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Self-Organizing Map and feature selection for of IM broken rotor bars faults detection and diagnosis

S. Haroun, A. Nait Seghir
Laboratory of Electrical and Industrial Systems (LSEI)
Department of Electrical Engineering, U.S.T.H.B.
El Alia, BP.32, Bab Ezzouar, 16111, Algiers, Algeria
haroun.smail@yahoo.com; naitseghir_a@yahoo.fr

S. Touati
Electrical Engineering Department (DGE)
Nuclear Research Center of Birine (CRNB)
Bp 180, Ain Oussera, Algeria
saidtouati@yahoo.fr

***Abstract*— This paper presents a new robust and high performances fault diagnosis scheme for broken bar fault detection and severity evaluation. The aim is to ensure an accurate condition monitoring and reduced false or missed alarms rate for induction motor operating in critical applications. It investigates the combination of features selection methods with the Self-Organizing Maps (SOM) neural network in a fault detection and severity evaluation system. This approach, based on the current analysis, uses multiple features extraction techniques, where the zero crossing times (ZCT) signal and the envelope are extracted from the three-phase stator currents. Then, statistical and frequency domains features are calculated from these extracted signals. The ReliefF feature selection technique is used to select from the extracted features the most sensitive and relevant ones. Next, the SOM neural network is used as a decision-making system. The experimental investigations, conducted using a healthy machine and a machine with broken bars, show the effectiveness of the proposed fault detection technique in terms of the classification accuracy.**

Keywords*— Induction Motor; Fault detection and diagnosis; Broken rotor bars; Self-Organizing Map; Relief feature Selection; multiple features extraction

I. INTRODUCTION

Induction motors are widely used in modern industry and commonly in diverse critical applications such as nuclear reactor coolant pumps, petrochemical turbines, and military applications, where high reliability and efficiency are required. They present 80% of the motors in use [1]. In spite of their robustness and high efficiency, they can be the seat of a wide-ranging of failures that can lead to total motor failure, and will directly influence the safe and reliable operation of the whole plant. In this context, condition monitoring and fault diagnosis systems are developed to guarantee a continuous safe operating, and early fault detection and severity evaluation. This system should be reliable and accurate with no false or missed alarms [2].

Broken rotor bars (BRB) is one of common faults that can appear on squirrel cage induction motors where they responsible for about 10% of the induction motor failures [3]. They can appear either as a consequence of mechanical stress coming from fast load variations, cyclic and pulsating load torques, or due to intrinsic manufacturing imperfections and dissymmetry [4]. BRB fault rarely cause instantaneous failures, nevertheless, it can cause severe secondary effects, such as torque fluctuations, poor starting performances, and excessive temperature and vibrations provoking deteriorations in bearings and other components [4]. Therefore, various BRB faults detection techniques have developed during the last two decades [5]. Although the importance of these techniques, the traditional motor current signature analysis (MCSA) [6] is the most used and well-known approach due to their low cost, and non-invasive nature. Although, the rotor faults characteristic frequency components are relatively close to the power supply frequency, specially, for low slip values when motor running at weak load. the amplitudes of these spectral components are related either to the number of broken bars and to the motor load variation [7], which can obscure the fault detection [20]. Furthermore, a low frequency oscillation in mechanical load torque has the same effects on the stator currents as the broken bars faults [6], so if the frequency of the mechanical load fluctuation is close to twice the slip frequency, it could interfere the broken bar fault detection, conducting to an incorrect fault diagnosis or false alarms [7].

Besides the MCSA, many other features extraction techniques from stator currents have been developed using differents signal processing techniques [3, 4, 8, 9, 10]. These techniques use the characteristic broken bar fault frequency, therefore, mechanical load fluctuations, unbalanced voltage supply, and noisy condition can also obscure the detection of the broken rotor bar fault and cause false alarms [7, 11]. All of the proposed signal-processing techniques require a prior expert knowledge, so, an automatic decision-making process to classify the extracted features into different health condition categories is required. Actually, several automatic decision-making systems based on artificial intelligence (AI) techniques have been reported in the literature. They include pattern recognition algorithms [10, 12] and artificial neural networks (ANNs) [13, 14].

A diagnosis process based on AI technique and multiple signal processing for features extraction, be more reliable in fault detection and severity evaluation and help to reduce the effect of some misinterpreted signatures which can cause false alarms or misclassified cases, but it can weighing down the classification process since much time is needed to calculate the results from the high dimensionality feature set [15].

Therefore, Feature Selection (FS) is necessary step to filter and select the features that contain the most discriminative information for the fault classifier.

This paper aims at developing a new automatic fault detection methodology for broken rotor bar fault detection and diagnostics based on multiple signature analysis extracted from time domain (statistical features) and frequency domain of the stator currents. The decision-making system is based on Self-Organizing Map (SOM) neural network and ReliefF algorithm as feature selection for enhancing the capability and reliability of the SOM.

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II. PROPOSED FAULT DIAGNOSTIC SYSTEM

The aim of the presented paper is to investigate broken rotor bar faults and classification using multiple fault signatures extracted from the stator currents. The adopted fault diagnosis procedure consists of data acquisition, signal processing, feature extraction and selection, and finally classification. For this purpose, the three-phase stator currents are first acquired from test induction motors.

The adopted procedure combines two pre-processing tools of the stator currents, which are the envelope, and the zero crossing times (ZCT) signal. Then statistical and frequency domain parameters are extracted as fault signatures from the current waveform and the two preprocessed signals (i.e. ZCT and envelope).

In order to improve the diagnosis process performances, the ReliefF feature selection technique is used for data dimension reduction and selection of the most significant features. In the last step, the classification task is carried out using the Kohonen Self organizing map neural network. The global framework of the developed algorithm is depicted Figure 1.

A. *Three-phase Stator Currents Pre-procecssing*

The purpose of signal pre-processing is to clean (suppress noise) and to transform the original measured signal to another form that contains useful information and excludes the data, which are less characteristic for the motor failures. In this paper, the zero crossing times (ZCT), and the envelope of the three phase currents are extracted.

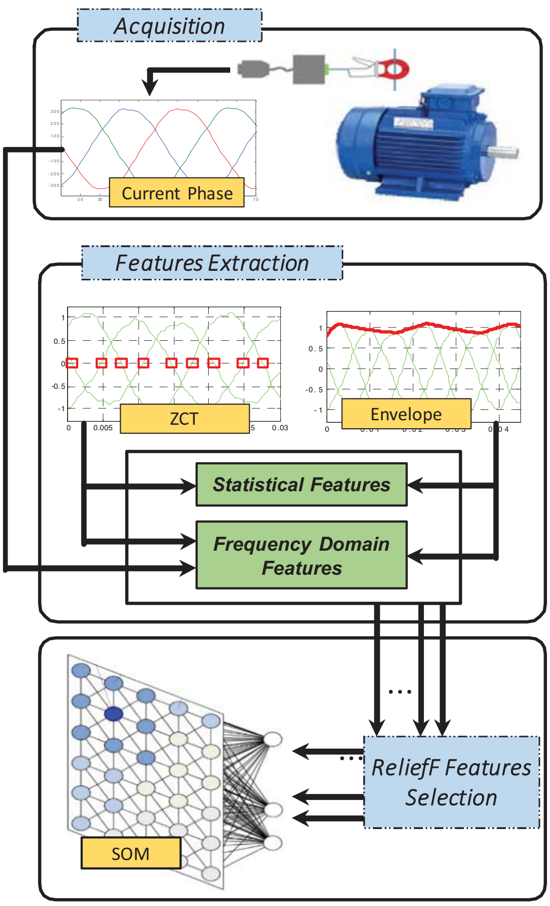

Fig. 1. Framework of the proposed intelligent fault diagnosis system.

1) *The Three-Phase Stator Current Envelope*

An envelope is the geometric "line shape" of a modulation in the amplitude of the three-phase stator currents due to motor faulty conditions [38]. Broken bars lead to a quasi-elliptical trace of the magnetic field's space vector and consequently modulate in a sequential manner the three-phase stator current. This phenomenon is cyclically repeated at a rate equal to twice the slip frequency (2sf) [10]. The envelope has been widely used for broken bar fault detection in many recent works [10,15, 16].

The applied technique to extract the three-phase stator currents envelope consist first by isolating the ripple of the three-phase stator current and then extracting only the positive peak of each period in each phase. The extracted points are interpolated to detect the dynamic behavior of the envelope [15]. Finally, the signal is normalized by eliminating its mean value.

2) *Zero Crossing Times Signal*

The analysis of the zero crossing times signal has been successfully investigated in rotor induction motor defect diagnosis [17].

The ZCT signal consists of a series of data values, obtained at each zero crossing time of the 3-phase current. The values of data are defined as the time difference between two successive zero-crossing instants (T(n), T(n-1)) minus the natural reference time (Tref) of the ZCT signal [18]:

$$T_{ZC}(n) = T(n) - T(n-1) - T_{ref} \tag{1}$$

In a 50 Hz supply system, If the ZCT signal is taken from three-phase stator current, the natural reference time (Tref) is 3.333 ms, giving a sampling frequency of 300 Hz for the ZCT signal spectrum.

Due to the discrete sampling time, it's impossible to find the exact time at which the current is equal to zero. Therefore, by assuming that the current is linear in a small time interval as presented in figure 4 and detecting when the product between the previous and actual value of the current is negative ($I(n-1) \times I(n) < 0$), the approximate zero crossing point T(k) can be calculated according to the equation (2) [18]:

$$T(k) = T(n) - \frac{I(n)\left[T(n) - T(n-1)\right]}{I(n) - I(n-1)} \tag{2}$$

The spacing between two successive zero crossings is unequal when the motor runs under abnormal conditions. The spectrum of the ZCT signal contains a 2sf frequency component, which is influenced only by the negative sequence current in the rotor as frequencies of the broken bar [19]. The components and the rotor frequency fr of the ZCT spectrum are also sensitive to broken rotor bar [17].

B. *Feature Extraction*

Feature extraction is the transformation of high-dimensional data sets into reduced representation, with minimal loss of information. Feature extraction leads also to significant improvements in fault detection performances. In the present paper, statistical indicators and frequency domain parameters are extracted from the envelope, the ZCT signal and the current waveform.

So total of 29 indicators are calculated. The mathematical expressions of the statistical and frequency domain indicators are presented in tables I and II.

TABLE I. THE EXTRACTED FREQUENCY DOMAIN FEATURES

Signal	Frequency Feature
Current Signal	$(1 \pm 2ks)f \quad , \quad k = 1, 2, 3$
ZCT Signal	$(1 \pm s)2f$ f_r $2sf$
Envelope Signal	$2sf$

f is the power frequency, s is the slip and fr is the rotor frequency.

TABLE II. THE EXTRACTED STATISTICAL FEATURES

Signal	Extracted Feature and expression	
Envelope ZCT Signal	Root Mean Square (RMS)	$X_{RMS} = \sqrt{1/N \sum_{i=1}^{n} (x_i^2)}$
	Peak to Peak	$X_{PtoP} = (\max(x_i) - \min(x_i)) / 2$
	Standard Deviation	$\sigma = \sqrt{1/N \sum_{i=1}^{N} (x_i - \bar{x})^2}$
	Skewness	$X_{SKEW} = 1/N \sum_{i=1}^{n} \left((x_i - \bar{x})/\sigma\right)^3$
	Kurtosis	$X_{KURT} = 1/N \sum_{i=1}^{n} \left((x_i - \bar{x})/\sigma\right)^4$
	Crest Indicator	$X_{CI} = \max\lvert x_i \rvert \Big/ \sqrt{1/N \sum_{i=1}^{n} (x_i^2)}$
	Clearance Indicator	$X_{CLI} = \max\lvert x_i \rvert \Big/ \left(1/N \sum_{i=1}^{n} \sqrt{\lvert x_i \rvert}\right)^2$
	Shape Indicator	$X_{SI} = \sqrt{1/N \sum_{i=1}^{n} (x_i^2)} \Big/ 1/N \sum_{i=1}^{n} \sqrt{\lvert x_i}$
	Impulse Indicator	$X_{IMP} = \max\lvert x_i \rvert \Big/ 1/N \sum_{i=1}^{n} \lvert x_i \rvert$

where xi is a time raw signal samples for i = 1, 2..., N,

C. Feature Selection

Many attributes from the extracted features data set can be irrelevant or redundant. The feature selection process object is to reduce the data set dimension by deleting the redundant indicators and select those that allow an accurate description of the motor condition, which leads to increasing learning accuracy and improving the fault classification process [20].

ReliefF is a simple and efficient technique to estimate the quality of features in machine learning problems with strong dependencies between features [21]. In practice, ReliefF is frequently applied in data pre-processing as a feature selection method and demonstrated excellent performance in both supervised and unsupervised learning. Due to such merit, the ReliefF technique is adopted in this paper.

- *ReliefF Algorithm*

The key idea of the ReliefF is to estimate the quality of attributes according to how well their values distinguish between instances that are close to each other [21]. Given a randomly selected instance *Insm* from class *L*, ReliefF searches for *K* of its nearest neighbors from the same class called nearest hits *H*, and also *K* nearest neighbors from each of the different classes, called nearest misses *M*. It then updates the quality estimation *Wi* for attribute *i* based on their values for *Insm*, *H*, *M*. If instance *Insm* and those in *H* have different values on attribute *i*, then the quality estimation *W* will be decreased. On the other hand, if instance *Insm* and those in *M* have different values on the attribute *i*, *W* will be increased. The whole process is repeated *n* times which is set by users.

D. Classification by SOM

The Self-Organizing Map (also known as Kohonen map) is an unsupervised artificial neural network, which is a powerful method for clustering and visualizing of high dimensional data [22] based on structural units called neurons, arranged as a two-dimensional lattice (map), called the topological map. A SOM network is composed by two layers of neurons. The first one, called input layer (composed by N neurons, one for each input variable), which is responsible for receiving and transmitting information from outside to the output layer.

The output layer (formed by M neurons) is in charge of information processing as well as the construction of map features. Usually, neurons in the output layer are arranged into a rectangular or hexagonal two-dimensional map [22] as shown in Fig. 2.

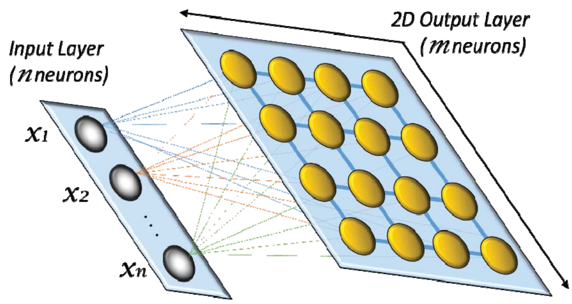

Fig. 2. SOM Architecture

The network is initialized by sampling random values for the preliminary reference vectors from a uniform distribution having limits defined by the input data. Another option is to use linear initialization, which is faster and less computationally arduous than the classic random initialization [22]. During training the input vectors are mapped one by one to particular neurons, called the best matching units (BMU) on the basis of the smallest n-dimensional distance (Euclidean distance) between the input vector and the reference vectors. Next, the nearest neighbors of an activated neuron are likewise activated according to a neighborhood function (e.g. Gaussian distribution) dependent on the network topology. Finally, the reference vectors of all activated neurons are updated and the next input vector is processed in the same manner.

After the training phase of the SOM, its quality can be evaluated by two parameters: quantization (*QE*) and topographic (*TE*) error. Lower *QE* and *TE* values specify superior mapping quality [23].

III. Experimental Implementation

In order to verify the proposed broken rotor bar fault diagnostics technique, experimental tests were carried out using data obtained from the LAII laboratory [24]. The process and results are described in detail below.

A. Implementation

The motor under observation is a four-pole three-phase squirrel cage induction motor with 18 rotor bars, 1.1kW rated power, 380 V and 50 Hz voltage supply. Three Hall Effect sensors are used to measure the three stator currents at 0.7 ms time sampling period. The currents are then filtered using a fourth-order anti-aliasing filter, with cross over frequency fixed at 500 Hz.

For the purpose of testing the broken rotor bar fault diagnosis task, the induction machine was operated in three different conditions. First using a healthy motor, a subsequent motor with one broken bar and finally using a motor with two broken bars. In each case, three different load levels were used: full (100%), medium (60%), and weak (22%) load.

The collected experimental data are decomposed into 972 segments (324 representatives from each case). After the acquisition of the stator currents, the ZCT signal and the envelope were extracted from the current segments, then the features were calculated from each signal to construct a database (size is 972 × 29). Two thirds of this database serve to train the SOM, and the rest were kept for the testing.

The data array was normalized before being admitted to the neural network, by normalization of the variance of vector components to unity, and its mean to zero. Then, a label and a color is associated to each case: (***B0***) green for the healthy, (***B1***) orange for the one broken bar fault, and (***B2***) red for the two broken rotor bars fault case.

Classification performance of the SOM can be analyzed by projection of the testing data sets on the trained maps then for each data sample, find the best matching unit from the map. After that, the class label of that unit is given to the sample. Classification accuracy can be evaluated as fraction of correctly classified input samples.

B. Results and discussion

After current acquisition, signal pre-processing, feature extraction and data set construction, data set are presented to dimensionality reduction based on ReliefF Feature selection approach.

Figure 3 presents the classification accuracy of the SOM versus the number of selected features by the ReliefF algorithm.

According to this figure, it can be found that the best number of selected features is eight (8), were the SOM gives a 100% classification accuracy, which means there is no false alarms or misclassified cases. Therefore, we can say that not all the extracted features are pertinent to classification by the SOM.

For more performance evaluation, and to present the effectiveness of the feature selection, we make a comparison of the trained SOMs using the MCSA, ZCT, and envelope features separately and all to gather with the eight (8) selected features by the ReliefF Algorithm.

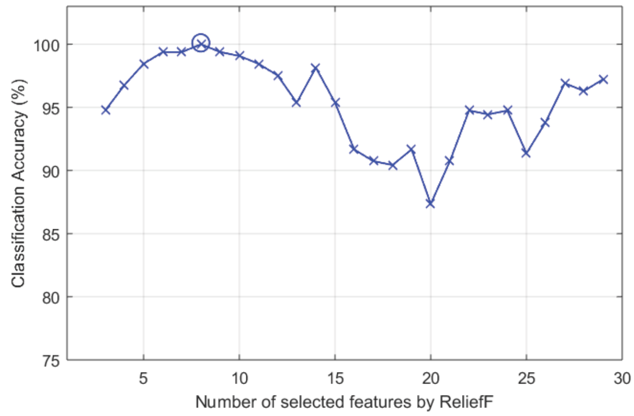

Fig. 3. Classification accuracy versus the number of selected features.

Figure 4 shows the trained SOM maps created for the studied cases, using the different features extraction techniques separately.

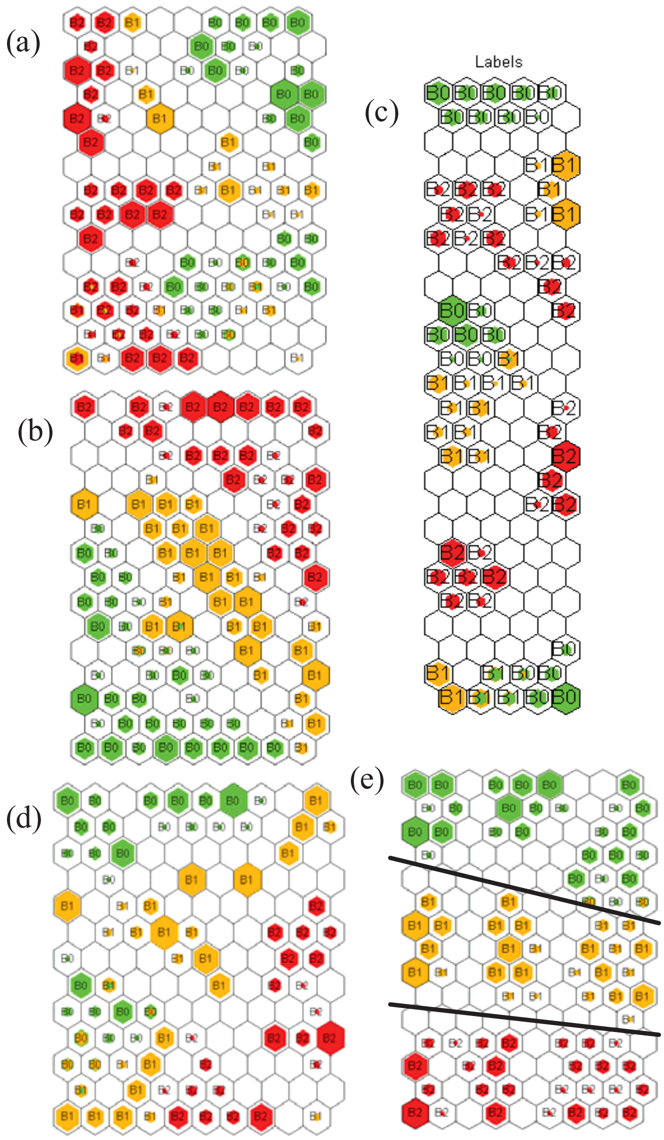

Fig. 4. Visualisation of the SOMs afer training using:

(a) Zero Crossing Times Features;
(b) Envelope Features;
(c) MCSA features;
(d) All included Features;
(e) Selected Features by ReliefF.

From the associated labels to the training data, we can see the projection of the motor condition cases (Healthy and faulty conditions), on the map. By visual inspection of this projection, we notice that there is no clear separation between condition cases except on the map trained using selected features by ReliefF were we can distinguish a three clusters corresponding to the three cases of the motor condition with real and very clear separation.

More performance parameters of the different maps such as training time, quantization error, topographic error, and training classification accuracy are presented in Table III.

TABLE III. PERFORMANCE PARAMETERS OF THE TRAINED SOMS

Training Features	Training Time	Quanti-zation Error	Topogr-aphic Error	Training Accuracy	Test Accuracy
Bar freq. feat.	0.5625	0.0735	0.0740	97.222	95.370
ZCT feat.	0.765	0.545	0.0123	96.450	81.481
ENV feat.	0.531	0.685	0.0385	99.537	95.061
All ext. feat.	0.781	1.274	0.0216	98.302	95.987
Selected feat.	0.578	0.258	0.020	99.382	100

This table show that the training using the selected features has the best classification accuracy with no misclassified cases, good topographic and quantization error, and consume less time compared to the use of the all included data.

From the obtained results, one can say that the multiplication of the features extraction techniques and the use of the ReliefF feature selection algorithm is very relevant to enhance the performances of the SOM as classifier of the motor condition.

The figure 5 represents a performance and error Radar Chart of three classification tasks: classification using the MCSA features, classification using all the extracted features, and finally the classification using the selected features. This Radar Chart contains the training time, training and test errors, topographic and quantization errors. So the graph who has the smallest area could be the best one.

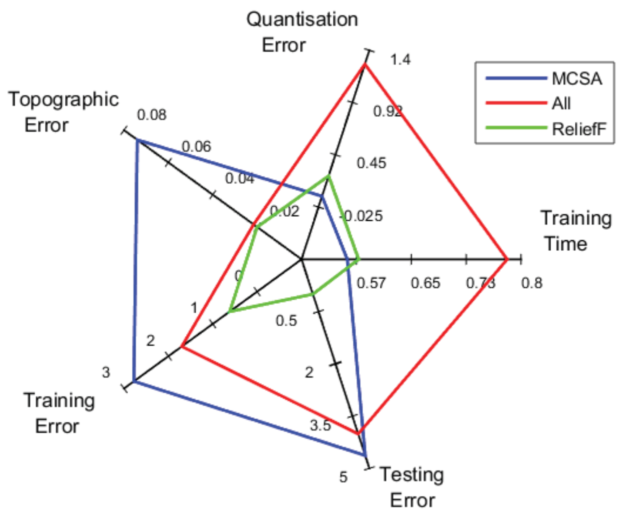

Fig. 5. Performance and error Radar Chart of the classification tasks.

From this figure, it can be noted that the classification using the selected features by the ReliefF feature selection technique is better than the classification using the whole features set or the MCSA features in term of the classification performances.

IV. CONCLUSION

This study presents a methodology for detection of broken rotor bar faults in induction motors by classifying them using self-organizing map (SOM). This methodology incorporates multiple signature analysis by using three pre-processing techniques, MCSA, envelope, and the zero crossing times signal analysis. From The implementation results, we can say that the fault diagnosis and classification accuracy of the SOM using the selected features was clearly higher than those using different features extraction techniques separately or all to gather. In addition, the quality of the learned map and the training time greatly improved as well.

We can then conclude that the proposed approach is a very attractive tool for broken rotor fault detection and diagnosis, because it is not only possible to detect the broken rotor bar faults, but it is also able to estimate the extent of the faults by separating the two faulty condition (one and two broken bars).

In a future work, further investigation will be conducted to the implementation of this strategy in a real time application.

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