Journal of Energy and Power Engineering 7 (2013) 361-369

Industrial Fault Signals Propagation and Current Signature Analysis

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Received: February 05, 2012 / Accepted: April 18, 2012 / Published: February 28, 2013.

Abstract: Motor current signature analysis provides good results in laboratory environment. In real life situation, electrical machines usually share voltage and current from common terminals and would easily influence each other. This will result in considerable amount of interferences among motors and doubt in identity of fault signals. Therefore, estimating the mutual influence of motors will help identifying the original signal from the environmental noise. This research aims at modelling the propagation of signals that are caused by faults of induction motors in power networks. Estimating the propagation pattern of fault signal leads to a method to discriminate and identify the original source of major events in industrial networks. Simulation results show that source of fault could be identified using this approach with a higher certainty than anticipated output coming of any individual diagnosis.

Key words: Motor current signature analysis, signal interference, decision making, signal propagation.

1. Introduction

Various types of faults are associated with electrical drives and rotating components. Various methods have been published and are commercially available to observe the behaviour of electrical motors. There are many research interests to improve the diagnostic through vibration, magnetic field, current and other possible indicators. Diagnosis using current signal is flexible and less expensive approach. Remote fault detection and diagnosis is also dealt here.

Motor current signature analysis is one of the recent diagnosis approaches proposed for rotating components. This strategy utilises pattern recognition over current signals of electrical motors to estimate the presence of pre-recognized fault pattern.

Theory of MCSA (motor current signature analysis) is an established tool for predicting major events in electrical motors. MCSA based strategies compare the frequency spectrums of real time signals with known patterns to distinguish the type and intensity of significant events in industrial sites using pattern recognition strategy [1].

Recently, there have been number of research works that reported successful applications of motor current signature analysis for several types of induction machines [1-3]. The main challenges in diagnosis of motor faults using signature analysis are interferences among components of power systems and strong presence destructive noise in industrial area. There are some strategies recently proposed to monitor several signals and in order to increase the diagnosis reliability [1]. These strategies are more expensive than the normal diagnosis and still there are doubts about their reliability in a complex industrial site.

Reliability and viability concerns demonstrate a need to develop a strategy that utilizes necessary technology for effective and less expensive fault tracking and diagnosis in power systems.

Many papers and technical reports have been published to utilize different mathematical and intelligent methods to detect the fault problems in electrical motors. Fuzzy logic, neural network and genetic algorithm are widely implemented for different

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diagnostic systems [4].

Most of the experiments have been implemented in a lab situation or for big sized electrical motors [1] and hence influence of the noisy environment of industrial sites was not considered. Further investigation dealt with propagation of fault signals in industrial power networks and hence the confusion to identify the origin of faults in electrical networks [5].

Fig. 1 illustrates typical spectrum that may be part of signal content within individual and parallel operation of motors.

Here, presence of a fault in motor 4 causes significant frequencies in current signals of almost all electrical machines in the network. These results are extracted from simulation of a typical power system that is divided in four main buses.

Modelling the signal attenuation eases out estimating the behaviour of complicated power systems. However, it is difficult to extract all necessary information of present appliances within various frequency bands. As a solution, rough modelling of significant frequency bands has been proposed to negotiate the ownership degree of present significant faults and then a collective decision making may then provide more reliable outcome.

In order to verify the strategy, combination of real life experiments and MATLAB models has been utilized to have the main focus on signal attenuation.

1.1 Formulation of Faults in Electrical Motors

There are many studies to identify and formulate signatures of faults. Here, three types of serious faults in induction motors have been chosen to work out the process of diagnosis. The related formulation is extracted from Ref. [6]. They are rotor asymmetry, rotor unbalance and eccentricity. Analytical expressions for the spectrums of these signatures are listed below:

Rotor asymmetry:

$$f_{rs} = f\left[k\left(\frac{1-s}{p/2}\right) \pm s\right] \quad (1)$$

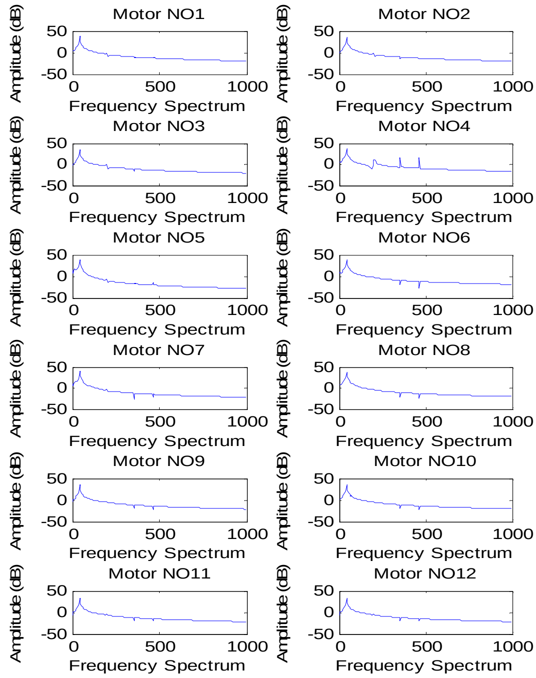

Fig. 1 Diffusion of the faults spectrum presence in motor 4 over the remaining motors within the network.

Rotor unbalance:

$$f_{ru} = f\left[k\left(\frac{1-s}{p/2}\right) \pm 1\right] \quad (2)$$

Air-gap eccentricity:

$$f_{ecc} = f_s\left[1 \pm k\frac{1-s}{p}\right] \quad (3)$$

where:

s: Motor slip;

p: Number of poles;

k: Number of harmonics (k = 1, 2, 3, …);

f_s: Synchronous frequency, 50 Hz is used in New Zealand.

These formulations are extracted from experimental results and to represent faults in different types of induction motors [1].

Here in order to analyze significant points captured from electrical motors, these formulations have been transposed as follows:

$$S_{rs} = \frac{\frac{Dp}{2} - f_0 K}{-f_0 K \pm \frac{p}{2}} \quad (4)$$

$$S_{ru} = \frac{\frac{Dp}{2} + f_0 K \pm \frac{p}{2}}{f_0 K} \quad (5)$$

$$S_{bq} = \frac{D-f}{2f_0^2} \quad (6)$$

where D is the frequency of the suspected significant point, f_0 is the nominal frequency and s is the motor's slip of the target motor.

And motor's speed may be calculated using Eq. (7):

$$V = (1-s)v_s \quad (7)$$

"v_s" means synchronous speed (for a four poles induction motors and 50 Hz frequency is 1,500 rpm).

By substituting any of calculated slips in Eqs. (4)-(6), speed of the motor can be calculated.

According to above formulas, a signature of a fault is a set of frequency components:

$$S_i = \{f_1, f_2, f_3 \ldots . f_n\} \quad (8)$$

Amplitude of any of these frequency components is a function of the amplitude of the frequency component in the signature set, the seriousness of the fault and amplitude and the nominal current of the motor.

$$M_i = AR\{M_1, M_2, M_3, \ldots \ldots M_n\} \quad (9)$$

where:

A: Motor's nominal current;

R: Index of seriousness of event: $0 < R < 1$;

M: Amplitude of the frequency component in a given signature;

i: Frequency components associated with the event i;

M indices are usually constant in any type of fault while A and R varies for different size electrical motors and different seriousness of the event. These formulations force a maximum possible strength for any frequency components of signature of events.

Here in order to simulate faults in electrical motors, a set of frequencies will be utilized as following:

$$\text{Fault}i \begin{cases} S_i = \{f_1, f_2, f_3 \ldots . f_n\} \\ M_i = AR\{M_1, M_2, M_3, \ldots \ldots M_n\} \end{cases} \quad (10)$$

1.2 Frequency Analysis and Picking up Significant Points

Current spectrums of electrical motors are usually continuous graphs. These graphs contain wide range of frequencies with different origin and hence an early frequency filtration is required to cancel unwanted and noise signals.

Placements of significant frequency components are very dependent on the velocity of the drive and its variation. Therefore, by looking at the rotor speed and deviation from the nominal speed, frequency spectrum is encapsulated in several significant frequency bands. As a case study, significant status bands for an induction motor with speed variation of 1,440 to 1,450 rpm and nominal frequency of 50 Hz are shown in Fig. 2.

Here in order to extract significant frequency points, concept of "local maximums" has been utilized as demonstrated in Fig. 2.

As shown in Fig. 3, significant frequency points will be extracted as a set of (f, M), where f is the frequency point and M is the magnitude of power spectrum of the current signal.

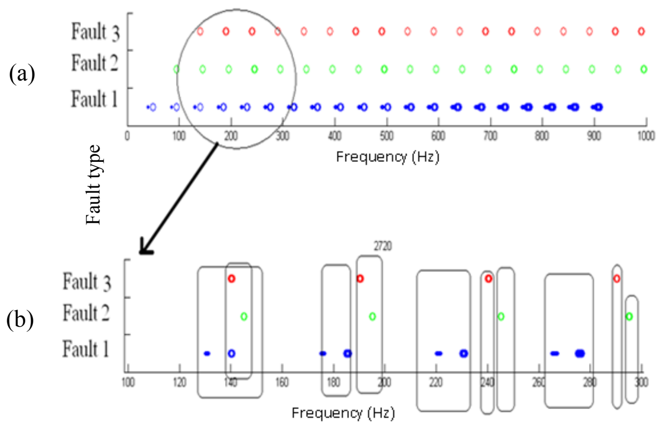

Fig. 2 Significant frequency bands related to the mechanical faults type 1, 2 and 3 as explained: (a) overview representation over the complete frequency band; and (b) detail spectrum within 300 Hz.

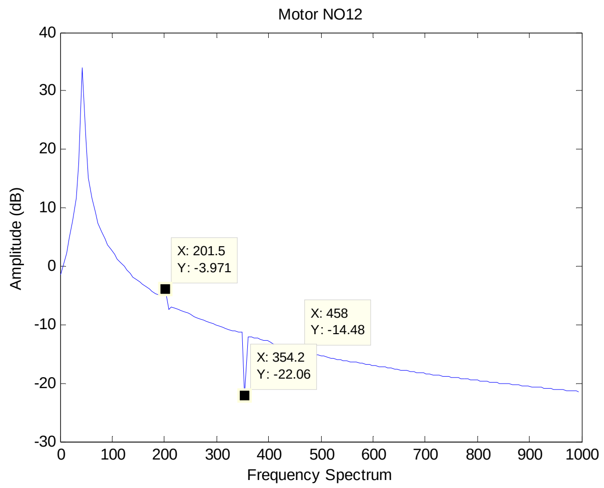

Fig. 3 Abnormalities have been picked up from the waveform. Note that the nominal frequency is 50 Hz and caused by the normal operation of electrical motor and hence is not considered as a component of fault signal.

In order to develop concept of fault diagnosis in electrical networks, concept of fault indices has been extend to cover events of suspected motors in the same neighborhood. And hence, fault indices are to be calculated for variation of behaviors reported by all electrical motors in the district. As a result, a matrix of fault indices for any measuring point will be generated. Also, there are several measuring points in any power network and hence there would be a two dimension matrix of fault indices for any suspected event.

$$\begin{pmatrix} F_{i,1,1} & F_{i,1,2} \ldots\ldots & F_{i,1,k} \\ F_{i,2,1} & F_{i,2,2} \ldots\ldots & F_{i,2,k} \\ : \; : & : \quad : & \\ F_{i,j,1} & F_{i,j,2} \ldots\ldots & F_{i,j,k} \end{pmatrix} \tag{11}$$

where:

$F_{i,j,k}$: Symbol for fault indices;

i: Type of the fault (there would be one matrix for each type of fault);

j: Speed band related to a group of electrical motors with the same speed;

k: Number of measuring point.

1.3 Formulations of Fault Tracking

Diagnosing the nature and detecting the location of events in power systems is always associated with reliability issues caused by unwanted noise signals. This is a common diagnosis problem especially in power system protection strategies. There are a number of successful strategies to model the attenuation of fault signals and hence identify the main problem in the network [7, 8]. These methodologies lead to a set of reliable recommendations for protection issues in industrial sites [9].

Most fault locating strategies work based on the fact that attenuation of the significant signals in power systems is relevant to the distance of sourceof events from the point of measurements. Relations between fault location and attenuation coefficients for short circuit faults have been estimated using the following formula [9, 10]:

$$\begin{bmatrix} V_a' \\ V_b' \\ V_c' \end{bmatrix} = \begin{bmatrix} V_a \\ V_b \\ V_c \end{bmatrix} - d \begin{bmatrix} Zl_{aa} & Zl_{ab} & Zl_{ac} \\ Zl_{ba} & Zl_{bb} & Zl_{bc} \\ Zl_{ca} & Zl_{cb} & Zl_{cc} \end{bmatrix} \begin{bmatrix} I_a \\ I_b \\ I_c \end{bmatrix} \tag{12}$$

$$d = \frac{V_{ar} I_{fi} - V_{ai} I_{fr}}{A.I_{fi} - B.I_{fr}} \tag{13}$$

where:

V_a: a-phase voltage;

I_a: a-phase current;

V_a': a-phase voltage at fault point;

Z_l: Line impedance matrix;

d: Fault distance.

This formula has been suggested for single frequency models and power networks have been considered linear and ohmic. Some modifications are required to build up an appropriate index for multi-frequency and nonlinear environments of significant fault signals.

2. Multi-frequency Modeling

Power networks are a collection of several load nodes that are physically connected to each other via electrical connections with a range of attenuation coefficients. Induction machines are the dominant load in most industry sites. Therefore, modelling and full understanding of all industrial motors is necessary to estimate the attenuation pattern of a fault signal within the electrical networks.

In order to estimate the attenuation of one significant signal in power networks, several issues should be considered:

- Most significant signal related to fault diagnosis is current signals and theoretically there is no attenuation oncurrent signals while travelling on a power line. This current signals cause voltage loss on electrical buses that results in derivative current;
- Level of current is not necessarily equal for different electrical motors. As a result, high power motor may generate a stronger signal while low power motor causes weaker signal in an equivalent significant event. And hence, the fault can not be discriminated by observing the signal in the target measuring point independently.

Fig. 4 is taken as example of power system model. In order to estimate the attenuation, it is assumed to have a known internal fault in motor 1. The fault causes a set of frequency magnitude signals as described in Section 1.1 above.

Motor 1 is connected to motor 2 and 3 in parallel and on the same busbar. Current of motor 3 is supplied by the main busbar via busbar B1. Propagation of fault signals to the main bus, influence the entire network .This causes a voltage drop in busbar B1 and which is followed by a voltage drop in the main busbar. Therefore:

$$V_{B1\text{-}1} = I_1 \times Z_1 \tag{14}$$

where:

$V_{B1\text{-}1}$: Resultant voltage in B1 that is caused by motor1;

I_1: Current of motor 1;

Z_1: Impedance of the connection between B1 and motor 1.

$$V_{B1} = V_{B1\text{-}1} + V_{B1\text{-}2} + V_{B1\text{-}3} \tag{15}$$

(for a known frequency)

Therefore, within a fixed frequency band, the resultant voltage of busbar Bj would be:

$$V_{Bj} = \sum_i V_{Bj-i} \tag{16}$$

V_{Bj-i}: The voltage generated by the fault current of motor i flows in the cable that connects motor i to Bj.

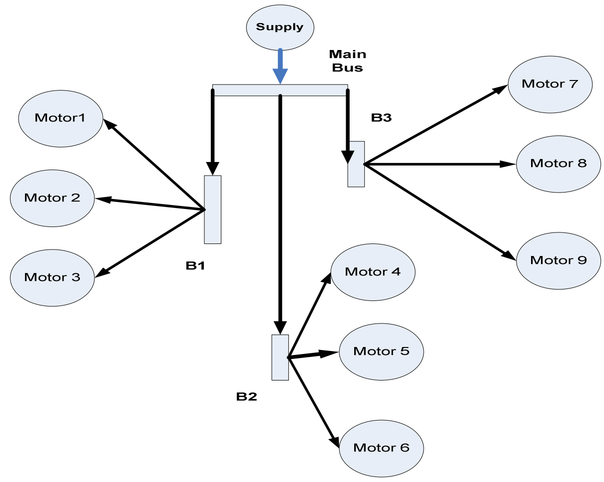

Fig. 4 A typical model of an industrial system with three busbars and electrical drives are connected to power buses.

Then mirror current caused by motor 1 and observed in current of motor 2 will be:

$$I_{2-1} < \frac{V_{B1-1}}{Z_2 + Z_{M2}} \tag{17}$$

This influences the main bus as well.

$$V_{main\text{-}1} = V_{B1\text{-}1} + I_1 \times Z_{B1} \tag{18}$$

where:

$V_{main\text{-}1}$: Voltage caused by motor 1 observed on main busbar;

$Z_{main\text{-}Ba}$: Equivalent resistance between bus a and the main bus.

Also, the voltage drop in the main bus originally caused by a machine originated in the second subsystem.

$$Z_{main\text{-}B2} = Z_{main\text{-}B2} + ((Z_4 + Z_{motor4}) \parallel (Z_5 + Z_{motor5}) \parallel (Z_6 + Z_{motor6})) \tag{19}$$

And then the strength of the fault signal flowing from the main bus to B2 can be estimated using the following formula:

$$I_{(main\text{-}B2)\text{-}1} = \frac{V_{main-1}}{Z_{main-B2}} \tag{20}$$

If the supply voltage and impedance of the connecting line is known, the resultant voltage signal related to faulty behaviour of the target motors can be estimated in another side of the cable.

$$V_{B2\text{-}1} = V_{main\text{-}1} - (I_{(main\text{-}B2)\text{-}1}\, Z_{main\text{-}B2}) \tag{21}$$

Voltages of buses are considered as an index that can demonstrate presence of frequency orders in the network. However, this index may be influenced by several appliance in power system; thus, it is not reliable enough for purpose of diagnosis.

The resultant voltage then causes current with the same frequency on neighbour equipments that feed from the same bus. For example, for motor 2:

$$I_{2\text{-}1} = \frac{V_{B1-1}}{Z_2 + Z_{M2}} \tag{22}$$

where:

Z_2: Total impedance of connection of motor 2 to bus 1;

Z_{M2}: Total impedance of motor 2 against the travelling signal;

$I_{2\text{-}1}$: The indirectinfluence of motor 1 observed in current of motor 2.

This influence is unavoidable that would be considered as an environment noise or may be utilized as an early indication of an imperfection in unidentified equipment(s). Applying the method eases out tracking the propagation of fault signals. This may lead to a strategy to discriminate original.

In order to estimate machine impedances at given frequencies, full understanding of machine models is necessary. Modelling information is available for most electrical appliances. However, for most industrial systems, practical model to explain their behaviour against variable frequency current signals is not yet identified. Impedance estimation by looking at the nominal power and voltage may perhaps be a practical approach in estimating the behaviour of industrial systems.

$$Z = \frac{V_{nominal}^2}{\sqrt{3}\,P_{nominal}} \tag{23}$$

Estimated impedance is valid for signals with nominal frequency (i.e. 50 Hz). But assessment of motors impedance in other frequency bands needs full understanding of the characteristics of equipments. On the other hands, environment of almost all electrical motors is inductive and most frequency components of significant signals related to motor faults are higher than the fundamental frequency. As a result, it is expected to have a higher value of impedance for current signals that are related to fault occurrence. Accordingly:

$$I_{2\text{-}1} < \frac{V_{B1-1}}{Z_2 + Z_{M2(atnominalfrequency)}} \tag{24}$$

where $I_{2\text{-}1}$ is the mirror significant current of motor 1 observed in current of motor 2.

2.1 Estimating the Ownership of Significant Fault Signals Using Rough Modelling

Fault index is an algebraic combination of spectrum coefficients. Mirror signals would also be attenuated more than the estimated impedance in nominal frequency. In other buses, the mirror current may be estimated in the same way. For example, magnitude of the fault current in motor 5 which is originated from a fault in motor 1 is estimated suing Eq. (25) below:

$$I_{5\text{-}1} < \frac{V_{B2-1}}{Z_5 + Z_{M5(atnominalfrequency)}} \tag{25}$$

This is an unavoidable mirror current and would appear in current of motor 5 beyond doubt. Based on Eqs. (10) and (11), a threshold index (*MT*) is defined to validate the originality of the signal.

$$MT = \frac{V_{target\ bus-original\ bus}}{Z_{lineof} + Z_{M(atnominalfrequency)}} \tag{26}$$

The mirroring influence can be calculated in further buses. However, these influences usually are very low and influence of far appliances (appliances with more than two buses between them and the faulty motors) could be neglected.

The above method shows a strategy to figure out rough magnitude of mirror signals in power systems. This information is useful to clarify the original signal from neighbour events and identify the ownership of signals caused by industrial faults.

2.2 Topographical Analysis

A typical case study with few electrical motors has been utilized (Fig. 2). Suppose there is a fault in one of the electrical motors. In order to identify possible situation in term of signal propagation, three possible situations may be identified. These are:

(1) If the signals detected are mirror of each other, then a strong arrow (→) is used to identify the source;

(2) If the suspected signal is stronger than the other

signal (small signal should not be the mirror of the strong signal), then the stronger signal will be identified usingan arrow (→). If the signals are reasonably equal and meet the requirements of Eq. (25), then circle around both is used;

(3) If the signals are reasonably equal (complement) but do not meet the requirements of Eq. (25), then equal sign (=) or a double direction arrow is used.

Subsequently, the above process can be repeated for all other electrical motors. In particular, those have a level of suspected fault signals. This process usually ends up with a directional graph similar to the one demonstrated in Fig. 4.

As shown in Fig. 5, the signal flow diagram shows a complement situation for all motors in bus 1 and bus 3. As a conclusion, all fault symptoms in B1 and B2 are originated by an external source. A complement situation is observable between motor 4 and motor 5. And finally, all arrows directly or indirectly indicate to motor 6 as the origin of the all symptoms in the network.

In the ideal situation where detailed characteristics of all equipments are available, the route direction graph will be without any weak arrow.

If a measuring point is missing, the alternative solution is to monitor its parallel equipments and route of the signal to identify whether significant signals are caused in that bus or not.

Here, a rewarding system has been utilized to identify and track the signals caused by motor faults. By looking at the signal transmission graph, three different zones are identifiable. The first zone where there is no influence of significant signals is observable. The second zone is where identified significant signals refer to motors in other zones, and hence they are not originated in measuring spots. The third area is where identifiers refer to one or a group of machines. Sometimes all signals refer to a machine and hence there is no doubt about origin of the fault. However, in real industrial situation attenuation of significant signal refers to more than one point.

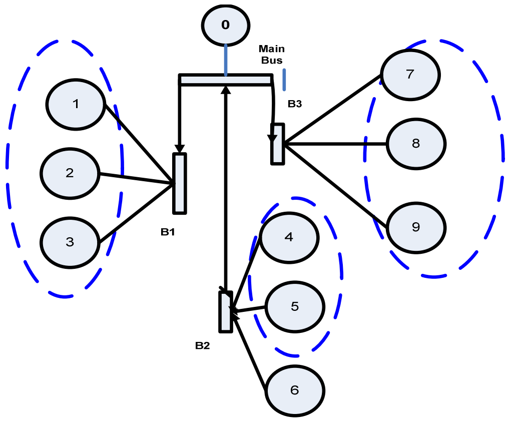

Fig. 5 Ideal routes direction model of attenuation of a significant signal caused by a fault in motor 3.

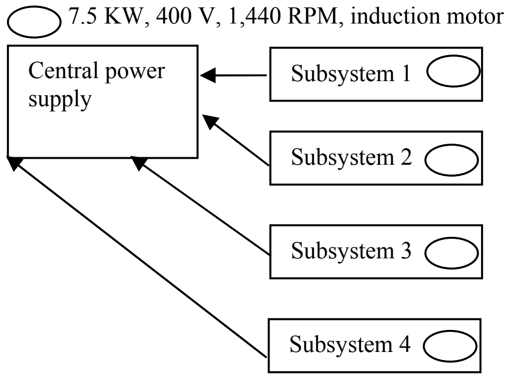

Fig. 6 Model of a typical 4-bus system. There is one induction motor in any substation.

3. Case Study

An industrial test bed has been simulated to verify propagation of fault indicators and study the concept of distributed diagnosis. The test bed is combined of several motors connected together via electric busbars and inductive connections and feed by a generator (Fig. 6).

MATLAB software package has been used to model the environment of industrial sites and machine faults. As described in Section 2, internal motor faults are associated with a set of frequency components; therefore, these events are modelled by a set of frequency generators with different amplitudes and damping coefficients.

Initially, a single frequency signal is injected to current of the motor in substation 4. Then a multi-frequency signal that represents a fault has been inserted to observe the behaviour of other electrical motors against the injected signals (Figs. 7 and 8).

As shown in Fig. 8, there is a reverse relationship between amplitude of fault indices and resistances of the cable that connects the motor to the bus of the faulty motor. Therefore, as explained, maximum amplitude of caused signals in other motors is predictable.

In order to discriminate the ownership of any significant signals, signal attenuation pattern will be estimated. This estimation proposes a boundary to identify the originality of the measured signals. Here initially the motor with the highest level of nominal current will be examined against the signals in other measuring points. The method then follows up with other suspected electrical motors to find the originality of the fault.

A closer view to the significant frequencies in subsystems 1-4 demonstrates the mutual influence of electrical machines in subsystem 1-4.

50, 92, 105 and 118 Hz are identified as significant frequencies. As shown in Fig. 9, in most situations, the significant signals are followed by other motors in the network.

The next stage is to identify the ownership of all frequency points. Using propagation modelling as explained earlier, the threshold level can be calculated for each possible destination. If the measured signal is smaller than the threshold, the signal is originated by an external source.

As shown in Fig. 9, using propagation modelling, it is concluded that motor 4 is responsible for causing a significant frequency points at frequency at 117 Hz. But the rest of frequency components are originally caused by motor 2.

This case study shows a successful implementation of propagation modelling to identify the original source of fault signals. Propagation modelling is expected to provide an acceptable answer for major faults of induction motors.

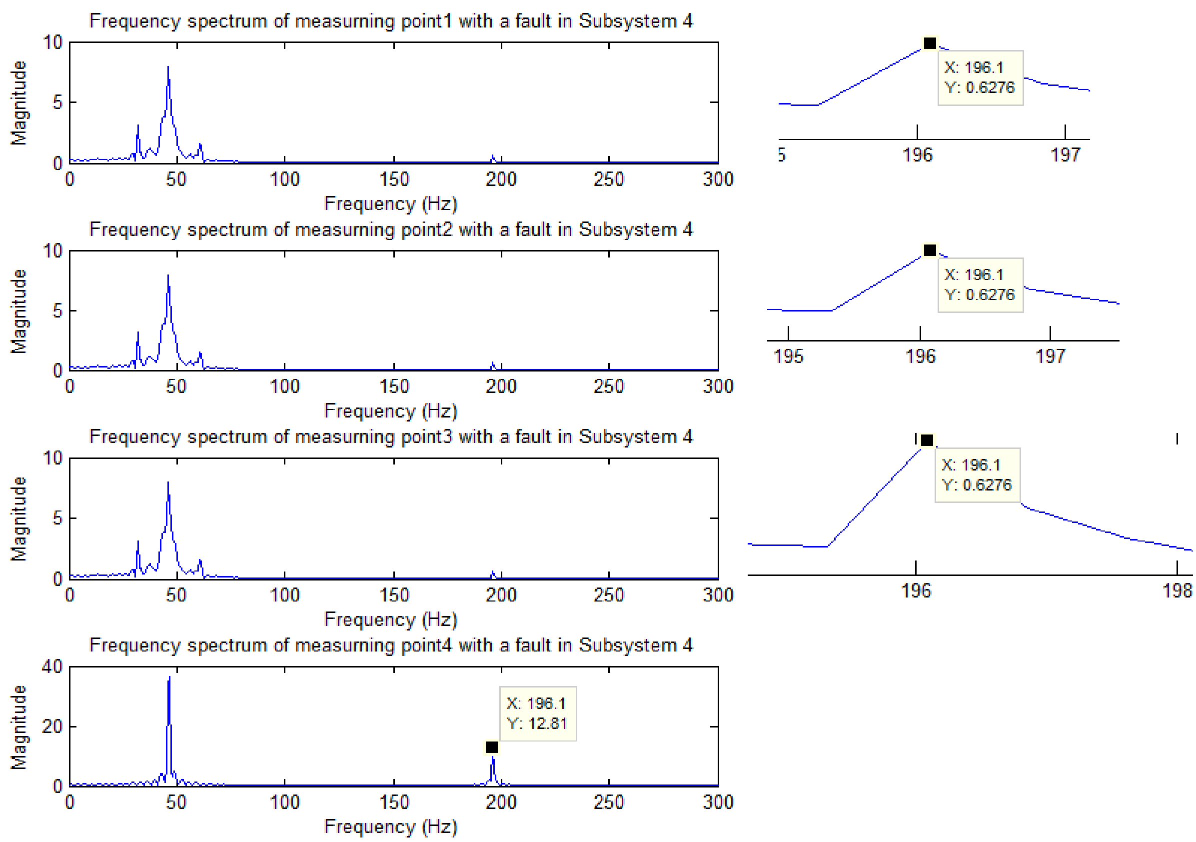

Fig. 7 Propagation of a single frequency-magnitude pair inserted in subsystem 4.

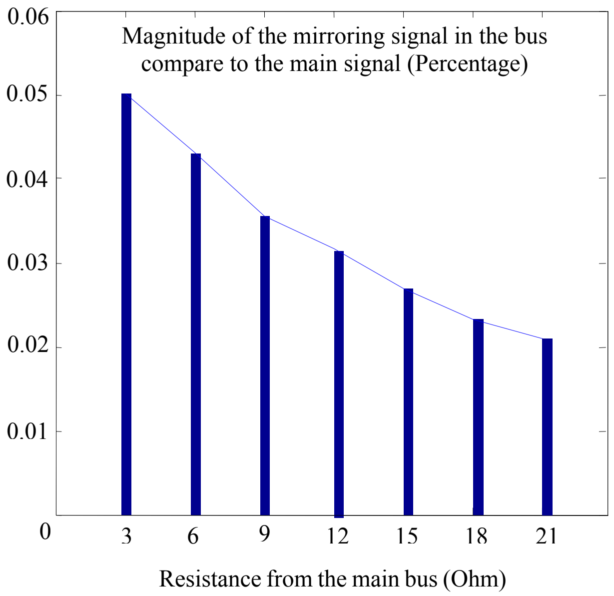

Fig. 8 Proportional magnitude of fault indices versus resistance to the target bus.

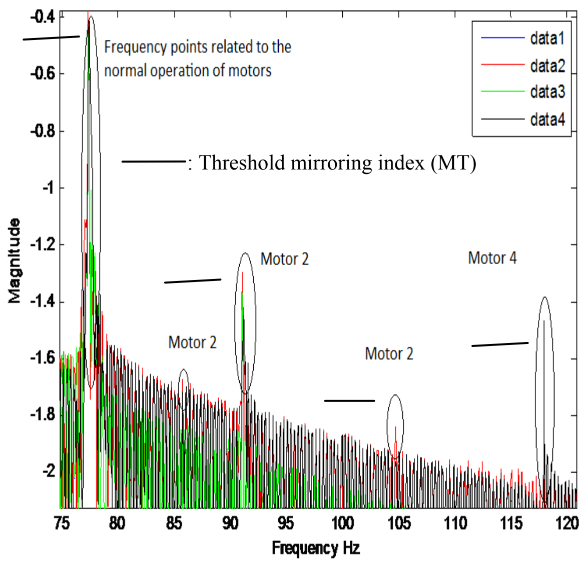

Fig. 9 Discriminated frequency spectrum of current of induction motors in the system (threshold mirroring index (MT) and dominant motor is shown).

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