Tracking Evolution of Stator-based Fault in Induction Machines using the Growing Curvilinear Component Analysis Neural Network

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***Abstract*— Stator-based faults are one of the most common faults among induction motors (IMs). The conventional approach to IM control and protection employs current sensors installed on the motor. Recently, most studies have focused on fault detection by means of stator current. This paper presents an application of the Growing Curvilinear Component Analysis (GCCA) neural network aided by the Extended Park Vector Approach (EPVA) for the purpose of transforming the three-phase current signals. The GCCA is a growing neural based technique specifically designed to detect and follow changes in the input distribution, e.g. stator faults. In particular, the GCCA has proven its capability of correctly identifying and tracking stator inter-turn fault in IMs. To this purpose, the three-phase stator currents have been acquired from IMs, which start at healthy operating state and, evolve to different fault severities (up to 10%) under different loading conditions. Data has been transformed using the EPVA and pre-processed to extract statistical time domain features. To calibrate the GCCA neural network, a topological manifold analysis has been carried out to study the input features. The efficacy of the proposed method has been verified experimentally using IM with 1.1kW rating and has potential for IMs with different manufacturing conditions.**

Keywords—Park vector, diagnosis, incremental neural networks, principal component analysis, stator fault, feature engineering, dimensionality reduction, intrinsic dimensionality

I. INTRODUCTION

Electrical faults are most common in rotating machines and involve mainly the incorrect connection of the motor windings, grounding errors, short circuit of stator windings, as well as the open circuit of the whole phase. In particular, stator-based faults contribute up to 38% of all the motor faults [1]. Within this category, inter-turn short circuit of the stator windings is the most common one. It deeply influences the machine since it adversely affects the reliability and safety during the operation. This class of fault has a very small time constant and evolves at a tremendous rate whereby many condition monitoring schemes fail to recognize its inception. Therefore, a much more robust detection method is necessary to recognize this type of fault on an online basis, such that users are constantly informed about the health of the machine.

While many protection systems for rotating machines (regardless of grid connected or inverter fed configurations) are designed to trip the circuit breaker off under these circumstances, a near to permanent damage is already done to the stator/stator windings. This mostly happens at the time between the inception of fault and tripping of the circuit breakers. The protection system for electrical drives accommodates a certain level of tolerance for phase unbalance during its transient and steady state operation [2]. For the case of stator inter-turn faults (SITFs), a low level of phase unbalance is initially not so evident (because SITF starts from a very low severity). On this basis, the protection systems do not cut off the supply unless it exceeds a fixed tolerance level for phase unbalance or simply when the fault evolves to higher severities. In other words, the protection system comes into effect only when the motor rating is violated by either a supply or a noticeable internal failure [3].

This study focuses on IM SITF because of its time varying nature and of its hard to detect incipient behavior. The authors propose a novel architecture for diagnosing and modelling the SITFs in IMs. The diagnosis scheme consists of a growing neural based technique known as the "Growing Curvilinear Component Analysis (GCCA)" [4], which is the non-stationary extension of the Curvilinear Component Analysis (CCA) [5]. The GCCA requires fewer parameters than CCA and it is completely online, i.e. it works on continuous data stream, not batches.

Moreover, an IM with 1.1kW rating has been used for experimentation. The phase current signatures of the healthy and faulty cases are acquired at varying loads with a realistic degree of voltage asymmetries. Thereafter, the phase current signatures are transformed using EPVA and then pre-processed (which involves data fusion, normalization, feature extraction). After this, the features are fed to the diagnosis scheme to detect and infer the level of fault severity. Differing from the existing strategy as presented in [6], the transformation of the phase currents using EPVA prior to feature extraction has significantly improved the results upon exploring the GCCA input quantization in this study. Through extraction of the statistical time domain features [7] from the EPV current (3), the data is well captured since all the phases have been used under this strategy. The data geometry has been studied in a much more efficient way to derive the SITF class cluster relative positions at different severity levels. Similarly, with this approach, a suitable judgement on the dataset intrinsic dimensionality (ID) has been accurately determined. With this ID value, the input dimensionality has been reduced and its projection contains only significant information that clearly indicates the SITF evolution over time.

This paper is organized as follows: Section II provides a theoretical overview of GCCA neural network followed an artificial example using this algorithm. Section III explains the SITF fault emulation and the feature engineering aspects. Then, Section IV presents the exploratory data analysis using PCA and CCA. Thereafter, Section V gives results and discussion for the proposed strategy to track the evolution of the stator inter-turn-fault using GCCA. Finally, Section VI summarizes this paper and gives direction for future works.

II. THE GCCA NEURAL NETWORK

A. *Theoretical Aspect*

The GCCA is a self-organizing neural network that is able to detect non-stationarity in the data flow. To demonstrate the detection of non-stationarity in the data, two different neuron connections (the "bridges" and the "links") and the colonizing seeds have been introduced in the algorithm [8, 9]. In case of IM operation, the occurrence of the "bridges", i.e. a change in the data distribution (non-stationarity), indicates the fault. Indeed, GCCA exploits bridges and seeds to learn how the input evolves over time. A comprehensive flowchart of the algorithm is laid out in [4].

The fact that GCCA is supervised and incremental is because the number of neurons is dependent on the input space quantization. Just like CCA, the neurons of GCCA have two weight vectors: (1) input space (X-weight) and (2) output/latent space (Y-weight), that eventually gives the projection of the data. For the aforesaid neuron of GCCA, it should be noted that it carries a threshold that represents the Voronoi region in the input space. This idea of threshold is quite important, and it is neuron specific; meaning that it is used to recognize novelty of the input data with respect to the existing quantization. The threshold is automatically calculated by considering distance in the input space between the considered neuron and its farthest neighbor. Considering the flowchart in [4], a new neuron is created when the input data is novel with respect to the first winner's threshold. In this case, the new neuron's weight vector in the X-space is the data itself. In the Y-space, its weight is deduced by CCA. However, if the oncoming data fails the novelty test, Soft Competitive Learning (SCL [10, 11]) is applied to the first winner and its neighbors to adjust their weight vectors in X-space. As for their projections, CCA is applied in the same manner.

To differentiate stationary and non-stationary dataflow, GCCA uses two different kinds of links to connect the neurons in question. These are edges and bridges: for edges, the Competitive Hebbian Learning (CHL [12]) technique is utilized to determine the topology of the data manifold while bridges track jumps in the input distribution. In particular, the bridge is a directional connection to link a new neuron to the existing quantization to represent non-stationarity in the data flow.

Moreover, the idea of seed has also been instrumental in the development of GCCA. It utilizes the hard competitive learning, HCL [10, 11] strategy to adjust the weight vector for a couple of neurons and its double (seed). The process of neuron doubling is carried out whenever the first winner is at the top of the bridge emanating from the second winner: it is under these circumstances GCCA populates a novel part of the input manifold. Besides, if the first winner is not at the top of the bridge (meaning it is the bridge tail), then the region formerly linked with a bridge does not present a change in the input distribution (stationary scenario). Therefore, this connection is turned into an edge, that details information only about the topology of the manifold.

GCCA adapts well with the data fed to it provided the input parameters are well defined. The projection of the data is entirely based on the CCA algorithm. For this application, due to the nature of the data, detection of the SITF is well presented for various levels of severities and also, degradation of the SITF is also observed to some extent.

B. *Artificial Example*

The GCCA neural network has been applied to two artificial examples: 3D rectangles, 2 rectangles. In Figs. 1-2 below, the bridges depict change in distribution of the data. Single long bridges represent abrupt changes in the distribution and the length of the bridges represents how far the clusters with different distribution are located. Indeed, for a smoother change in the distribution, more bridges are observed, and this is the case for Figs. 1-2, whereby the density of the bridges is proportional to the displacement speed of the distribution. The resulting quantization memorizes the previous positions of the distributions; the deformations in the grid are due to a lower number of data fed to the network. It should be noted that in spite of having a pruning parameter, GCCA is not a memoryless system. It organizes the data so that significant transitions in the distribution can be represented by bridges, while minor ones can be illustrated through links/edges. In addition, the structure of the shapes are well maintained, which implies the GCCA's adaptive ability to preserve the topology of the data.

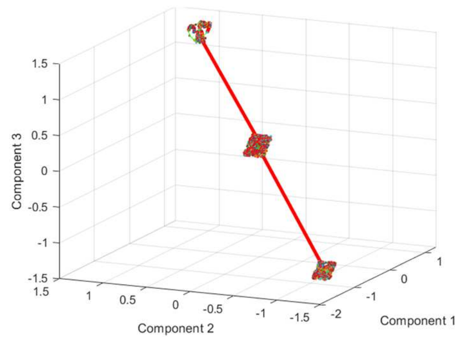


Fig. 1. GCCA Vector quantization: 3D rectangles – GCCA parameters $\boldsymbol{\alpha_{CCA} = 0.001, \lambda_i = 1, \lambda_f = 0.01, \alpha_1 = 0.01, \alpha_2 = 0.001, age_{max} = 4}$

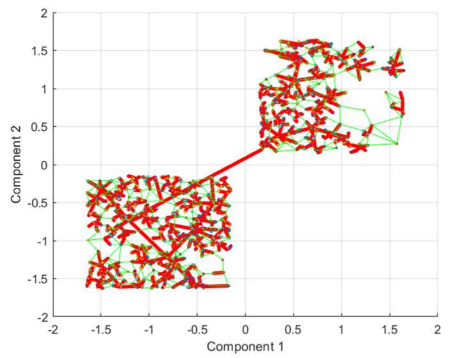


Fig. 2. GCCA Vector quantization: 2 rectangles – GCCA parameters $\boldsymbol{\alpha_{CCA} = 0.001, \lambda_i = 1, \lambda_f = 0.01, \alpha_1 = 0.01, \alpha_2 = 0.001, age_{max} = 4}$

III. Experimental Setup and Feature Engineering

A. Stator Inter-turn Fault Description and Emulation

To generate the SITF in hardware, a prior study of the SITF in IM was conducted using finite element analysis (FEA). For this purpose, up to 10% of the SITF was studied considering shorted turns in a single coil. This priory study was conducted to avoid permanent damage to the IM under test. It was evidenced in the FEAs that a single shorted turn in a coil resulted in a higher fault current way above the rated current of the IM. This phenomenon is due to very low short-circuit impedance with respect to the induced electromotive force (emf). To maintain consistency and considering safety of the IM, the SITF is characterized by using appropriate values of shunt resistors to limit the fault currents to sustainable values. Various trials via FEM were carried out to select the values of the shunt resistance for various levels of SITF severities.

Following the above setting, the severity of the SITF is varied in between ≈ 5% to ≈ 10%, by choosing appropriately the shunt resistance values and number of turns in the phase branch. Data is acquired by first obtaining the healthy current signal, after which, the faulty data (SITF) is acquired by using appropriate values of shunt resistance.

Considering the shunt resistance value and number of turns in the phase branch, following SITF severities were explored in this study: 5%, 5.77%, 6.85%, 8.42% and 10.92%. Data acquisition involved logging of the three-phase current signals for no-load, 25% load and 40% load conditions. For no-load operation, data has been acquired for all fault severity levels. However, for 25% and 40% loads, data has been acquired only up to the fault severity of 6.85%. This was to avoid excessive vibrations and permanent damage to the stator of the IM.

B. Feature Engineering

Since the three-phase stator current signal of the IM is insufficient to separate the fault and differentiate the levels of fault severity, statistical time domain features were calculated. A total of fifteen statistical time domain features were extracted from the Extended Park Vector (EPVA) [13].

The EPVA transforms the three-phase stator current signal (i_{sa}, i_{sb}, i_{sc}) into direct and quadrature axis components (i_d, i_q) and computes their combination modulus (i_P) as follows:

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

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

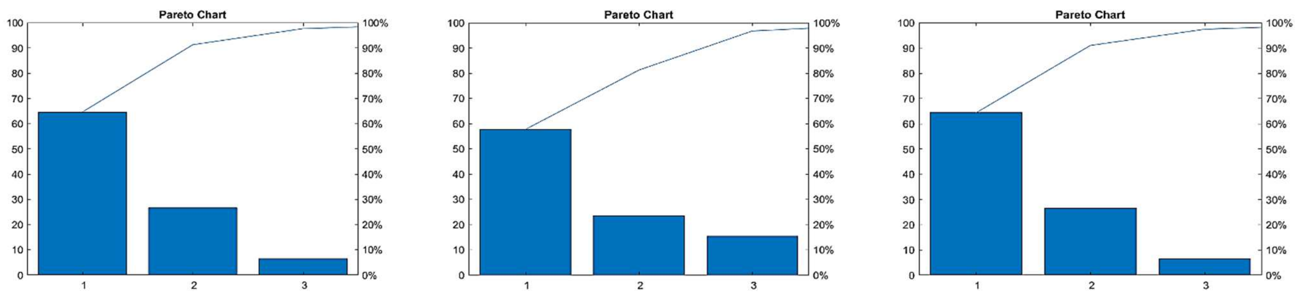
$$i_P = \left|\left(i_d + j i_q\right)\right| \tag{3}$$

In this work, only the i_P current is used to calculate the fifteen statistical time domain features [7] because, by definition, it includes all the dynamical information of the three-phase stator current signal.

IV. Data geometry and intrinsic dimensionality (ID) estimation

After the feature extraction and preprocessing phase, the resulting data geometry was analyzed to determine its intrinsic dimensionality (ID), since it is one of the most important GCCA hyper parameters. More in detail, the ID is defined as the dimensionality of the smallest space able to represent completely the input data. This value is normally used by the dimensionality reduction techniques, such as CCA and its variant (e.g. GCCA), to project the data into a lower dimension space for clear visualization.

To estimate the dataset ID, both linear (Principal Component Analysis - PCA) and non-linear (CCA) techniques have been used. The PCA associated Pareto charts of the evolving IM SITFs under different loads (no load, 25% load and 40% load) are shown in Fig. 3: for all cases, the first three principal components (PCs) are able to explain more than 95% of the feature set. The first PC is able to explain over 60% variability, while the following second and third PCs explain the rest and amount to over 95% of explained variability. Hence, from this linear analysis it can be inferred that the ID of the feature-set is three.



(a) (b) (c)

Fig. 3. Linear intrinsic dimensionality estimation: PCA Pareto charts – (a) No load, (b) 25% Load, (c) 40% Load

To further confirm these results, a deeper non-linear analysis was performed using CCA to project the feature-set from 15 to 3 dimensional space. To assess the projection quality, the plots of the inter-sample distances in the output space versus their corresponding ones in the input space, say *dy-dx* diagram, have been studied (see Fig. 4).

In the perfect input-output mapping, all *dy-dx* points (blue dots) must align onto the bisector (red segment). Because the blue cloud is well onto the bisector, with respect to the chosen λ, it can be deduce that the projection has not lost information. In this sense, the latent space dimensionality (or ID), i.e. three, can be considered as the sought ID.

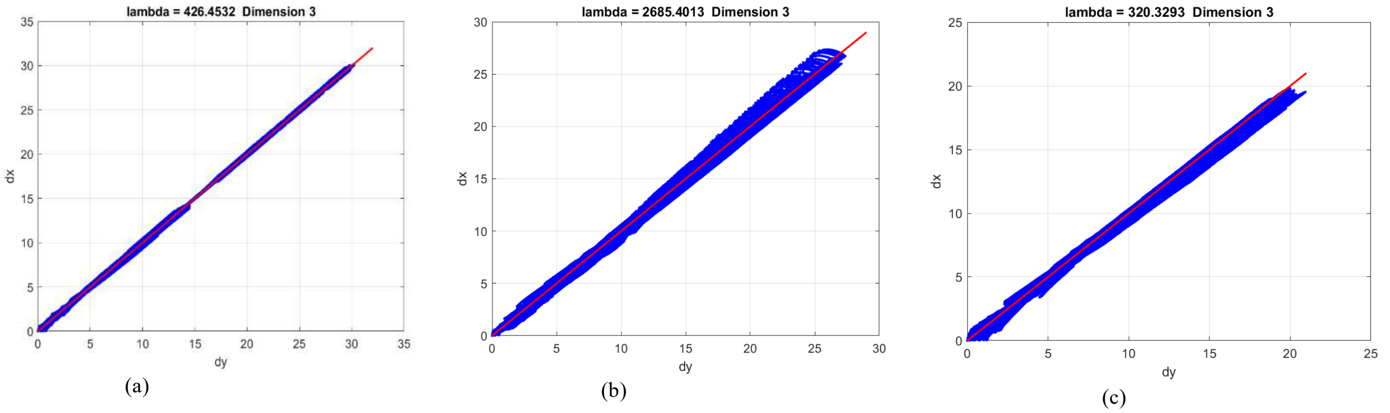


Fig. 4. Non-linear intrinsic dimensionality estimation: CCA *dy-dx* diagram - (a) No load, (b) 25% Load, (c) 40% Load

V. Stator Fault Tracking using GCCA

To detect and track the SITF using the aforementioned feature-set, GCCA has been applied on the three different loading conditions (no load, 25% load and 40% load) by projecting the input into a 3-D space (as the ID derived before). Fig. 5 shows the GCCA quantization of the input space, using the first three PCs for visualization. The red segments are the "bridges", showing transition from healthy to faulty regions. It can be observed, the healthy cluster (black data cloud) is always well isolated from the faulty ones (yellow, green, blue, cyan, magenta points), demonstrating the robustness of the method. In this sense, it enables fast and accurate detection of SITFs in IMs. Similarly, long bridges indicate the transition from one level of fault severity to another: therefore, the degradation of the stator windings can be accurately tracked and appropriate measures can be taken to avoid severe damage to IMs. The fact that the IM operating at 25% and 40% load did not exceed 6.85% of SITF severity was because the protection system of the IM fed by the inverter took effect, thus tripping the circuit breaker off. Similar explanation is for the no load condition which only went up to 10.92% of SITF.

In addition, the GCCA is not only able to learn the time varying manifold but is also able to extract important features and projects it to the latent space, which can later be used for other analyses. For instance, the bridge lengths can be used as an early detector and an indicator of the level of fault in case of SITFs. This is because, as per Fig. 5, higher values of bridge lengths correspond to transition from healthy to faulty states. Compared to the results emanating from only using the affected phase current of the IM in [6], the proposed strategy in this paper, i.e. GCCA aided by EPVA captures all the phase information and shows adequate amount of separation upon tracking the Stator inter-turn fault (SITF) as it evolves from healthy to faulty states. Moreover, unlike the GCCA input quantization of the affected phase in [6], the proposed strategy using EVPA shows very clearly the changes in the severity of the SITF. While using only the affected phase is instrumental in isolating the fault, there is very little information about the SITF severity levels. A major reason behind this setback is the changes in the loading condition for the induction motor; i.e. under no load condition, the SITF tracking with severities are to some extent apparent. But, when there is a load change, the GCCA input quantization plot is unable to describe correctly the faulted states (severity). In the proposed strategy, both fault isolation and different fault severities are clearly denoted by the bridges regardless of the IM being subjected to different loads or operating at no load condition.

It is worth mentioning that the cluster (healthy or faulty) positions correlates with the severity of the SITF for the IM. According to Fig. 5, the transition from healthy to faulty state is abrupt due to the 5% SITF, which is currently the lowest SITF percentage as per our hardware experimentation. However, to measure the sensitivity of the proposed strategy, even small percent changes in the fault severity is captured by the GCCA. Considering Fig. 5a, the SITF percentages are: 5%, 5.77%, 6.85%, 8.42% and 10.92%. The increment of 0.77% SITF (fault transition from 5% to 5.77%) is clearly captured in the GCCA input quantization plot not only in Figure 5a, but under all loading conditions (Figures 5a-c). Thus, regardless of the constraints in terms of the hardware (lowest SITF severity being 5%), it can be confirmed that the proposed strategy will also be able to detect even small degree of SITF. Thus, for this application, the lowest percentage of SITF change detected and tracked by GCCA neural network is 0.77%.

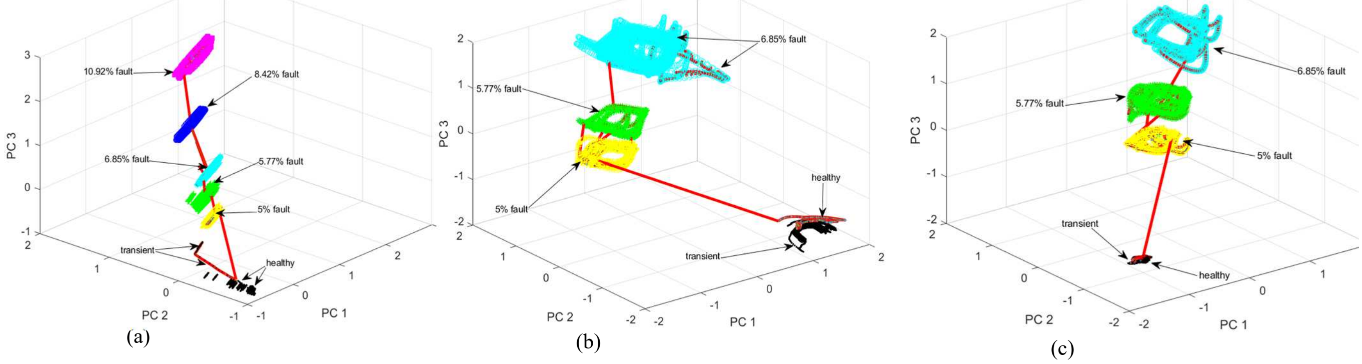


Fig. 5. The GCCA input quantization of IM SITF datasets - (a) No load, (b) 25% Load, (c) 40% Load

VI. CONCLUSION

In this paper, the GCCA neural network has been employed for detecting and tracking SITF in IMs, which were the root cause of non-stationarity in the data flow. While other non-linear techniques and neural based methods are computationally expensive, GCCA is the only neural network available that is able to track non-stationarity and, at the same time, project input data to a lower dimension space. It should be noted that EPVA played an important role at the prior stage of pre-processing in order to transform the three-phase current signals into a lower dimension that has improved the preceding results in case of a single-phase (affected phase) analysis. In terms of fault detection, GCCA results in a much more accurate detection of SITFs as well as the inference on the fault severities in IMs. For this study, the lowest percentage of fault severity change detected by the GCCA neural network was 0.77%.

Its effectiveness in alarming the fault conditions at low severities would aid the protection systems to shut down the operation of the IMs at very early stages to avoid permanent damages. This has been demonstrated under the results explaining at which SITF severity the protection systems take effect. Moreover, because GCCA is an online technique, it is possible to embed on single board computers or FPGAs for real time condition monitoring and fault diagnosis of not only IMs, but other rotating machines and electrical systems.

Future work will involve analysis of the SITF using IM with different manufacturing conditions, particularly to observe the starting point of SITF using GCCA neural networks. This will involve an in-depth study of “bridges” and “links”.

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