lower frequency,

f_1 is upper frequency,

n is the number of balls in the bearings

f_{rm} is the rotor's mechanical frequency

Frequencies due to bearing damage are illustrated in Figure 7.

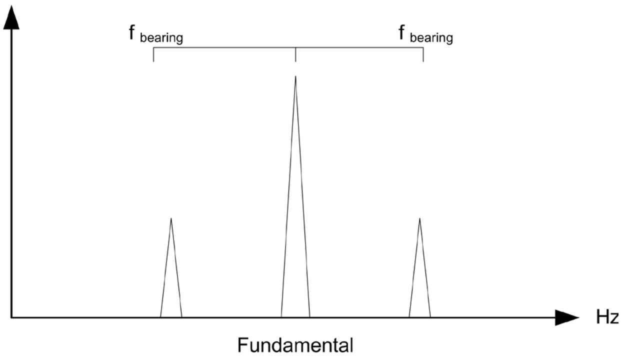


***Figure 7** Sideband frequency components due to bearing damage*

3.4. SHORTED TURNS IN STATOR WINDINGS

Most stator failures are related to stator windings. Shorted turns produce excessive heat in stator coil and current imbalance, [13]. MCSA exploits the fact that rotating flux waves can induce corresponding components in the stator windings, [3,30]. Motor current components that are influenced only by shorted turns can be detected at frequencies shown in Figure 8 and described by (8):

$$f_{st} = f_g\left(\frac{n}{p}(1-s) \pm k\right) \tag{8}$$

where

f_{st} is the component related to shorted turn

f_g is electrical supply (grid) frequency

n = 1,2,3,…

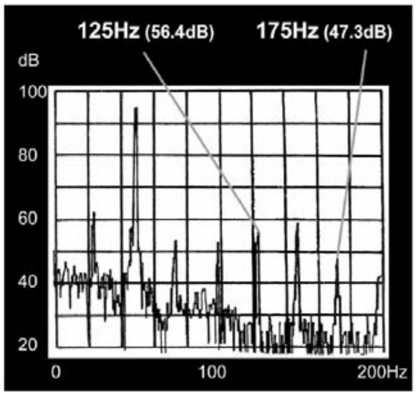


Figure 21. Current Spectrum – Shorted Turns.

***Figure 8** Frequency components corresponding to shorted turns, [3]*

3.5. Load Effects

Electrical motors are converters of electrical energy to a mechanical torque. Load torque may vary with rotor position. These variations cause corresponding variations in the motor current. In that case supply current will contain spectral components related to load torque variability, [5,31]. Variability in load torque at multiples of rotational speed mf_r produces stator currents at frequencies f_{load} as described in (9):

$$f_{load} = f_s \pm mf_r = f_s\left[1 \pm m\left(\frac{1-s}{p}\right)\right] \tag{9}$$

where

fload frequencies related to load torque variation

f_s is electrical supply (grid) frequency

f_r is rotational frequency

p is number of pole pairs

s is per unit slip

m=1, 2, 3, ...

Example of MCSA applied to monitoring gear vibrations (produced by load fluctuations on the gearbox) is described in [22].

3.6. EQUIPMENT WEAR

With equipment wear motor current spectrum changes as well. This is applicable to transmission system failures and attached load failures. There is not available general formula for frequency components associated with equipment wear. However, since most wear is random, faults appear in current spectrum as change in tilt (noise floor), Figure 9, [4].

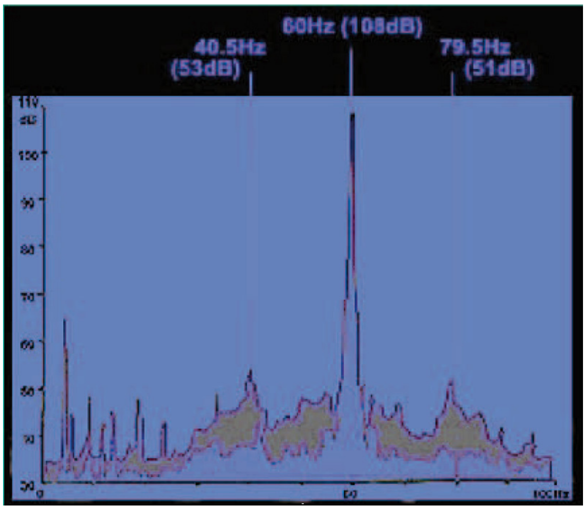


Figure 9 *Change in current spectrum due to equipment wear, [4]*

Multiple faults present in induction motor can be detected simultaneously, as described in [31]. Fault detection is not limited only to large motors powered by 50 Hz o 60 Hz current, but also on smaller motors, like one used in airborne application and powered by 400 Hz current, [32].

Brief intro regarding practical application of MCSA for previously mentioned faults and more, bypassing advanced math and complex considerations can be found in [22,33].

4. FAULT DETECTION TECHNIQUES

As already mentioned, motor faults modify the harmonic content of motor supply current. Several methods may be used in preprocessing stage for extracting features of measured motor supply current for the sake of comparison with known motor fault signatures, [21].

4.1. FAST FOURIER TRANSFORM

Motor current readings are recorded in time domain. After the signal conditioning analog-to-digital conversion is performed. Spectar of the motor current is typically analyzed using some of spectral analysis techniques. If signal is represented by x(t) as N discrete samples it can be expressed as a sum of N sinusoidal components of frequencies ω_i, and phase shifts θ_i, as described in (10) and (11):

$$x(t) = A_0 + \sum_{i=1}^{N} A_i \sin(\omega_i t + \theta_i) \qquad (10)$$

$$\omega_i = \frac{2\pi f_s i}{N} \qquad i=1, \ldots, N \qquad (11)$$

where ω_i, is circular frequency and f_s signal sampling rate.

Same signal expressed using sinus and cosinus terms is given in (12):

$$x(t) = A_0 + \sum_{i=1}^{N} \left(a_i \cos(\omega t) + b_i \sin(\omega t)\right) \qquad (12)$$

Values of coefficients can be determined by Discrete Fourier Transform, (13),(14),(15):

$$a_{i_i} = \frac{2}{N} \sum_{i=1}^{i=N} x(t) \cos(\omega_i t) \qquad (13)$$

$$b_{i_i} = \frac{2}{N} \sum_{i=1}^{i=N} x(t) \sin(\omega_i t) \qquad (14)$$

$$A_i = \sqrt{a_i^2 + b_i^2} \qquad (15)$$

where

a_i is cosinus term,
b_i is sinus term
A_i amplitude for frequency component i.

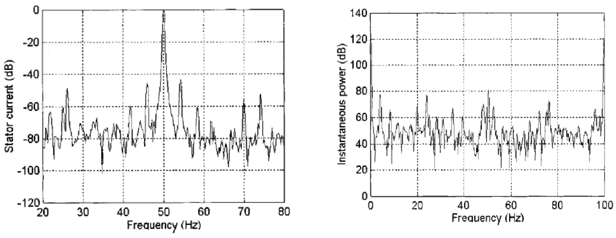
For analyzing signals in frequency domain the most common technique used is Fast Fourier Transform (FFT), [34]. It is a computational efficient version of Discrete Fourier Transform algorithm that greatly reduces the necessary number of computations (from O(N^2) to O($N\log N$)). After applying FFT to stator supply current, amplitudes of resulting frequency components are normalized by the value of the amplitude of first harmonic. The normalization process reduces influences of motor's load conditions, [25]. FFT is suitable for characterization of stationary signals. However it is not suitable for signals with transitory characteristics, [5].

4.2. INSTANTANEOUS POWER FFT

Application of instantaneous power requires additional measurement of supply voltage (it is not considered strict MCSA as it needs additional instantaneous voltage measurements). Instantaneous Power *p(t)* is the product of supply voltage u(t) and the motor current *i(t)*, (16):

$$p(t) = u(t)i(t) \tag{16}$$

Amount of information provided by instantaneous power is greater than available in motor supply current alone (including less noise and well bounded dynamic range of remaining harmonics in the absence of power grid component) providing more reliable analysis, [5,11], as shown in Figure 10, [5].



a) b)

Figure 10 *a) stator current spectrum, b) instantaneous power spectrum, from [5]*

4.3. DEMODULATED CURRENT SPECTRUM

Carrier frequency (50 Hz in EU, 60 Hz in USA) presents the dominant peak in the FFT spectrum. Lot of the information is blurred in the noise floor of the current spectrum. Demodulation is the process of removing the carrier frequency from the spectrum. Use of demodulation as a step in MCSA is illustrated in Figure 11. After the carrier frequency is removed, the remaining frequencies related to repetitive load variations appear distinctively in the demodulated current spectrum, [9,20], as shown in Figure 12

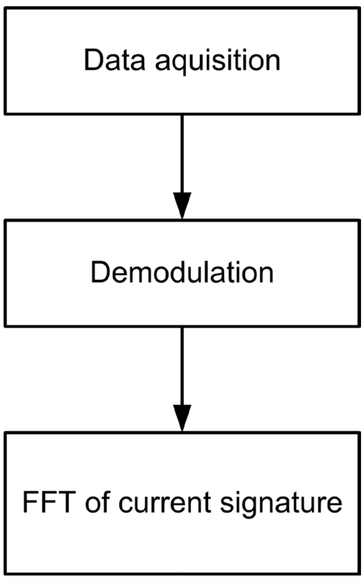


Figure 11 *Use of demodulation step in MCSA*

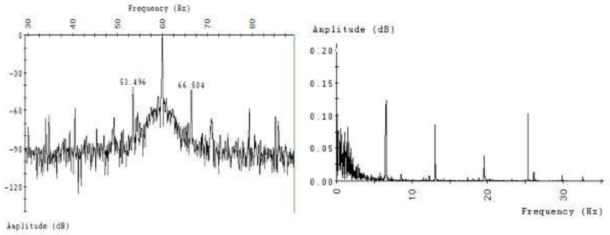


Figure 12 *a) Machine current spectrum and b) demodulated spectrum, [20]*

Interesting approach for removing fundamental component in MCSA using synchronous reference frame is described in [35].

4.4. WAVELET ANALYSIS

Disadvantage of a Fourier series expansion is that it provides only frequency resolution but lacks time resolution. Wavelet is a basis function isolated with respect to time or spatial location and frequency or wavenumber, [36,37]. It enables analysis localized in the time-frequency or the time-scale domain, [5]. Wavelet transform decomposes a signal into a family of wavelets, providing a time-frequency representation of the signal. [38, 39]. Wavelets are irregular in shape and finite in length. They can be successfully applied to analysis of signals with transitory characteristics and variable spectral content, [38]. The Continuous Wavelet Transform (CWT) for a continuous signal *x(t)* is defined by following relation, (17):

$$CVT_x(\tau, a) = \frac{1}{\sqrt{2}} \int x(at) g^*\left(\frac{t-\tau}{a}\right) dt \tag{17}$$

Where *g(t)* is the mother or basic wavelet,

* denotes a complex conjugate, *a* is the scale factor and *τ* is a time shift, [37].

The complex-valued Morlet's wavelet is common choice for signal analysis using the CWT. Morlet's wavelet, shown in Figure 13, is defined in (18):

$$g(t) = e^{j2\pi f_0 t} e^{-\frac{t^2}{2}} \tag{18}$$

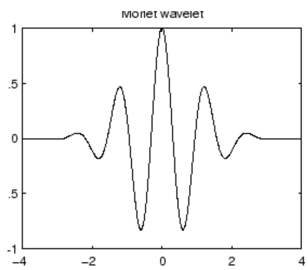


Figure 13 *Morlet wavelet*

In real world we are dealing with discrete (sampled) signal and Discrete Wavelet Transform (DWT) is used. DWT is any wavelet transform for which the wavelets are discretely sampled. Because of localization property of wavelets, the wavelet transform can represent the signal of interest with few coefficients. One algorithm for application of MCSA during startup transients using wavelets is described in [40].

4.5. PARK'S VECTOR APPROACH

This approach requires current sensing not on one but on all three phases, Figure 14. Park's current vector can be computed from the symmetrical three-phased current system, having the components: i_a, i_b and i_c giving Park's vector components i_d and i_q, as described in (19) and (20), [5]:

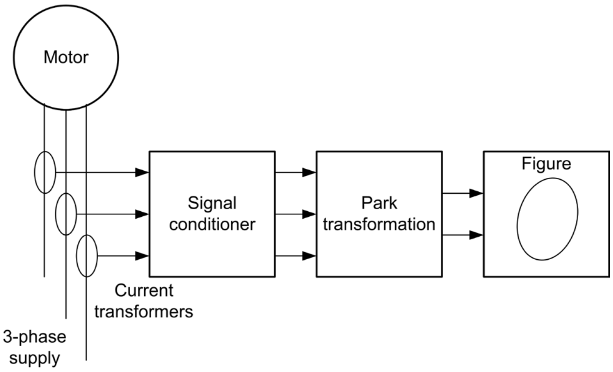


Figure 14 *Block Diagram of MCSA using Park's vector approach*

$$i_d = \sqrt{\frac{2}{3}} i_a - \frac{1}{\sqrt{6}} i_b - \frac{1}{\sqrt{6}} i_c \qquad (19)$$

$$i_q = \frac{1}{\sqrt{2}} i_b - \frac{1}{\sqrt{2}} i_c \qquad (20)$$

When no faults are present in the motor previous components may be expressed as follows, (21), (22):

$$i_d = \frac{\sqrt{6}}{2} i_M \sin \omega t \qquad (21)$$

$$i_q = \frac{\sqrt{6}}{2} i_M \sin(\omega t - \frac{\pi}{2}) \qquad (22)$$

where i_M is the maximal value of the supply phase current and ω is its frequency. Presented in a plane vector components i_d and i_q produce circular pattern. In the presence of various faults supply current contains sideband components and circular pattern will be distorted, [24,38,41,42]. Method for damage detection is based on detection of the distortion suffered by circle of Park. The three phases of currents in a healthy motor can be described by simple reference figure shown in Figure 15. Faults in motor contribute to distortion of the reference figure, as shown in Figure 16.

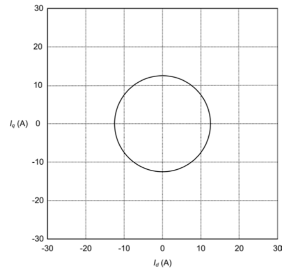


Figure 15 *Reference figure – healthy motor*

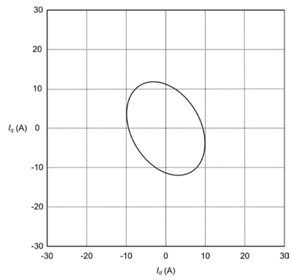


Figure 16 *Distorted figure - faulty motor*

Instead of detecting distortion in shapes of Park's vector patterns in Enhanced Park's Vector Approach (EPVA) magnitudes that Park's vector takes through time are monitored and analyzed, [11,24], Figure 17. Value of the radius oscillates between its extreme values

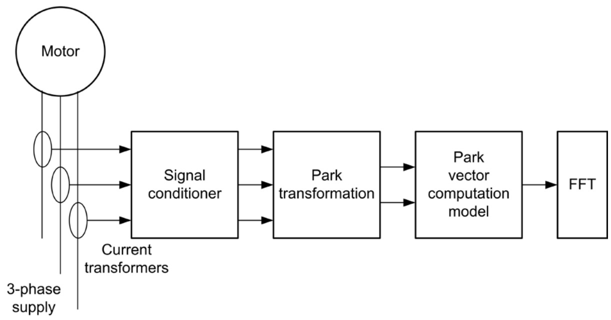


Figure 17 *Block Diagram of the EPVA technique*

twice during each power grid cycle. When analyzed in frequency domain, these oscillations appear in the spectrum as frequency component located at twice the motor supply frequency, [11,24]. The amplitude value of this frequency component is related to

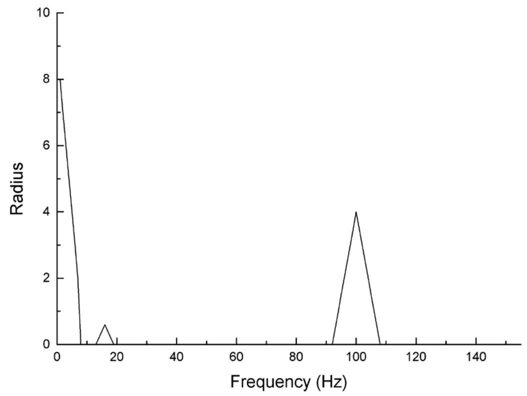


***Figure 18** Use of demodulation step in MCSA*

the relevance of the fault, [24]. Example of faults present in the stator coils is shown in Figure 18.

5. ARTIFICIAL INTELLIGENCE TECHNIQUES APPLIED TO MCSA

Recognition of motor current fault signatures requires from user considerable degree of expertise and experience. After fault signature is obtained it can be used for diagnostics, either by experienced engineer/technician or using some of techniques from the field of Artificial Intelligence (AI). Expert systems and various pattern recognition techniques from the field of Artificial Intelligence (AI) can be applied to MCSA.

Automatic diagnosis and analysis of MCSA using expert system as is illustrated in block diagram shown in Figure 19, according to [11].

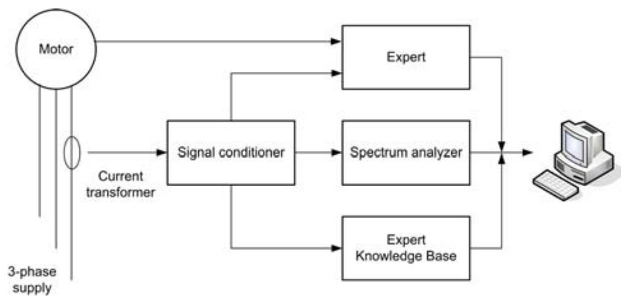


***Figure 19** Automatic diagnosis and analysis system*

Expert system may also employ fuzzy logic knowledge and rules, [31], that may be expressed using linguistic variables, fuzzy membership functions and IF-THEN rules, Figure 20. Domain expert knowledge in such a system may be expressed in more natural way.

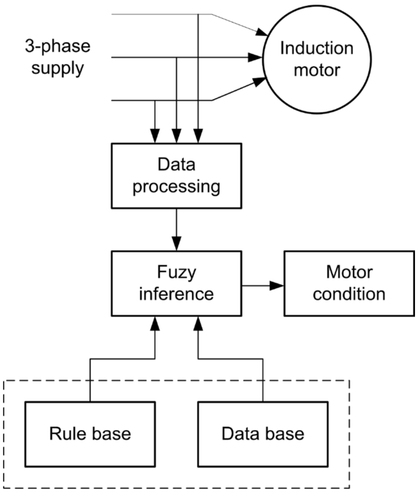


***Figure 20** Fuzzy logic applied to MCSA*

When a sufficient number of current signatures that correspond to various motor fault conditions are available, statistical methods may be applied for the task of data classification. General overview of a system

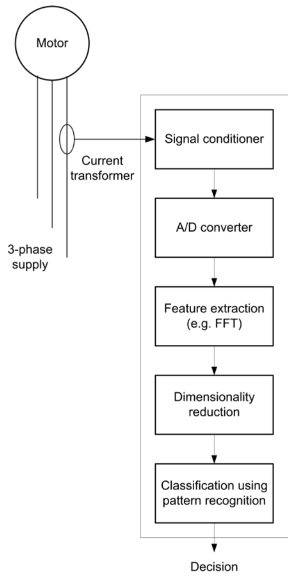


***Figure 21** MCSA using statistical pattern recognition (drugačija slika)*

that uses statistical pattern recognition is illustrated in Figure 21. After the signal conditioning, analog-to-digital conversion is performed. Some of preprocessing techniques are used (FFT, wavelets, etc) are used for feature extraction. Dimensionality reduction follows in the next step. Classification of unknown current signature is preformed by statistical pattern recognition with recognizers previously trained on a large number of correct and faulty signatures.

Support Vector Machine (SVM) is a machine learning method successfully applied to a wide range classification and pattern recognition problems. The most important benefit is efficiency of SVM in high dimensional classification problems. SVM can be applied to MCSA as well, as described in [43].

Classification can also be performed using decision trees like Classification And Regression Tree (CART). Application and comparison of three different classification methods (CART, Discriminant Analysis and SVM) applied to MCSA is described in [44] and illustrated in Figure 22. System consists of four steps: data acquisition, feature extraction, feature selection and fault classification. During feature extraction statistical parameters are calculated from acquired current signal. Feature selection and dimensionality reduction is performed using Principal Component

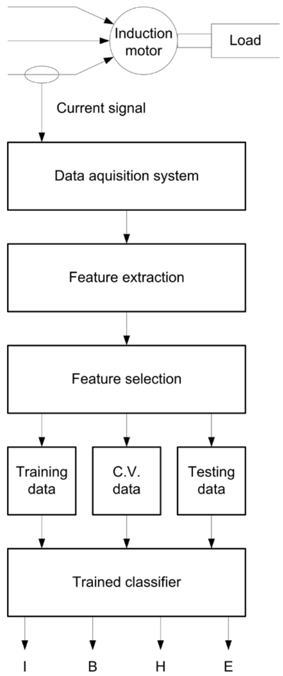


***Figure 22** Automatic motor current signature classification*

Analysis (PCA). Trained classifier can detect most common faults: stator winding interturn short (I), rotor dynamic eccentricity (E) as well as both of these faults (B). Output H corresponds to a healthy motor state.

Artificial Neural Networks (ANN) with their learning and generalization are particularly suitable for performing pattern classification. Examples of ANN used as statistical pattern recognizers for MCSA are described in [26,41,44,45]. ANN are trained, mostly using supervised learning, on datasets involving normal and faulty conditions.

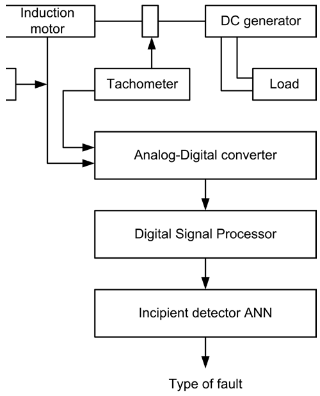


***Figure 23** Neural net MCSA of induction motor, [26]*

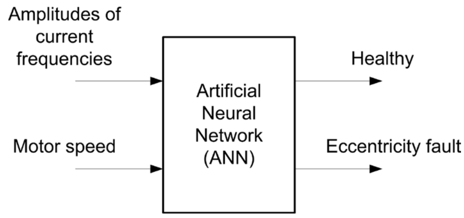


***Figure 24** Inputs and outputs of the ANN*

Solution for detection of air-gap eccentricity using artificial neural network is described in [26], and illustrated in Figures 23 and 24. Two different types of inputs to ANN are used, spectrum of the motor current organized in a number of frequency beans and motor speed (from the tachometer). Inputs have been properly scaled before feeding the ANN. The ANN has been trained using supervised learning on 120 datasets (including 20 datasets representing the eccentricity fault condition). There are two outputs available from the ANN, one corresponding to a healthy motor and another for presence of an eccentricity fault.

System for detection of bearing faults in three phase induction motor using MCSA combined with ANN is described in [29]. Magnitudes of side band frequencies are fed to ANN that is later trained in supervised mode on available datasets representing normal and faulty conditions under various loads (no-load, half load and full load).

6. SOFTWARE AND EQUPMENT FOR INDUSTRIAL APPLICATIONS

Beside conventional use of MCSA with interpretation of measured data by skilled engineer/technicians new generation of interesting products has emerged. Various automatic diagnosis and analysis systems have been developed.

Some products specifically developed for easier application of the MCSA are mentioned bellow.

AnomAlert Motor Anomaly Detector is a system of software and networked hardware that continuously identifies faults on electric motors and their driven equipment, [46]. It's operation is based on energy determined in 12 spectral frequency ranges. System posses learning ability and alarming function based on statistical analysis. It does not for the most part provide precision diagnostic of particular fault but reports indication of particular categories of faults for closer inspection.

Today various expert systems exist to aid and simplify the diagnosis process. One such system is Electric Motor Performance Analysis & Trending Hardware (EMPATH) developed by Framatome ANP, [47]. System consists of a laptop computer with signal conditioning and acquisition board and analyzing software.

ALL-TEST is a system for troubleshooting equipment using Electrical Signature Analysis. An ALL-TEST Pro kit includes ALLTEST IV PRO 2000 motor circuit analyzer, the ALL-TEST PRO OL motor current signature analyzer, EMCAT motor management software, Power System Manager software, and ATPOL MCSA software, [48].

System for automatic monitoring and diagnosis of faults in induction motors that can be operated remotely (including web interface) and in real-time is described in [25], with block diagram shown in Figure 25. It can trigger alarms whenever a fault is detected including turning off a motor in case of a short-circuit detection.

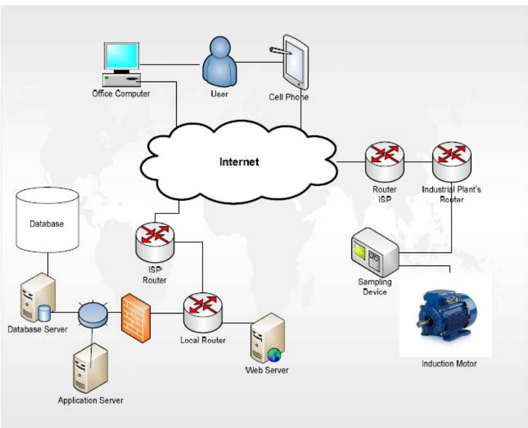


Fig. 17. General View of the System.

***Figure 25** General view of the system, from [25]*

Končar Institute has developed the Fault Detector Smart Sensor (FDSS). It provides on-line analysis, measured data export, detailed off-line measurement data analysis, data storage and wireless data transfer, [49].

7. CONCLUSIONS

Electrical machinery is the powerhouse of the modern industry. Failures of induction motors cause production downtime and may generate large losses in terms of maintenance and lost revenue. Timely detection of incipient motor faults is hence of great importance. Developing motor faults have its counterparts in waveform and harmonic content of the motor supply current. MCSA can be applied everywhere in industry where induction motors are used enabling non-intrusive on-line (even remote) analysis of motor supply current and detects faults while motor is still operational and without interrupting its service. It can be efficiently applied to detection and the localization for variety of motor faults. As such it is important contribution to tools for condition monitoring of induction motors.

All references listed below can be found on the internet.

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