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Induction Machine Fault Diagnosis Using Stator Current Subspace Spectral Estimation

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***Abstract* — This paper presents a subspace-based approach to identify and extract harmonics of interest for the diagnosis of stator and rotor related faults in induction machines. The major goal of this paper is firstly to introduce and highlight the effectiveness of prominence measure upon preparing features for classification of faults. Secondly, a new approach is presented here to retrieve harmonics by using prominence measure of the peaks for each case of the fault. Finally, a hierarchical multi-layer perceptron neural network has been used as the classifier and compared with other existing classification algorithms to deduce the best model. The effectiveness of the developed scheme is verified experimentally.**

Keywords—fault diagnosis, induction machine, parametric methods, signal processing, feature extraction, neural networks

I. Introduction

Rotating machinery systems have become essential pillars of modern human society. In particular, Induction Machines (IMs) have dominated the field of electromechanical energy conversion for the past few decades. The IMs are involved in assuring the continuity of the process and production chains of many industries. These include: electric-utility industries, mining industries, petro-chemical industries and domestic appliances industries. While the industry and application list for IMs is rather long, they are often used as critical components in applications such as nuclear plants, aerospace and military based applications where reliability of IMs must be of high standards.

It is common that IMs are subjected to hostile environments and are exposed to various sorts of undesirable conditions. These factors when ignored, may result in the failure of IMs with serious repercussions to the industry economically and non-economically as well. In fact, loss of lives can also be a result if proper precautions are not taken. Based on the statistics from IEEE and EPRI for motor faults [1-3], in most scenarios, IMs contribute to as much as 80% of the failed components under all the categories of faults which is also confirmed in the surveys by authors of [4-8]. Therefore, monitoring the health of electric machinery is of great importance and has gained high interest over the past few decades.

The oldest method for maintenance started from breakdown maintenance where appropriate repairs were carried out after the failure [9]. This is, however, a big disadvantage, as it entails huge downtime and is not acceptable since it results in unexpected service interruptions and massive financial loss. Later on, the method of preventive maintenance was introduced where maintenance tasks were carried out at planned regular intervals. This involved needless planned shutdown and high maintenance costs. Few decades later, condition based maintenance (CBM) were slowly adopted by industries [10]. The CBM has been recognized as the best modern practice for enhancing reliability of machines, reducing maintenance costs and service availability. Under CBM, continuous monitoring is carried out to detect faults in the system. It involves observation of machine conditions which arranges the maintenance tasks by using a data driven approach. The data can be temperature, vibration, motor current, images, acoustic emission signals, shock pulses, etc.

With respect to IMs in the arena of CBM, efforts have been made to perform Fault Diagnosis (FD) by using a sensorless approach. While most FD approaches can be summarized into model based or data driven, the latter has become more common as in this case, a predetermined model of the system is not required. The stator current spectrum of an IM contains vast amount of information on its performance and health. When coupled together with advanced Digital Signal Processing Techniques (DSPTs), it becomes a very powerful tool for FD and Condition Monitoring (CM) for rotating machinery.

In addition to DSPTs for FD of IMs, novel AI-based algorithms for fault detection, classification, and diagnosis have been produced throughout the years. Some recent works have revamped the utilization of the AI tools, exploiting either novel and enhanced system topologies or the mix of cutting edge DSPTs (for feature extraction) and Neural Networks (NNs - for classification). Moreover, some recent contributions have strengthened the use of statistical information and NNs for fault detection and classification. More particularly, [11] proposes a strategy in view of the blend of feature extraction system that depends on the smoothed ambiguity plane intended for boosting the separability between classes utilizing Fisher's discriminant ratio and a feature selection procedure taking into account an error likelihood model to choose an ideal number of extracted features. The proposed plan gives great results in regards to the FD of broken bars as well as stator or bearing. Reference [12] utilizes the statistical features of time-domain information and also spectral information as a basis for the development of a NN for rotor fault detection and classification.

As mentioned earlier, an aspect which highly contributes to the robustness of a FD and CM scheme is the calculation of appropriate features. Signal-based fault diagnosis has been one of the most noticeable techniques to analyze non-linear signals in an IM. This is because any sort of shortcomings would result in asymmetries in its electromagnetic field, and consequently in introducing characteristic fault frequencies to the underlying sensor signal. Some of the current DSPTs are listed in [2]. In addition to that, the time-frequency domain features which include peak, root-mean-square (RMS), power, energy, mean value of the signal have also been used for feature calculation.

Once features are calculated, to automate the process for extraction (to be used for training the classifier for FD), a common practice is to use the maximum peak values of the harmonics of interest for a given window of signal, followed by extraction of the appropriate frequencies and its corresponding amplitudes. In some cases, this becomes complicated due to interference of noise and inverter harmonics. Various approaches have been tried to eradicate this problem. In this regard, much attention has been diverted to techniques using parametric approaches for spectral estimation due to its superiority over non-parametric based techniques. The parametric approach is divided into two classes: parametric techniques for continuous spectra and parametric techniques for line spectra [13]. While parametric methods for continuous spectra is suitable for linear prediction techniques such as Prony method, they work poorly when the frequency content of the signal changes abruptly. On the other hand, parametric techniques for line spectra which include subspace methods can avoid computational complexity and improve the accuracy when it comes to estimate frequencies of interest for FD [4]. However, a major drawback of these high resolution techniques is that the estimation degrades when the model order is incorrectly specified. This is apparent for non-stationary data flow, which is the case with FD of IMs. While many researchers strive to generalize this procedure, it is still an open issue to date.

This paper is directed towards developing a more robust classifier to detect and classify different types of faults in IMs. As this is a pattern recognition problem, different subspace-based feature extraction techniques [14-16] are used to confirm the best methodology for FD and classification. Three types of faults which are related to stator and rotor of an IM are studied in this paper. These are: stator inter-turn fault (SITF), broken rotor bar fault (BRBF) and combination of SITF and BRBF. A two stage classification system is developed which at the first stage detects whether the incoming anonymous signal from IM is either healthy or faulty, and at the second stage, if it is faulty, the type of fault is denoted by the second classifier. Figure 1 illustrates the proposed scheme.

In addition to the comparative approach taken in the feature extraction stage, the harmonic retrieval problem is also addressed. Apart from extracting fault frequencies using only the maximum peak values given a pseudo-spectrum estimate of a current signal, a new approach is presented here to retrieve harmonics by using prominence measure of the peaks. Unlike recognizing just the maximum peaks, the prominence measure quantifies how much the peak stands out due to its intrinsic height and its location relative to other peaks. This property helps to identify true harmonics when SNR is low (in case of interference of noise and inverter harmonics) as well as when the pseudo-spectrum estimate of the signal is degraded due to model order miss-specification (in case of frequency estimation using subspace methods).

This paper is organized as follows: Methodology involving the study of characteristic fault frequencies for each type of fault, harmonic identification and retrieval techniques, as well as two stage classification are described in Section II. Section III consists of experimental results along with the discussion where a thorough comparison to deduce the best model for FD and classification are carried out. The concluding remarks are made in Section IV about the choice of feature extractors and classifiers suitable for FD and classification for IMs.

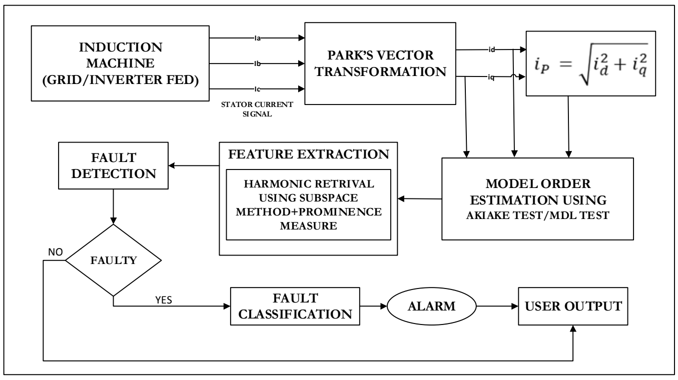

Fig. 1. Proposed FD and Classification Scheme

II. Methodology

A. *Characteristic fault frequencies* [4, 6, 17]

The introduction of a fault in the IM results in an asymmetry which persists in every rotation. The effects of the fault appear as a characteristic frequency in the 3-phase stator current, which can be detected via MCSA. The Extended Park Vector Approach (EPVA) [18] is one of most reliable approaches used in identifying faults in electrical drives. It transforms the 3-phase currents (i_{sa}, i_{sb}, i_{sc}) into direct and quadrature axis components (i_d, i_q) and finds the norm of both (i_P) as follows:

$$i_d = \sqrt{2/3}\, i_{sa} - \sqrt{1/6}\ i_{sb} - \sqrt{1/6} i_{sc} \tag{1}$$

$$i_q = \sqrt{1/2}\, i_{sb} - \sqrt{1/2}\, i_{sc} \tag{2}$$

$$i_P = \left|\left(i_d + j i_q\right)\right| \tag{3}$$

Table I lists the characteristic frequencies for: SITF, BRBF and combined SITF and BRBF which will be explored in this paper.

TABLE I
CHARACTERISTIC FAULT FREQUENCIES OF IM

IM FAULT TYPE	i_{sa}, i_{sb}, i_{sc}	i_d, i_q	i_P
SITF [2, 4, 17]	$f_s\left(\frac{m}{p}(1-s) \pm k\right)$, $2f_s$	$2f_s$	$2f_s$
BRBF [2, 4, 17]	$f_s(1 \pm 2ls)$	$2sf_s$	$2sf_s$
COMBINED SITF AND BRBF	$2f_s$, $f_s(1 \pm 2ls)$	$2f_s, f_s(1 \pm 2ls)$	$2f_s, 2sf_s$

where f_s is the supply frequency, s is the slip in percent (%), p = number of pair poles, $m = 1,2,3, \ldots (2p-1)$, $k = 0,1,3,5, \ldots$ and $l = 1,2,3, \ldots$

B. *Harmonic Identification*

For the estimation of frequency and power of signals from the noise corrupted measurements, subspace based techniques are used. They are characterized by eigen-decomposition of the correlation matrix of the noise corrupted signal. An advantage of these type of techniques is that they provide high resolution frequency spectra even if their SNR is low. In this paper, 4 subspace based procedures (Pisarenko, MUSIC, Minimum Norm and Eigenvector) were used to generate the frequency spectra of the 3-phase stator current and EPVA current of the IM.

1) Pisarenko Harmonic Decomposition [14]

Developed by V. Pisarenko in 1973, this is a frequency estimation method which is based on Carathedory's theorem which demonstrates that frequencies could be derived from the eigenvector corresponding to minimum eigenvalue of the autocorrelation matrix. While this technique had some limitations due to its sensitivity to noise, it has led to important insights into the frequency estimation problem.

Given a signal $x(n)$ with p complex exponentials in white noise, the Pisarenko method assumes $p+1$ values of the autocorrelation matrix (either known or estimated). The dimension of the noise subspace is equal to one spanned by the eigenvector corresponding to the minimum eigenvalue, $\lambda_{min} = \sigma_{\omega}^2$ with $(p+1) \times (p+1)$ as the autocorrelation matrix. The noise eigenvector v_{min} is orthogonal to each of the signal vectors, e_i as portrayed in (1).

$$e_i^H v_{min} = \sum_{k=0}^{p} v_{min}(k) e^{-jk\omega_i} = 0 \quad ; i = 1, 2, \ldots, p \tag{1}$$

This leads to:

$$V_{min}(e^{j\omega}) = \sum_{k=0}^{p} v_{min}(k)\, e^{-jk\omega} \tag{2}$$

which is referred to as an *eigenfilter* and the frequencies of the complex exponential are extracted from its roots. Upon rooting in order to find the location of the peaks, a frequency estimation function (3) is obtained:

$$P_{PHD}(e^{j\omega}) = \frac{1}{|e^H v_{min}|^2} \tag{3}$$

where $P_{PHD}(e^{j\omega})$ is called a pseudo-spectrum estimate of the signal $x(n)$ using Pisarenko method.

2) MUltiple Signal Classification Method (MUSIC) [15]

An improvement to the Pisarenko method, presented by Schmidt in 1979, the MUSIC method is also a noise subspace frequency estimator which is intended to distinguish zeros from the spurious ones. In MUSIC algorithm, the pseudo-spectrum of signal $x(n)$ is given by performing eigenspace analysis of its autocorrelation matrix R_x of dimension $M \times M$ with $M > p + 1$ (note that $M = p + 1$ is the case for Pisarenko method) in order to estimate the frequency content of the signal. Based on the specification of p, the eigenvalues and its corresponding eigenvectors of R_x are arranged in descending order and divided into two groups: p signal eigenvalues with its corresponding eigenvector, and the $M - p$ noise eigenvectors that have eigenvalues approximately equal to variance in white noise σ_{ω}^2.

Since the eigenvectors of R_x are of length M, the noise subspace *eigenfilter* now becomes:

$$V_i(e^{j\omega}) = \sum_{k=0}^{M-1} v_i(k)\, e^{-jk\omega} \; ; i = p+1, \ldots M \tag{4}$$

Which will have $M - 1$ roots and p of these roots will lie on the unit circle at the frequencies of the complex exponentials for signal $x(n)$ (in the z-domain). When only one noise eigenvector is specified (as is the case for Pisarenko) to estimate the complex exponentials, there's always some ambiguity in detecting the correct peaks in case of noisy signals due to occurrence of spurious peaks. In case of MUSIC algorithm, the effects of these spurious peaks are reduced by averaging using the following frequency estimation function (5):

$$P_{MUSIC}(e^{j\omega}) = \left[\sum_{i=p+1}^{M} |e^H v_i|^2 \right]^{-1} \tag{5}$$

where $P_{MUSIC}(e^{j\omega})$ is called a pseudo-spectrum estimate of the signal $x(n)$ using MUSIC method.

3) Eigenvector or Modified-MUSIC method (EV) [19]

A variant of MUSIC algorithm, the EV method with estimated autocorrelations differs from MUSIC algorithm and appears to produce fewer spurious peaks. EV performs similar procedure like MUSIC by estimating exponential frequencies from the peaks of the eigen-spectrum, but unlike the original MUSIC, it also takes into account the eigenvalue λ_i associated with eigenvector v_i in averaging as shown in (6):

$$P_{EV}(e^{j\omega}) = \left[\sum_{i=p+1}^{M} \frac{1}{\lambda_i} |e^H v_i|^2 \right]^{-1} \tag{6}$$

where $P_{EV}(e^{j\omega})$ is called a pseudo-spectrum estimate of the signal $x(n)$ using MUSIC method.

4) Minimum Norm Method (MN) [16]

This is another eigendecomposition-based method which instead of forming an eigen-spectrum using all of the noise eigenvectors (just like in MUSIC and EV algorithms), uses a single vector a that is constrained to lie in the noise subspace which is incorporated in the frequency estimation function in (7) below:

$$P_{MN}(e^{j\omega}) = \frac{1}{|e^H a|^2} \tag{7}$$

For this method, the vector a has three constraints: 1) vector a lies in the noise subspace, 2) should have a minimum norm and, 3) the first element of a is a unity. See [19] for more details.

C. Model Order Estimation

Prior to calculating the pseudo-spectrum estimates, the aforementioned techniques in this section require knowledge of dimension of the signal subspace. The Akaike Information Criterion (AIC) and Minimum Description Length (MDL) [20] are two frequently-used estimators for deducing that dimension. Upon testing, it was found out that MDL provided consistent approximation using forward-backward averaging in comparison with AIC. Therefore, MDL estimator was preferred for all the subjects, and the value of p was approximated to be 4 in this study.

D. Harmonic Retrieval

After generating the pseudo-spectrum estimates of the signal, harmonics of interest are extracted using prominence measure of the peaks. While a common practice is to use maximum peak values for retrieving the harmonics, this has some limitations. Upon automating this process for continuous monitoring, often is the case when incorrect frequencies are extracted. This happens when performing peak analysis for retrieval of the harmonics for cases where the fundamental frequency is not always dominant or when SNR is very low. This leads to inaccuracies in the feature-set causing problems upon learning when developing the classifier for identification of fault.

Retrieval of the harmonics using prominence measure helps in reducing these inaccuracies by using not only maximum peak values but also its intrinsic height and location with respect to other peaks within the signal. An isolated lower peak can have more prominence than a peak which is higher in dependence on the shape and location of the peaks. The procedure for retrieval of harmonics given a pseudo-spectrum estimate of the signal using prominence measure is outlined in Fig. 2.

Harmonic Retrieval Procedure:

Require: Pseudo-spectrum estimate of the signal $(\boldsymbol{M}, \boldsymbol{f})$, Number of harmonics to be extracted $(\boldsymbol{p})$

1. Select the number of harmonics $\boldsymbol{p}$ to be obtained from the given frequency $\boldsymbol{f}$ and magnitude $\boldsymbol{M}$ pair.
2. Find the peaks $\boldsymbol{P}$ in the graph of magnitude $(\boldsymbol{M})$ vs frequency $(\boldsymbol{f})$. A local peak is defined as a data sample which is larger than the two neighboring samples.
3. Measure prominence* $\boldsymbol{K}$ of each of the obtained $\boldsymbol{P}$ peaks.
4. Sort the prominence, $\boldsymbol{K}$ in the descending order and equally maintain the corresponding $(\boldsymbol{M}, \boldsymbol{f})$ index pair.
5. Extract the first $\boldsymbol{p}$ elements from the $(\boldsymbol{M}, \boldsymbol{f})$ pair.
6. **Return** the extracted $(\boldsymbol{M}, \boldsymbol{f})$ pairs.

*** Measuring Peak Prominence**:

Require: Peaks $\boldsymbol{P}$ from pseudo-spectrum estimate of the Signal.

1. Place a marker on the peak.
2. Extend a horizontal line from the peak to the left and right until the line does one of the following (see Fig. 3):
   a. Crosses the signal because there is a higher peak.
   b. Reaches the left or right end of the signal.
3. Find **minimum** of the signal in each of the two intervals defined in Step 2b. This point is either a valley or one of the signal endpoints.
4. Find the reference level (**higher** of the two interval minima specified in 3).
5. The height of the peak above reference level is its prominence $\boldsymbol{K}$.
6. **Return** the value of $\boldsymbol{K}$.

Fig. 2. Procedure for Harmonic Retrieval using Prominence Measure

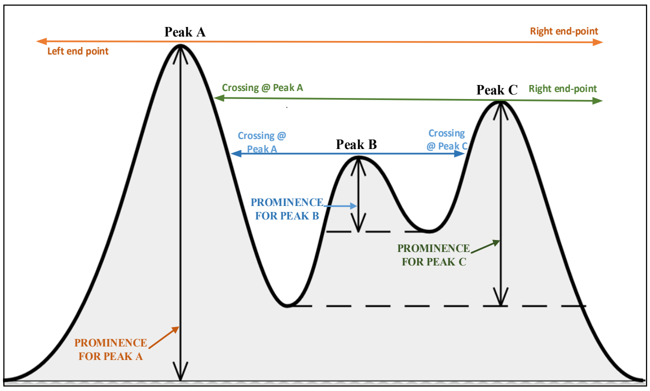

Fig. 3. Finding Peak Prominence

E. Classification using Neural Networks

In this paper, a hierarchical classification system is developed (two-stage classifier). The first stage is the distinction between "healthy" and "unhealthy" case, given the 3-phase stator current signal of IM. The second stage gives the class or type of fault (SITF or BRBF or combined SITF and BRBF) if the first stage classifier gives an "unhealthy" class. After the feature extraction stage, both classifiers are developed using MLP NNs. A major reason for using MLP NN classifiers is the fact that NNs exhibit a property to learn highly nonlinear models without a priori information about the model, because data itself represents the model. Such an advantage, however, comes with some complexities, since overfitting might occur which would result in good behaviors for training set points, but poor generalization for test set points. This is a problem of generalization which can be addressed by choosing an appropriate configuration setting, a suitable architecture of NN and by partitioning the dataset into training, validation and test sets.

Using features deriving from Pisarenko, MUSIC, EV and MN methods, the MLP NNs and other classifiers from the literature are trained and subjected to the same test set. Comparison is done under results section to select the best feature extractor and classifier for both the stages.

III. Experimental Results and Discussion

A. Description of Experimental Test Rig

The experimental test-rig consists of three identical 3-phase squirrel cage IMs of 1.1 kW supplied by a SEMIKRON IGBT Voltage Source Inverter of 12 kVA. The 3-phase stator currents are acquired using LEM (LA 55-P) current transducers which are connected to dSPACE MLBX system. For the conditions stated in Table I, parameters of the IMs (procedure adopted from [21]) are identical and shown in Table III. The SITF is introduced by employing a variable power resistor connected in parallel to one of the stator phases. In this study, it occurs in phase C of the IM, and the severity of the fault ranges from 0% to 10%. For BRBF, a CNC machine has been used to drill holes on the rotor bar. It should be noted that data is acquired for both grid and inverter fed configurations for different levels of loading conditions. For the inverter-fed configuration, IM is controlled by using a scalar control method. After acquisition of the 3-phase stator current signal, the acquired data is segmented into equal samples to build up the database. A total of 5345 observations were made which includes samples of Healthy, SITF, BRBF and combination of SITF and BRBF conditions.

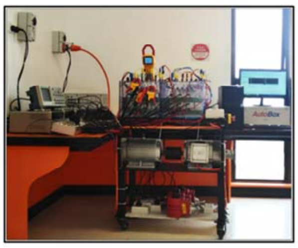

Fig. 4. Experimental Setup

TABLE III
Parameters of the Squirrel Cage IM

No. poles	4
Supply Frequency	50 Hz
Stator Resistance	3.6760 Ω
Rotor Resistance	3.8270 Ω
Stator Leakage Inductance	0.0268 H
Rotor Leakage Inductance	0.0400 H
Magnetizing Inductance	0.4490 H
Moment of Inertia	0.0059kg/m^2

TABLE IV
STAGE 1 CLASSIFICATION RESULTS AND COMPARISONS WITH CLASSIFIERS (% ACCURACIES)

PSD Estimator	**Harmonic Extractor**	**MLP NN**	**Cubic SVM**	**LDA**	**LR**	**LSVM**	**QDA**
MUSIC	Maximum Peak	95.36	10.78	90.64	90.64	53.21	90.64
MUSIC	Peak prominence	95.36	31.87	90.64	90.64	50.82	90.64
EV	***Maximum Peak***	***99.00***	***13.24***	***90.64***	***90.64***	***46.93***	***90.64***
EV	***Peak prominence***	***99.70***	***19.31***	***90.64***	***90.64***	***79.57***	***90.64***
MINIMUM NORM	Maximum Peak	93.86	82.56	90.64	90.64	90.64	90.64
MINIMUM NORM	Peak prominence	93.79	82.63	90.64	90.64	79.18	90.64
Pisarenko	Maximum Peak	89.45	90.64	87.80	90.64	14.67	85.85
Pisarenko	Peak prominence	89.52	90.94	87.73	90.64	15.79	84.96

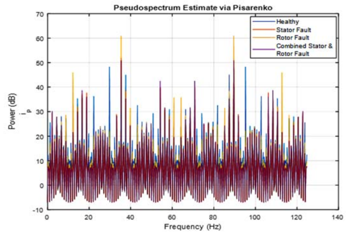

Fig. 5. Frequency Estimate via Pisarenko

TABLE V
STAGE 2 CLASSIFICATION RESULTS AND COMPARISONS WITH CLASSIFIERS (% ACCURACIES)

PSD Estimator	**Harmonic Extractor**	**MLP NN**	**Linear SVM**	**Cubic SVM**	**Ensemble Subspace kNN**	**Fine Tree/Ensemble Bagged Trees/ Complex Trees**
MUSIC	Peak prominence	92.22	82.10	92.00	85.70	87.70
MUSIC	Maximum Peak	90.97	79.90	92.90	92.10	88.00
EV	***Peak prominence***	***99.83***	***98.50***	***99.40***	***99.50***	***96.50***
EV	***Maximum Peak***	***99.25***	***97.40***	***99.10***	***96.80***	***96.50***
MINIMUM NORM	Peak prominence	82.53	70.10	81.74	90.60	92.40
MINIMUM NORM	Maximum Peak	81.02	70.00	81.60	91.10	92.40
Pisarenko	Peak prominence	53.43	20.23	20.24	84.90	87.50
Pisarenko	Maximum Peak	53.18	20.23	20.24	83.30	86.10

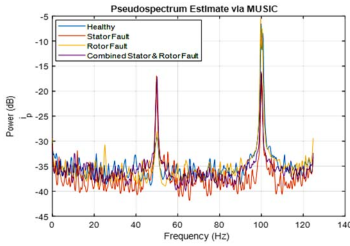

Fig. 6. Frequency Estimate via MUSIC

B. *Pseudo spectrum Estimates*

As observed in Figs. 5-8, MUSIC and EV methods show promising results in accordance with the theoretical description of the characteristic fault frequencies (described in Section II). Despite the misspecification on the number of harmonics present in the actual signal, MUSIC and EV methods yield the actual number. In few cases, some spurious peaks did emerge next to the actual harmonics. (Figs. 9-12) when identifying the frequencies of interest. This, however, can be disregarded when using prominence measure of the peaks. Indeed, a clearer representation of the peaks (for harmonics of interest) is best given by EV as opposed to MUSIC method. This is because its pseudo-spectrum estimate is calculated in the same fashion as MUSIC, but a further advantage is that it also takes into account the eigenvalue (of the current sample) when averaging (6). This is the reason why its graph has less spurious peaks than that of the MUSIC. In the case of Pisarenko method (Fig. 5), a lot of spurious peaks appear and it is very difficult to identify the actual harmonics. This phenomenon is apparent, because the data contains harmonics from the inverter ,which would make the pseudo-spectrum ambiguous. Moreover, the dimension of the noise subspace is equal to one in Pisarenko method. As for the MN method, by using the modulus of EPVA, the correct number of harmonics is identified (Fig. 7). The second harmonic is also identified but its value is incorrect in phase, direct and quadrature current spectra. Figures 9-12 represent the comparison between peak prominence measure and maximum peaks values for the retrieval of harmonics by using MUSIC and EV methods for the harmonics listed in Table I. It is clearly shown that the method of peak prominence is able to pick out correct harmonics better than the method using maximum peak value, which picks correct harmonics but at the same time selects incorrect harmonics for extraction.

These incorrect harmonics can give an improper indication on the explained variance of features in the data. Hence, this would affect the classification accuracy, since the input pattern given for the training would be incorrect at the learning stage.

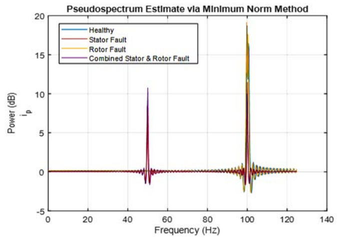

Fig. 7. Frequency Estimate via MN

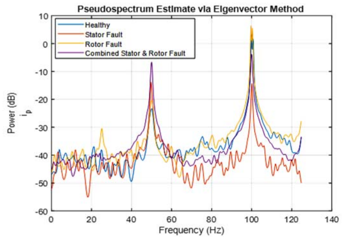

Fig. 8. Frequency Estimate via EV

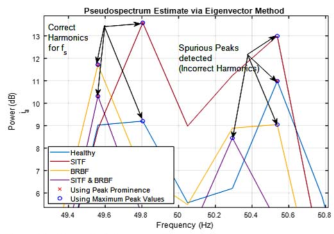

Fig. 9. Peak Extraction Comparison for f_s using EV

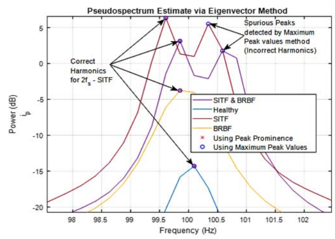

Fig.10. Peak Extraction Comparison for $2f_s$ using EV

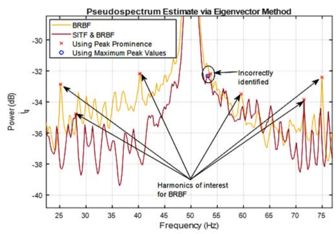

Fig.11. Peak Extraction Comparison for $f_s(1 \pm 2s)$ using EV

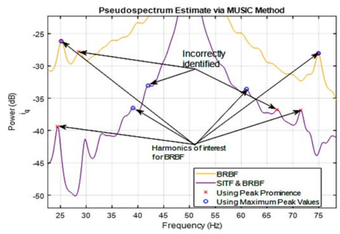

Fig.12. Peak Extraction Comparison for $f_s(1 \pm 2s)$ using MUSIC

C. Classification Results

Tables IV and V represent the classification accuracies for stage 1 and stage 2 classifiers, respectively. Both tables show the comparison of: **Pseudo-spectrum Estimators** (using Pisarenko, MUSIC, MN and EV methods), **Harmonic Extractors** (using peak prominence measure and maximum peak values method) and variety of **Classifiers** (MLP NNs, Support Vector Machines (Linear SVM and Cubic SVM) [22], Discriminant Analysis (Linear DA and Quadratic DA) [23], Logistic Regression (LR), Ensemble method using subspace kNN [24] and Ensemble method using Trees [24]).

The proposed method for extracting harmonic (using peak prominence measure) has proven its superiority over the other. As it is apparent in all the cases (Table IV and V), regardless of the frequency estimation or classification method, the accuracy of the classifier using peak prominence measure is always higher than the one obtained with the maximum peak value method. In addition, the best classifier is found to be the MLP NN (having 111 and 114 neurons in its hidden layer for stage 1 and stage 2, respectively), which also has higher accuracy in most cases than others using EV as its pseudo-spectrum estimator. The MUSIC method, along with its classifier and harmonic extractor, is ranked second for reasons explained in part *B* about the selection of incorrect harmonic when building the feature-set.

IV. Conclusion

By using the proposed methodology (Fig. 1), classification of stator and rotor related faults can be achieved at varying slips on an online basis. This paper introduces a harmonic extraction methodology which is fast and simple as it performs peak analysis not only taking into account the maximum values of peaks, but also its prominence. The peak prominence measure takes into account the peak's intrinsic height and how much it stands out with respect to others. This helps to retrieve correct harmonics when SNR is low or in case of model order misspecification (as was the case in this paper) or especially when the method of using maximum peaks values fails to recognize correct harmonics. The subspace methods for pseudo-spectrum estimation along with peak prominence measure and maximum peak values method have been utilized as the feature extractors, together with various classification algorithms. A thorough comparison was made (Tables VI and V) and the best model has been found to be the EV for the pseudo-spectrum estimator, with peak prominence measure as its harmonic extractor, and MLP NNs as the classifier. This model had 99.70% and 99.83% accuracies for stage 1 and stage 2 classifiers, respectively, when subjected to experimental observations in the test set.

Finally, it should be noted that the proposed method for harmonic extraction can also be applied in conjunction with other non-parametric techniques for the retrieval of harmonics.

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