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# A PMSynRM stator winding fault detection approach using an optimized PCA-based EWMA control scheme

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**Abstract**—This paper aims to present a statistical methodology for inter-turn short-circuit fault detection in a PMSynRM for electrified vehicles in closed-loop operation. The proposed methodology is based on the combination of the Principal Component Analysis (PCA) and Exponentially Weighted Moving Average (EWMA) whose performance strongly depends on its control parameters. The False Alarm (PFA) probability is minimized to tune the control parameters correctly. Additionally, we develop a strategy based on comparing the eigenvalues of the data in the PCA subspaces to automatically select the statistical index allowing the best fault detection with the minimum missed detection probability (PMD). A hybrid Finite Element-Analytical model of a PMSynRM has been simulated to generate synthetic data. For seven fault severities and three different loads, the performance is evaluated. We show that for all operating and fault conditions, fault detection is ensured in the worst case with  $PMD < 0.02$  and  $PFA < 0.055$ . The proposed methodology outperforms traditional approaches, and its efficiency is proven.

**Index Terms**—Fault detection, PMSynRM Inter-turn short-circuit fault, PCA, EWMA, optimization

## I. INTRODUCTION

The reliability of electric motor drive systems in electric vehicles (EVs) has attracted considerable interest in recent years. Among the electric machines faults, inter-turn short-circuits are the most common ones [1]. They are usually the cause of several other winding defects [2]. Then, for security reasons, early inter-turn short-circuit fault detection is very important. To generate the motor data to analyse for fault detection, a hybrid Finite Element-Analytical model of a three-phase Permanent Magnet-Assisted Synchronous Reluctance Motor (PMSynRM) developed in [3] and [4] has been developed. It has been simulated in closed-loop with a two-level inverter, and validated under different operating conditions.

In recent inverter-fed motor applications, conventional motor monitoring tools face challenges due to high noise level, the dynamic changes that affect the excitation frequencies and closed-loop action that could affect the fault signatures [5]. To meet the need for comprehensive failure diagnosis tools, valid for all applications under different operating conditions, statistical analysis tools are an alternative to conventional

methodologies [6]. For multivariate systems, the Principal Component Analysis (PCA) has been widely used because of its good performance in highlighting variables' correlation and its no prior knowledge requirement [7]. However, conventional PCA-based fault detection solutions using the fault indices Hotelling  $T^2$  and Squared Predicted Error ( $SPE$ ), are less suitable to detect mild changes [8]. This limitation leads to the adoption of the Exponentially Weighted Moving Average (EWMA) monitoring chart where the state of the process at a point depends on the exponentially weighted average of all prior data. The sensitivity of the EWMA control procedure to gradual faults in the process highly depends on the choice of its tuning parameters [9]: the weighting factor  $\eta$  and the control limits' parameter  $L$ .

In this paper, a methodology to optimally tune the parameters  $\eta$  and  $L$  is proposed. We show how to calibrate these parameters using an optimization scheme that minimizes the probability of false alarm (PFA). This methodology is illustrated in the case of inter-turn short-circuit fault detection for a PMSynRM. Additionally, the issue of noise influence in PCA feature space selection is addressed using an eigenvalue comparison test. Then, the most efficient framework and index can be automatically selected leading to the reduction of the probability of missed detection (PMD). The rest of the paper is organised as follows. In section II, after recalling the basics on PCA and EWMA for fault diagnosis, the proposed methodology is presented and the optimization procedure described. Section III presents the results and performance of the method. Section IV concludes the paper.

## II. FAULT DETECTION METHODOLOGY

Let us consider  $N$  observations for  $n$  measured variables arranged in a data matrix  $\mathbf{X} \in \mathbb{R}^{N \times n}$ , with zero mean and unit variance. In this matrix, each vector is written as  $\mathbf{x}_i^T = [x_{i,1}, \dots, x_{i,n}]$  where  $x_{i,j}$  is the  $j$ th observations of the  $i$ th variable. In this approaches, the collected data in healthy operating conditions are used to build a reference model. Then the elements of this model are used to evaluate the faulty data.

The fault detection methodology proposed in this paper is based on the improvement of the limitations shown in conventional approaches using PCA and EWMA. These two approaches are first described and the improved optimized solution is further derived.

#### A. Principal Component Analysis for fault detection

Basically, PCA is used to reduce data dimensionality by grouping correlated variables in a set of new uncorrelated ones [10]. Then, the data matrix  $\mathbf{X}$  is subject to a linear transformation matrix  $\mathbf{T}$  to express the variation in the observations such as  $\mathbf{T} = \mathbf{X}\mathbf{P}$ , with  $\mathbf{T} \in \mathbb{R}^{N \times n}$  the principal component matrix and  $\mathbf{P} \in \mathbb{R}^{n \times n}$  the eigenvectors matrix containing the eigenvalues  $\lambda_i$  of the correlation matrix  $\mathbf{\Sigma}$  of  $\mathbf{X}$  such as:

$$\mathbf{\Sigma} = \mathbf{P}\mathbf{\Lambda}\mathbf{P}^T \quad (1)$$

Where  $\mathbf{\Lambda} = \text{diag}(\lambda_1, \dots, \lambda_n)$  is a diagonal matrix with diagonal elements in decreasing magnitude order. The reduced  $l$ -dimensional space of the data is obtained by retaining only the principal components that correspond to the  $l$ -highest eigenvalues of the covariance matrix. They represent the feature space where most of the pattern in the data are represented (generally up to a given percentage of cumulated variance). The remaining components with the smallest eigenvalues represent the noise contribution. Once the number of components  $l$  to retain is determined, the eigenvectors matrix  $\mathbf{P}$  and the principal component matrix  $\mathbf{T}$  are partitioned into the form:

$$\begin{aligned} \mathbf{P} &= \begin{pmatrix} \hat{\mathbf{P}}_l & \tilde{\mathbf{P}}_{n-l} \end{pmatrix} \\ \mathbf{T} &= \begin{pmatrix} \hat{\mathbf{T}}_l & \tilde{\mathbf{T}}_{n-l} \end{pmatrix} \end{aligned} \quad (2)$$

$\hat{\mathbf{X}}$  is the principal part of the data explained by the  $l$  first eigenvectors and the residual part  $\tilde{\mathbf{X}}$  is explained by the residual components [11]:

$$\begin{aligned} \hat{\mathbf{X}} &= \hat{\mathbf{P}}_l \hat{\mathbf{P}}_l^T \mathbf{X} \\ \tilde{\mathbf{X}} &= \tilde{\mathbf{P}}_{n-l} \tilde{\mathbf{P}}_{n-l}^T \mathbf{X} \end{aligned} \quad (3)$$

They respectively lead to the principal and residual subspaces used for fault diagnosis.

A process monitoring with PCA uses Hotelling's  $T^2$  and  $Q$  statistics also called Squared prediction error ( $SPE$ ) to detect abnormal behaviours. The Hotelling's  $T^2$  and  $SPE$  represent the variability in the Principal Component Subspace (PCS) and the Residual Subspace (RS), respectively.  $T^2$  can be expressed by using the estimated value  $\hat{\mathbf{\Sigma}}$  of the correlation matrix as follows [12]:

$$T^2 = \hat{\mathbf{X}}^T \hat{\mathbf{\Sigma}}^{-1} \hat{\mathbf{X}} \quad (4)$$

Under normal conditions if the data set is multivariate Gaussian distributed, the  $T^2$  can be approximated by a  $\chi^2$  distribution with  $l$  degrees of freedom and a significance level  $(1-\alpha)$ . The system operation is considered healthy if:

$$T^2 \leq \chi_{l,1-\alpha}^2 \quad (5)$$

A variation of the variables' correlation indicates an abnormal behaviour. Under this condition, the sample matrix  $\mathbf{X}$  increases its projection to the  $RS$  and the magnitude of  $\tilde{\mathbf{X}}$  reaches abnormal values compared to those obtained during healthy conditions.  $SPE$  is the magnitude of  $\tilde{\mathbf{X}}$  and is written as:

$$SPE = \|\tilde{\mathbf{X}}\|^2 \quad (6)$$

The process is considered healthy if the  $SPE$  statistic is under its control limit which is expressed as follows:

$$SPE \leq (\check{\mu} + \check{\sigma} z_{1-\alpha})^3 \quad (7)$$

with  $z_{1-\alpha}$  as the  $(1-\alpha)$  significance level of a Gaussian distribution  $\Phi$ .  $\check{\mu}$  and  $\check{\sigma}$  are respectively the estimated mean and standard deviation of  $SPE^{2/3}$  [12].

Unfortunately the process monitoring using  $T^2$  and  $SPE$  is not always effective as they only use the current observation information for decision making. Hence, these detection indices are relatively insensitive to minor changes in the process variables, and thus may result in missed detections. To overcome these limitations, an alternative approach has been developed, where PCA is used as a modelling framework for fault detection using an EWMA control scheme [13].

#### B. PCA-based EWMA control scheme for fault detection

In the EWMA control scheme, the moving average is calculated by multiplying the historical observations with weight coefficient that exponentially decays with time. The EWMA decision statistic criterion is then described as follows:

$$z_t = \eta \times x_{i,t} + (1-\eta)z_{t-1} \quad (8)$$

where  $\eta$  is a weight parameter, with  $0 < \eta \leq 1$ , and  $x_{i,t}$  is the value of the monitored variable  $i$  at time  $t$ . The starting value  $x_{i,0}$  is set equal to the mean  $\mu_0$  of the process in-control. Generally, smaller values of  $\eta$  increase the chart's sensitivity to smaller shifts in the process mean, while larger values of  $\eta$  increase its sensitivity to larger shifts. The standard deviation of  $z_t$  is approximated as follows:

$$\sigma_{z_t} = \sqrt{\frac{\eta}{2-\eta}} \quad (9)$$

The EWMA control scheme declares an anomaly when the value of  $z_t$  falls outside of the interval between the upper and lower bounds of the control limits. The upper and lower control limits, denoted as  $UCL$  and  $LCL$  are set as:

$$\begin{aligned} UCL &= \mu_0 + L\sigma_{z_t} \\ LCL &= \mu_0 - L\sigma_{z_t} \end{aligned} \quad (10)$$

Where  $L$  is a multiplier of EWMA standard deviation  $\sigma_{z_t}$ . As stated in Section I, the sensitivity of the control procedure to small or gradual faults highly depends on the settings of  $L$  and  $\eta$ . The fault detection using PCA-based EWMA scheme involves the evaluation of these residuals from the PCA framework using a statistical EWMA to set the control limits  $UCL$  and  $LCL$ . It allows to determine if the system

is healthy or faulty. If the EWMA statistic exceeds any of the control limits, this is an indicator of an abnormal (faulty) behavior [13].

### C. Optimized proposed fault detection scheme

The proposed solution for this study has to tackle two main limitations of the EWMA control scheme: (1) the selection of the correct PCA feature space, (2) the tuning of the weight and the control limit parameter.

1) In the conventional PCA-based EWMA fault detection algorithm, one major limitation using the EWMA monitoring scheme is in the exclusive use of the residual components of the PCA model. Indeed, this is valid in ideal systems where the presence of faults affects mostly the components in the residual subspace, but this is not always true. In some cases, the system modelling errors could be projected onto the residual subspace making it less sensitive to the fault and the principal subspace more sensitive. So, it is necessary to analyse the information in both subspace as a whole set to obtain more accuracy in the fault diagnosis results.

In our work, we propose to apply the EWMA monitoring scheme to either the principal and residual subspace depending on the evaluation of the eigenvalues of the test data in the PCA subspaces. We compare the smallest eigenvalue in the principal subspace to the highest one in the residual subspace. The higher the ratio between these aforementioned eigenvalues is, the more the fault signature is found highly represented in the residual component and vice versa. The correct subspace can then be automatically selected.

2) Usually, the EWMA control limit parameters  $L$  and  $\eta$  are chosen depending on the type of system under monitoring. In most of applications, the EWMA standard deviation amplifier  $L$  is set equal to 3 while the weighted parameter  $\eta$  is set depending on the importance one wants to give to the current observation in the calculation of the EWMA. To accurately tune these parameters, we propose to set them from the solution of an optimization problem. For that purpose we show how to obtain them following the minimization of the probability of false alarm ( $PFA$ ) on healthy data. This probability is a useful criterion to set a preliminary detection threshold without any a priori knowledge on the faulty data. All the data that are above this threshold will be falsely considered as faulty (false positive). The others are truly considered as healthy (true negative). Then the  $PFA$  is given as :

$$PFA = \frac{N_{FP}}{N_{FP} + N_{TN}} \quad (11)$$

Where  $N_{FP}$  is the number of false positive values and  $N_{TN}$  is the number of true negative ones. The problem in our case is to find the couple of  $(\eta, L)$  that minimizes the  $PFA$ . The fact that the conventional  $PFA$  parameters  $N_{TN}$  and  $N_{FP}$  are only defined by crossing the two

EWMA control limits makes the problem divergent. To get a convergent problem we define a new objective function relating the distance between the EWMA observations  $z_i$  and their control limits  $UCL$  and  $LCL$  as follows:

$$\begin{aligned} \min_{\eta, L} & \sqrt{(z_{max}(\eta_j, L_j) - UCL(\eta_j, L_j))^2} \\ \min_{\eta, L} & \sqrt{(z_{min}(\eta_j, L_j) - LCL(\eta_j, L_j))^2} \\ \text{s.t.} & 0 < \eta_j \leq 1, \quad 0 < L_j \leq 3 \end{aligned} \quad (12)$$

Where  $(\eta_j, L_j)$  are the potential solutions,  $z_{max}$ ,  $z_{min}$  are respectively the maximum and the minimum of the EWMA observations. The multi-objective function can be reformulated into a mono-objective one such as:

$$\begin{aligned} \min_{\eta, L} & F_{obj}(\eta_j, L_j) \\ \text{s.t.} & 0 < \eta_j \leq 1, \quad 0 < L_j \leq 3 \end{aligned} \quad (13)$$

Where:

$$F_{obj}(\eta_j, L_j) = \sqrt{(z_{max}(\eta_j, L_j) - UCL(\eta_j, L_j))^2} + \sqrt{(z_{min}(\eta_j, L_j) - LCL(\eta_j, L_j))^2} \quad (14)$$

The proposal is described in the flowchart displayed in Figure 1.

## III. RESULTS AND DISCUSSIONS

In this section, the PCA-based EWMA methodology is used to detect stator inter-turn short-circuit fault in a PMaSynRM.

### A. Data generation

To assess the performance of the proposed fault detection scheme, the model of the PMaSynRM presented in [3] and [4] is used. The motor characteristics and simulation parameters are displayed in Table I. The PMaSynRM winding under an inter-turn short-circuit in phase  $a$  is shown in Figure 2.

Under this fault condition, the phase  $a$  current  $i_a$  is divided into  $i_s$  the current in the defective part of the winding and  $i_f$  the current in the inter-turn fault's contact branch.  $L_{a1}$  and  $L_{a2}$  represent the inductances of the healthy and faulty sub-coils of the phase  $a$  winding respectively. In one hand,  $M_{a1b}$  and  $M_{a1c}$  denote the mutual inductances between the healthy sub-coil  $L_{a1}$  and the coils  $L_b$ , and  $L_c$  respectively. On the other hand  $M_{a1a2}$ ,  $M_{a2b}$  and  $M_{a2c}$  denote the mutual inductances between the sub-coil  $L_{a2}$  and the healthy sub-coil  $L_{a1}$ , and coils  $L_b$ , and  $L_c$  respectively.

Three different mechanical load conditions ( $\Gamma_1 = 18Nm$ ,  $\Gamma_2 = 134Nm$ ,  $\Gamma_3 = 260Nm$ ) have been applied to the machine during 3s each, with a controlled rotating speed at 1500rpm. The generated data include the motor stator phase currents  $i_a$ ,  $i_b$  and  $i_c$ . The faults which are changes in the values of the stator resistances and inductances are introduced after 1s of healthy state for each load case. The duration of the fault is also 1s. To assess the abilities of the various fault detection of the methodology, seven different severity levels are considered in this study. The fault severity levels are ranked

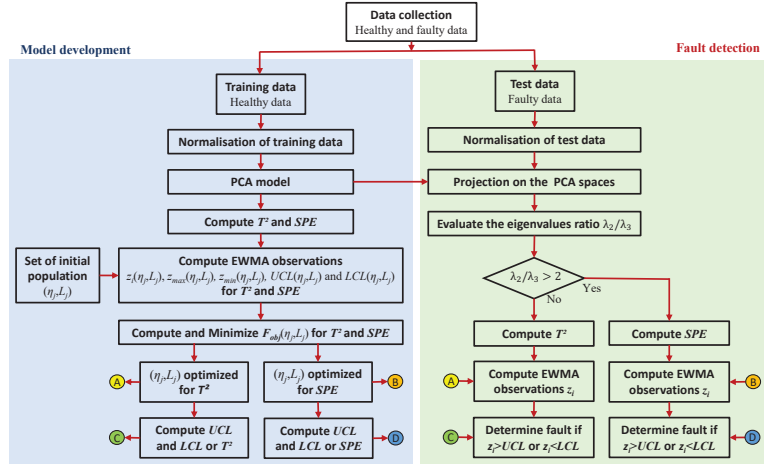


Fig. 1: Optimized PCA-based EWMA methodology

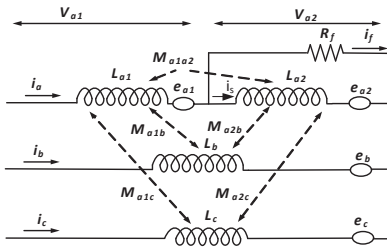


Fig. 2: Stator windings circuit under an inter-turn fault

TABLE I: The PMSynRM characteristics

Motor characteristics	
Number of poles	8
Number of PMs per pole	5
Rated power [kW]	208
Maximum operating speed [rpm]	14000
Number of turns	8
Stator phase winding resistance value at 20° [mΩ]	6.1
Simulation parameters	
Permanent Magnet flux amplitude [Wb]	$6.24 \times 10^{-2}$
Moment of inertia [kgm <sup>2</sup> ]	0.0357
Input DC voltage amplitude [V]	412

from 2 to 8. This rank is related to the number of turns short-circuited in the phase  $a$  of the winding. As an example, the time series stator's current for the phase  $a$  of the PMSynRM drive is shown in Figure 3. The fault occurrence with severity level 2 and load change ( $\Gamma_1, \Gamma_2, \Gamma_3$ ) are displayed highlighting the healthy and faulty current information.

In our case studies, using the time series currents of the three phases, the statistical moments are first calculated for consecutive independent windows of the current signal samples containing at least one signal period. The goal of these features is to highlight the quantitative insights of these currents and be used as the variables for the fault diagnosis study. Among these

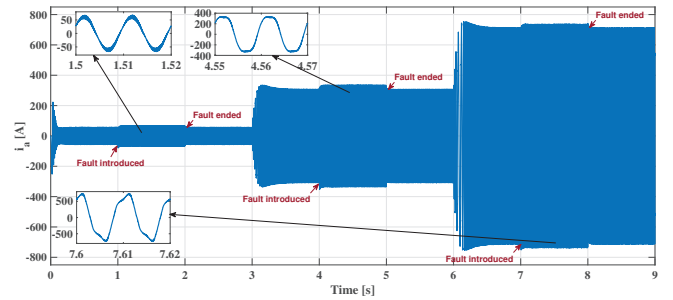


Fig. 3: Time series stator current in phase  $a$  for the healthy and faulty motor (level 2) for the three loads

features, the variance appears to be the best representative one to characterize the considered fault signature. Then the variances,  $\sigma_a^2, \sigma_b^2, \sigma_c^2$  of the phase currents in healthy and faulty conditions have been calculated and organised in the data matrix to be used as the input of our fault detection procedure. The following results highlight the performances of our proposal.

### B. Simulation results

As stated in Figure 1, the procedure is decomposed in two parts: one using the healthy data for modelling the process and the other considering the faulty data for the fault detection. With the healthy data, the process is trained to construct the PCA model. In this study, the threshold of cumulative variance is settled to 75%. In our PCA model, this results in retaining the first two components for the principal subspace and the third one for the residual subspace. This principal subspace captures in the first two principal components 43.31% and 32.94% for  $\Gamma_1$ , 75.62% and 14.36% for  $\Gamma_2$ , 53.82% and 24.91% for  $\Gamma_3$  (see Figure 4).

With the faulty data, the fault detection ability of the proposed PCA-based EWMA fault detection algorithm is assessed. All the seven severity levels and the three load levels are considered. The conventional PCA-based EWMA fault detection algorithm with the application of  $T^2$  and  $SPE$

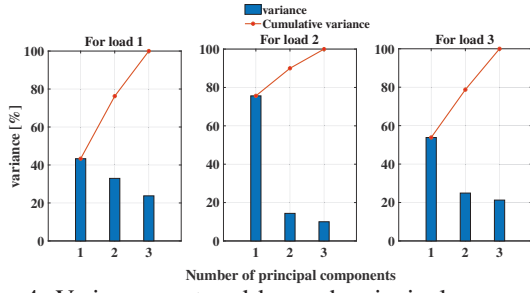


Fig. 4: Variance captured by each principal component

statistics with the parameters  $\eta = 0.5$  and  $L = 3$  are used for comparison. The results for load 1 and fault severity level 2 are shown in Figure 5.

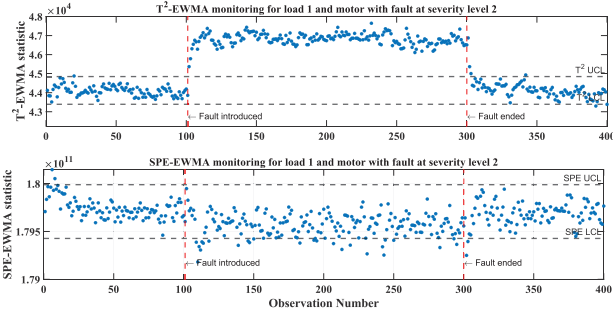


Fig. 5: Conventional PCA-based EWMA fault detection

In this Figure 5 the dashed lines represent  $UCL$  and  $LCL$ . The results using PCA-based EWMA on the  $SPE$  statistic, show that it failed to detect some faults and produce a high number of false alarms. The results using PCA-based EWMA on the  $T^2$  statistic allow to detect the fault with few false alarms. This result is because the conventional PCA-based EWMA with the arbitrary choice of the parameters  $\eta$  and  $L$  is not always sensitive to the fault due to the control limits that are not particularly calibrated with the considered healthy data.

Figure 6 shows the overall performance in terms of probability of missed fault detection  $PMD$  and probability of false alarm  $PFA$  for our case studies of three load levels and all fault severity levels. Usually, for fault detection, the acceptable  $PMD$  and  $PFA$  are typically set to 0.02 and 0.05 respectively [14]. In Figure 6, these typical values are highlighted with dashed lines. One can notice that the conventional PCA-based EWMA fails to provide acceptable  $PFA$  using  $T^2$  and  $SPE$ . The  $PMD$  performance for low severity levels are good only when using  $T^2$  for the highest load conditions. These results are also acceptable when using  $SPE$  for the lowest load conditions. Indeed, the fault signatures are not always high enough in the residual subspace to allow the detection in the presence of noise.

To cope with these limitations, our proposed methodology include the optimization tuning of  $\eta$  and  $L$  for a minimized  $PFA$  value through an objective function. Figure 7 shows the surface of the objective function using  $T^2$  and  $SPE$  for a

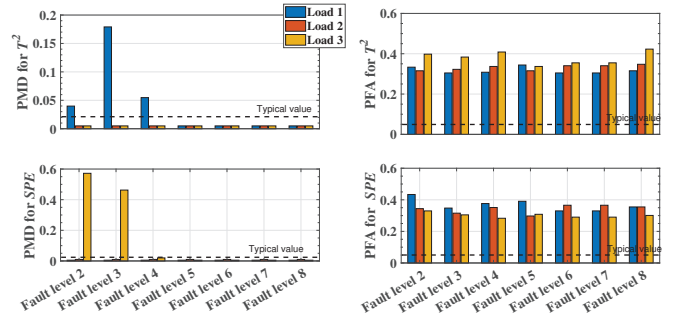


Fig. 6: Performance of the conventional PCA-based EWMA fault detection

range of values of  $\eta$  and  $L$  such as  $0 < \eta \leq 1$  and  $0 < L \leq 3$ . The optimization solutions leads to the couple  $(\eta, L)$  depicted as the red point in Figure 7.

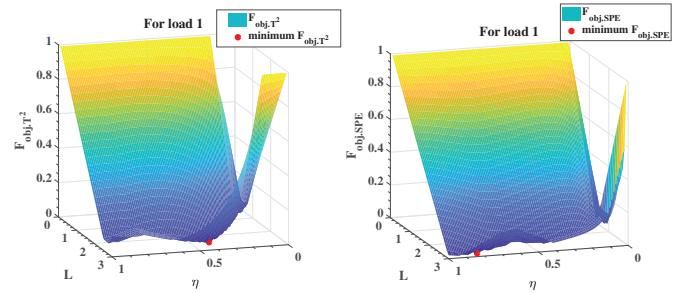


Fig. 7: Surface of the objective function for  $\eta$  and  $L$

The overall performance with the optimized couples  $(\eta, L)$  defined for each load condition is shown in Figure 8. Compared to the conventional approach, the performance is improved but show a sensitivity to the load value and fault severity level depending on the chosen detection index.

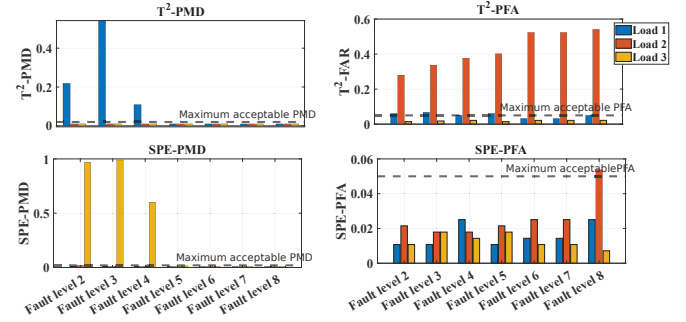


Fig. 8: Performance of the improved PCA-based EWMA with two fault indices

The last step of the proposal concerns the automatic selection of the detection index by using the ratio of selected eigenvalues in the PCA framework. In our case study the reference of the ratio is set equal to 2 to set the most efficient fault detection index. A ratio less than 2 sets the  $T^2$  as detection index while a ratio greater than 2 sets the  $SPE$  as the detection index.

Figure 9 shows the results of the fault detection of the proposed optimized PCA-based EWMA scheme with the

automatic selection of the detection index in the case of fault severity level 2, and for the three load conditions.

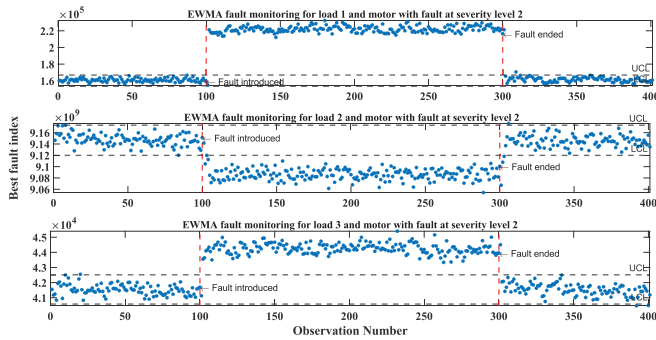


Fig. 9: Fault detection with the improved PCA-based EWMA with automatic detection index selection

The overall performance of the proposed methodology is shown in Figure 10. This result highlights that the proposed methodology can reach good fault detection performance as the  $PMD$  and  $PFA$  almost comply with the usual typical values. The only exception is for fault severity 8 and load 2. In that case, the  $PFA$  is slightly higher ( $PFA = 0.052$ ) than the typical value without being critical. Most of the False alarms in our case studies are due to the transient between the faulty and healthy conditions.

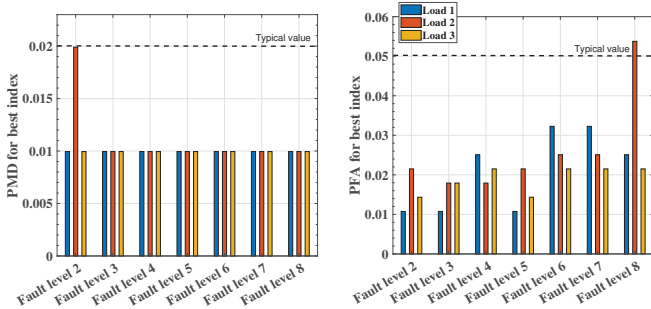


Fig. 10: Performance of the improved PCA-based EWMA automatic detection index selection

#### IV. CONCLUSION

In this paper, a fault detection approach is proposed for inter-turn short-circuit monitoring in the electrical drive. A hybrid Finite Element-Analytical model of a PMSynRM has been simulated to generate the stator phase currents for analysis. Three load conditions and seven fault severities are considered. The proposal is based on PCA and EWMA that are efficient techniques for fault diagnosis. Nevertheless, these techniques suffer from two major limitations: (1) the tuning operation of the control parameters to reach the best performance, (2) the selection of the most relevant transformation subspace with the adequate detection criteria.

This paper proposes solutions to cope with these limitations and an optimized procedure with the automatic selection of the most efficient detection criteria. The paper presents how to optimize the EWMA weighting factor  $\eta$  and control limit

parameter  $L$  with the constraint of minimizing the probability of false alarm. Additionally, we show that the comparison of the eigenvalues of the test data in the PCA subspace allows to automatically choose the most efficient subspace framework and adequate fault index. The simulation results show encouraging performance. Compared to the traditional approaches, the advantage of the proposed optimized PCA-based EWMA fault detection method is demonstrated whatever the load condition and for all the inter-turn short-circuit severity levels.

In future works, the application to real data will be studied, and the influence of disturbances will be included. The reliability of the decision will also be evaluated in terms of mean delay for detection and mean time between false alarms. Moreover, the performance of the proposed approach to detect other faults in the electrical drive will be investigated.

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