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► **To cite this version:**

Mehdi Baghli, Claude Delpha, Demba Diallo, Abdelhamid Hallouche. Three-level Inverter Fault Detection and Diagnosis Using Current-based Statistical Analysis. Prognostics and Systems Health Management Conference (PHM-Chongqing 2018), Oct 2018, Chongqing, China. 10.1109/phm-chongqing.2018.00123 . hal-01895228

HAL Id: hal-01895228

<https://centralesupelec.hal.science/hal-01895228v1>

Submitted on 12 Mar 2020

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Three-level Inverter Fault Detection and Diagnosis Using Current-based Statistical Analysis

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Abstract— This paper deals with open switch Fault Detection and Diagnosis (FDD) in three-level Neutral Point Clamped (NPC) inverter for electrical drives. The approach is based on the already available phase current measurements. The fault features that are evaluated in the time domain are the first four statistical moments. Three methods of FDD have been evaluated. The first one analyses the time domain evolution of the fault features. With this method, the fault is detected with a probability of detection higher than 80% when the operating speed is higher than a tier of the nominal speed and the SNR ≥ 40 dB. However, the performances are degraded for low speed and for lower SNR. To improve the performances, we use the Cumulative Sum (CUSUM) algorithm designed for mean and variance variations. The optimality has been verified with the Kolmogorov-Smirnov test of the selected features Probability Density Functions (PDF). The fault is detected efficiently with both CUSUM indicators with almost 100% of detection probability even for the smallest considered fault duration of 100 μ s.

Keywords— Three-level Neutral Point Clamped (NPC) inverter; Open Switch Fault (OSF); Intermittent faults effect; Fault Detection and Diagnosis (FDD); Cumulated Sum (CUSUM) analysis

I. INTRODUCTION

Electrical drives are widely used in a variety of applications industrial, manufacturing, and transportation applications. Their reliability is closely related to the robustness of each component. In particular, the voltage source inverters are key components of these electrical drives.

During the last decades, multilevel inverters have become more and more popular because of the improvement of the output voltage quality, the reduction of the electrical constraints on the power switches and the reduction of the switching frequency. Indeed, they generate less electromagnetic perturbations and therefore the size and the cost of the main filter can be reduced [1]. However, the main drawbacks are the higher number of components (compared to the classical 2-level inverter) and a more complex control [2]. In [1] the authors have made a comparison between four

topologies of inverters in terms of semiconductor and capacitors losses: the conventional structure, an interleaved two-level inverter; the Neutral Point Clamped (NPC) structure and the cascaded three-level H-bridge. The NPC inverter has proved to be the most efficient.

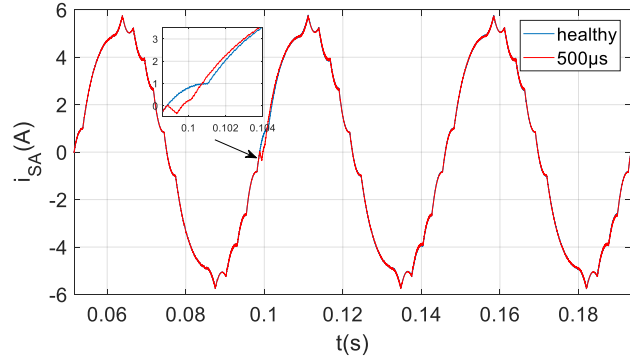
In this paper, the three-level NPC inverter is chosen because it has lower inverter losses and lower stress on the power switches at higher switching frequencies compared to a two-level inverter for electric vehicle applications [3].

It has been estimated that about 38% of the faults in variable-speed AC drives in industry are due to failures of power devices [4]. We can classify the faults in three groups: abrupt, gradual and intermittent faults. The impact of abrupt faults on electrical machine has been more often treated [5] than intermittent ones.

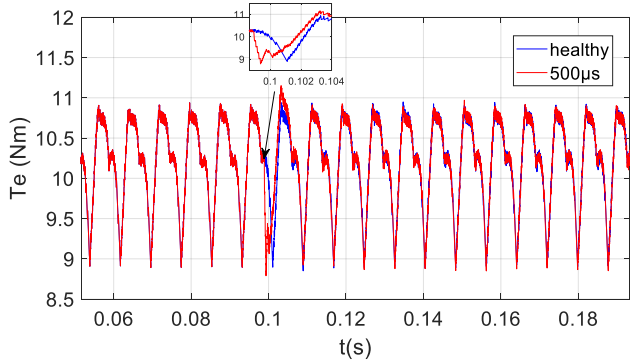
In this work, we are interested in the intermittent open-switch faults. Even they do not induce so critical modifications (as it can be seen in Fig.1 on the inverter output current I_s or the drive electromagnetic torque T_e), the frequent occurrence of such faults will generate a cumulative stress that can lead to failure of the inverter.

Recently, several methods have been developed for fault detection in power converters. The methods based on Park's vector [6, 7] unfortunately require complex pattern recognition algorithms. The methods based on voltages require undesirable extra hardware [8]. We propose in the following to use the already available current measurements.

This paper is organized as follows. Section I gives the introduction and the existing literature background and section II introduces the statistical moments used as fault features for Fault Detection and Diagnosis (FDD). In Section III, the FDD method based on CUSUM test is detailed and the overall performances are discussed. Finally, conclusions are given in Section IV.



(a) Current waveforms in healthy and faulty cases



(b) Electromagnetic torque in healthy and faulty cases

Fig. 1. Intermittent 500 μ s fault impact on current and torque

II. FAULT DETECTION USING STATISTICAL MOMENTS

A. System description

The three-level NPC inverter is one of the famous multilevel configurations explored in the literature [9-11]. Fig. 2 shows the topology of a three-level NPC inverter. The inverter has three legs (A, B and C) each one has four active switches with anti-parallel diodes. The DC bus has 2 capacitors, thus providing the middle point "O".

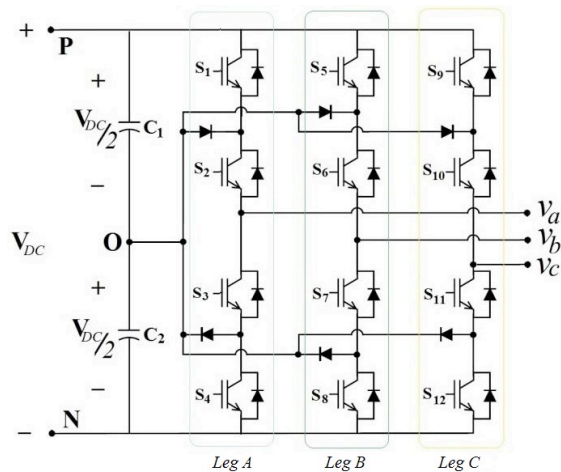


Fig. 2. Schematic representation of a three-level NPC inverter

This work is focused on the Open Switch Fault (OSF) on the first switch S_1 of leg A (Fig. 2).

With no loss of generality, for this work, the considered NPC inverter is switched at 10kHz with a sampling frequency of 100kHz. This inverter feed an asynchronous machine drive in a speed controlled loop (Fig. 3).

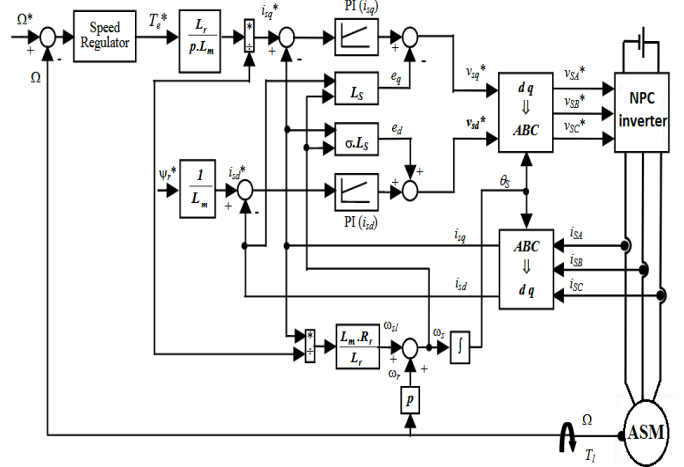


Fig. 3. Block diagram of indirect field oriented control scheme

The main characteristics of this machine drive are summarized in the Table 1.

TABLE I. ASYNCHRONOUS MACHINE MAIN CHARACTERISTICS

Charateristic	Value	Unit
Nominal voltage	$U_n = 220/380$	Volts
Nominal speed	$N_n = 1420$	rpm
Nominal power	$P_n = 1.5$	kW
Rated torque	$T_n = 10$	N.m
Nominal frequency	$f = 50$	Hertz
Number of poles	$p = 2$	
Stator resistance	$R_s = 4.85$	Ω
Rotor self-resistance	$R_r = 3.805$	Ω
Stator self-inductance	$L_s = 0.274$	Henry
Rotor inductance	$L_r = 0.274$	Henry
Mutual inductance (stator-rotor)	$L_m = 0.258$	Henry
Moment of inertia	$J = 0.031$	kg.m^2

The output currents feeding the asynchronous machine drive are observed and considered for the FDD study.

The classical field oriented indirect method is adopted as displayed in Fig. 3 [12].

B. Application of statistical moments on current measurement

The first four statistical moments of the current flowing in phase A are computed. If we denote the current as a variable

$X = (x_1, \dots, x_j, \dots, x_N)$ composed of N samples, the first four statistical moments are defined below as:

- $\mu = \frac{1}{N} \sum_1^N x_j$ is the mean value; it represents the center of the signal distribution,
- $\sigma^2 = \frac{1}{N} \sum_1^N (x_j - \mu)^2$ denotes the variance and measures the dispersion within the signal distribution,
- $Skw = \frac{1}{N} \sum_1^N \left(\frac{x_j - \mu}{\sigma} \right)^3$ is the Skewness value that measures the dissymmetry of the signal distribution,
- $Kur = \frac{1}{N} \sum_1^N \left(\frac{x_j - \mu}{\sigma} \right)^4$ is the Kurtosis value that measures the flatness of the signal distribution.

The faults can be classified according to their time durations. In the following ten cases are under study from $100\mu\text{s}$ to 1ms with a $100\mu\text{s}$ step ($100\mu\text{s}$, $200\mu\text{s}$, ..., $900\mu\text{s}$, 1ms). The smallest fault duration value is related to the switching frequency set at 10kHz .

The analyses of the ten faulty cases are done for:

- Three rotating speeds (20, 40 and 60rad/s) according to European Urban Driving Cycle (EUDC).
- Three different loads (no load, 50% and 100% of the rated torque).

In the following, only a selected part of the obtained results will be presented. Those chosen best highlights the global behaviour with the fault occurrence and the detection performances for the different speed and load conditions.

Fig. 4 shows the evolution of the first four statistical moments for two faulty OSF ($100\mu\text{s}$ and $500\mu\text{s}$ of duration) at 60rad/s for the rated load. The first 500 realisations correspond to the healthy case and the last 500 ones to the faulty case for a noise level such as $\text{SNR}=40\text{dB}$.

From Fig. 4, we can draw the following remarks:

- For both faults, the skewness and the kurtosis exhibit significant variations between healthy and faulty cases,
- For both faults, the variance has a less significant variation,
- For both faults, the mean value is obviously not a reliable fault indicator.

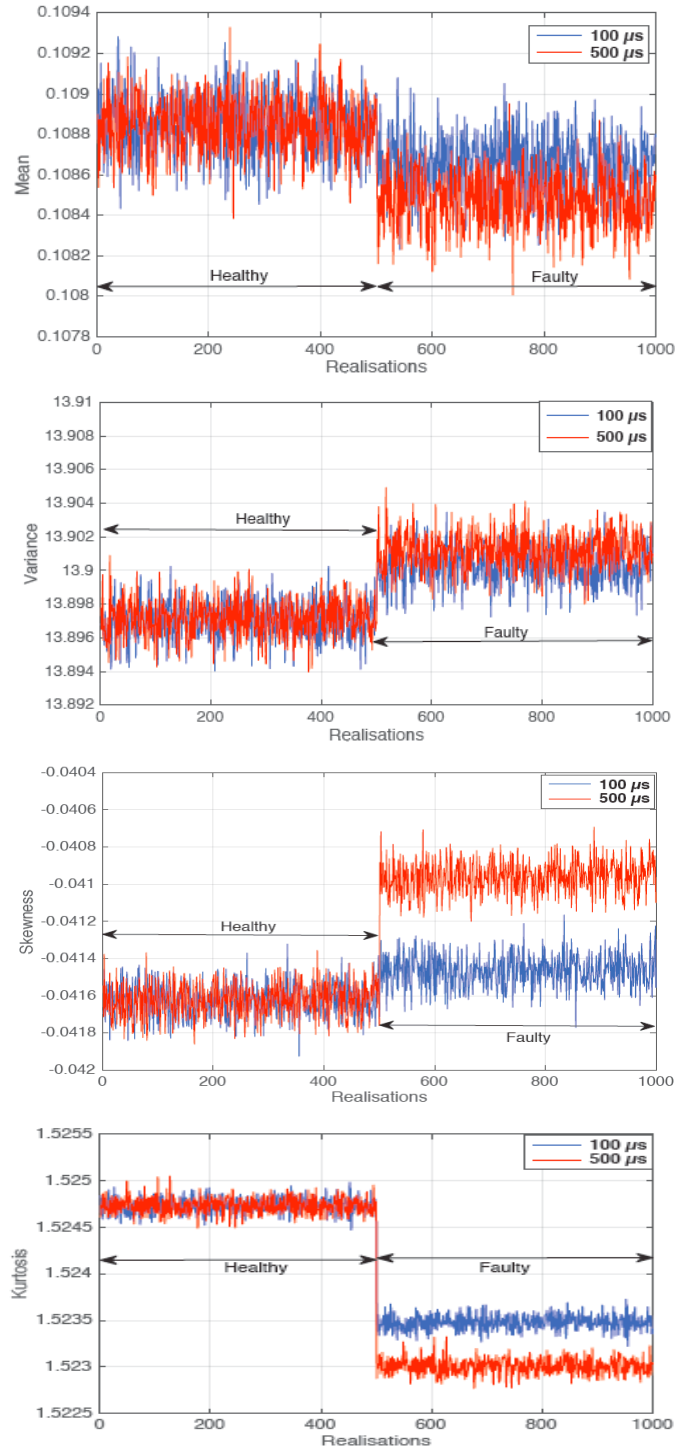


Fig. 4. Statistical moments for the two faults with $\text{SNR}=40\text{dB}$

For the same fault durations, we have evaluated only the skewness and the kurtosis with lower SNR (35, 30, 25 and 20 dB) meaning a higher level of noise in the measurements. The results are displayed in Fig. 5 only for 20dB (most severe noise conditions here) for the same operating points.

From Fig. 5, we can notice that the kurtosis exhibits a small variation between the healthy and faulty cases but the performances of the fault detection will be very low (in terms of fault probability of detection and false alarms). The other features are almost constant for both cases (healthy and faulty). We can conclude that the fault detection is almost impossible with these four features in these extreme conditions of noise (low SNR).

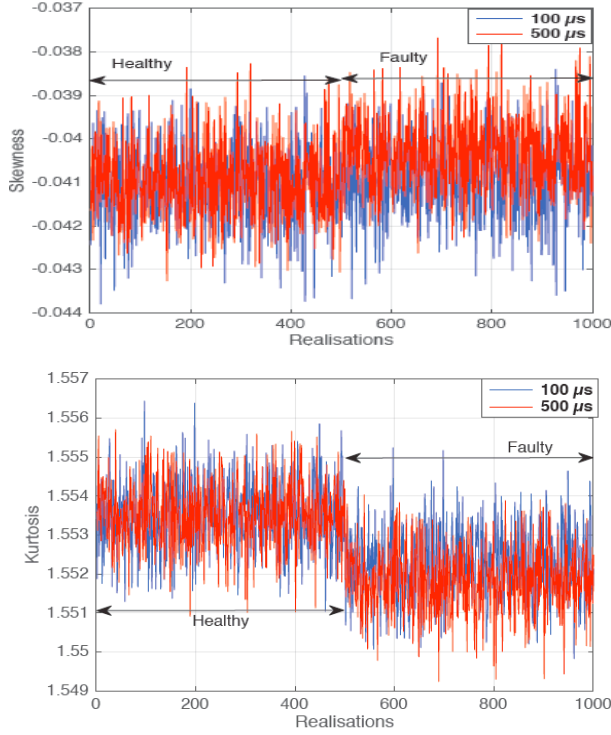


Fig. 5. Statistical moments for the two faults with SNR=20dB

The probability of detection (P_D) and the probability of false alarm (P_{FA}) are calculated as follows:

$$P_D = \frac{TP}{TP + FN} \quad \text{and} \quad P_{FA} = \frac{TN}{TN + FP} \quad (1)$$

Where TP is true positive and represents the number of realisations for faulty cases (501 to 1000) that are higher or equal than the detection threshold, while FN is false negative and is calculated by $FN = (\text{number of realizations}) - TP$. The FP is false positive and it represents the number of realisations for healthy cases (1 to 500) that are higher or equal than the threshold and true negative $TN = (\text{number of realizations}) - FP$.

The performances regarding the SNR evolution is computed for the two considered features. The Receiver Operating Characteristics (ROC) curve is then computed and presented in the Fig. 6 for the smallest fault occurrence (100μs), with speed 60rd/s and torque 10Nm.

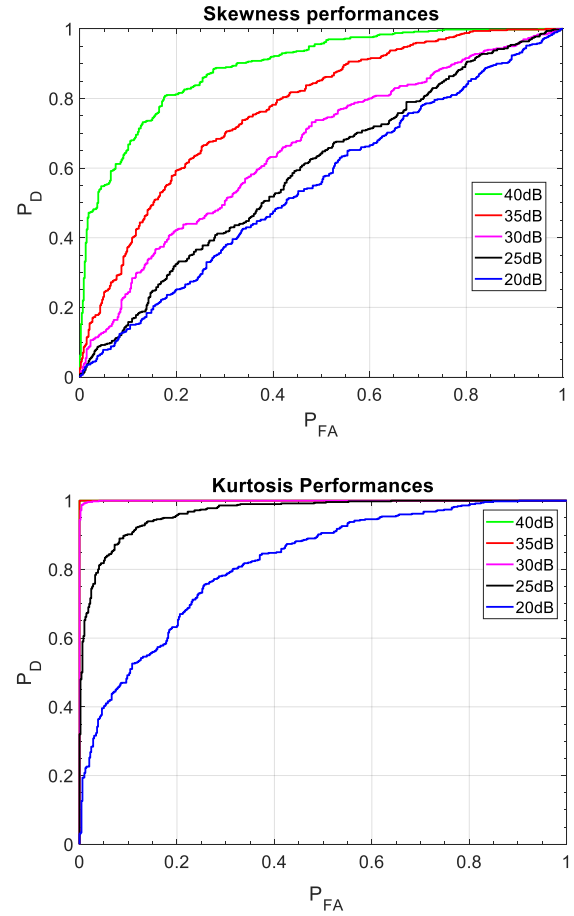


Fig. 6. Performances of Skewness and Kurtosis for several noise conditions (60 rd/s)

With these ROC curves (Fig. 6) we can derive an optimal fault detection threshold for these features leading to the best trade-off value between P_D and P_{FA} . It is clear that while the noise conditions became more severe (SNR decrease), the optimal fault detection will lead to $P_D < 0.7$ and $P_{FA} > 0.3$. It means that the fault detection efficiency using these selected features in severe noise conditions will be reduced.

Nevertheless, in these conditions, the feature allowing to obtain the best performances is the Kurtosis even for the smallest fault occurrence (Fig. 6).

When the rotational speed is reduced, these performances will decrease. Fig. 7 displays the performances for the Kurtosis for the same load (torque 10 Nm) and noise (SNR=20dB) conditions. This confirms that the detection performances will be decreased along with the machine drive speed. For 20 rd/s, the optimal threshold will lead to $P_D = 0.56$ and $P_{FA} = 0.44$. This is must be improved for an efficient FDD process. Using the Skewness, the results are quite similar ($P_D = 0.63$ and $P_{FA} = 0.4$).

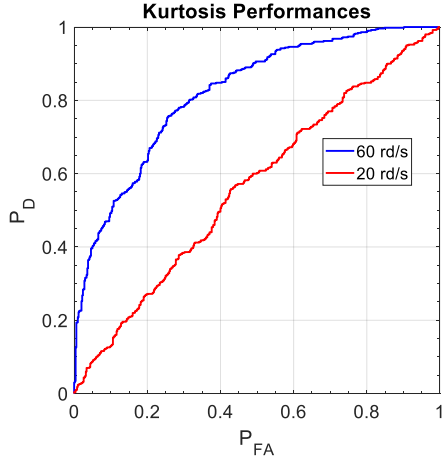


Fig. 7. Performances of Kurtosis in different speed conditions (SNR=20 dB)

Hence, it is necessary to improve the FDD with these features for these particular high noise and low speed conditions. For this purpose, in the next section we propose to apply the CUSUM algorithm to these statistical moments. This methodology is described below.

III. DETECTION USING CUSUM ALGORITHM

The CUMulative SUM (CUSUM) algorithm is widely used to detect changes in the mean value or variance for an independent Gaussian sequence; it is based on log-likelihood ratio. The theoretical background of CUSUM can be found in [13-15].

A. Probability Density Function (PDF)

Most often, a PDF is used to specify the probability of the random variable falling within a particular range of values. Its integral across an interval gives the probability that the value of the variable lies within the same interval.

In order to take benefit from the optimality of the CUSUM algorithm, the Probability Density Function (PDF) of the variables under study should be Gaussian. This is checked with the Kolmogorov-Smirnov test evaluated on the PDFs displayed in Fig. 8. This test is a nonparametric criteria used to evaluate the difference between two standard normal distributions (SND), and also to compare a reference distribution with SND.

Fig. 8 displays the PDFs of the 4 statistical moments in healthy and faulty conditions (100, 200 and 500 μ s OSF duration) at a speed of 20rad/s for the rated load with SNR=20dB.

The results of the application of the Kolmogorov-Smirnov test on the PDFs for all the operating conditions and for the considered SNR (20 to 40dB) confirms that the features PDF can be considered as Gaussian. The CUSUM can be the applied optimally.

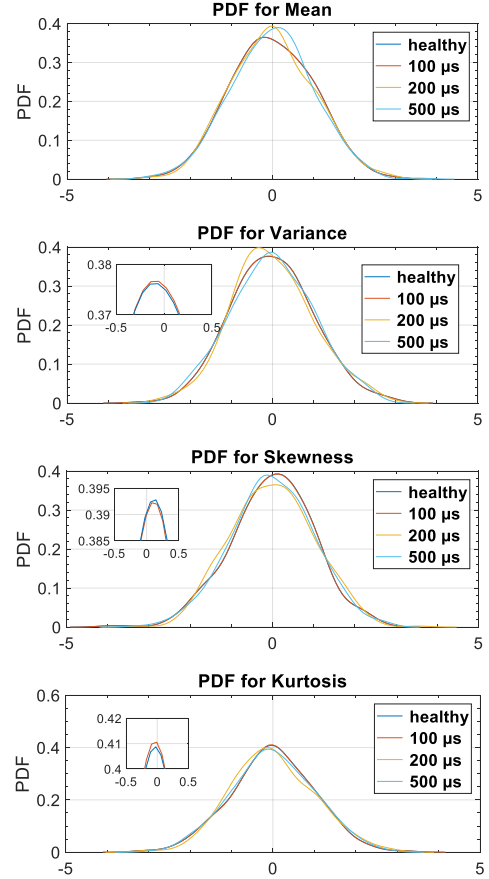


Fig. 8. PDF of the first four moments with SNR=20dB (20 rd/s)

B. CUSUM

As defined earlier, the CUSUM is used to detect small changes. It is hereafter applied on each of the 4 statistical moments (μ , σ^2 , Skw , Kur) [14, 15]. The CUSUM function denoted S_N is optimally derived as the sum of the sufficient statistics s_k such as:

$$S_N = \sum_{k=1}^N s_k \quad (2)$$

Where N is the number of realisations and s_k can be considered in the case of mean changes (μ) or variance changes (σ^2) for the first four statistical moments as defined below:

$$s_{k_\mu} = \left(\frac{\mu_f - \mu_h}{\sigma^2} \right) \times \left(x_k - \frac{\mu_f + \mu_h}{2} \right) \quad (3)$$

$$s_{k_\sigma} = \ln \frac{\sigma_h}{\sigma_f} + \left(\frac{1}{\sigma_h^2} - \frac{1}{\sigma_f^2} \right) \times (x_k - \mu_h) \quad (4)$$

Where μ_h and μ_f are respectively the mean values in the healthy and faulty conditions, σ_h and σ_f are respectively the standard deviation values in healthy and faulty conditions, and x_k stands for the statistical moment under consideration for the k^{th} observation over N. While computing the CUSUM S_N , we can

then set a threshold T_h at 0.99 of its maximum value in healthy case S_{max} . If the CUSUM value is higher than T_h then it means that a faulty behaviour has been detected.

Fig. 9 and Fig. 10 show respectively the application of S_{k_μ} and S_{k_σ} on the samples for the skewness with SNR=20dB at 20rad/s for the rated load. The first 500 samples represent the healthy condition and the 500 others the faulty condition.

The fault is detected efficiently with both indicators: only 20 faulty realizations needed for CUSUM mean and 23 faulty realizations for CUSUM variance. There is no missed detection for CUSUM variance and only one for CUSUM mean.

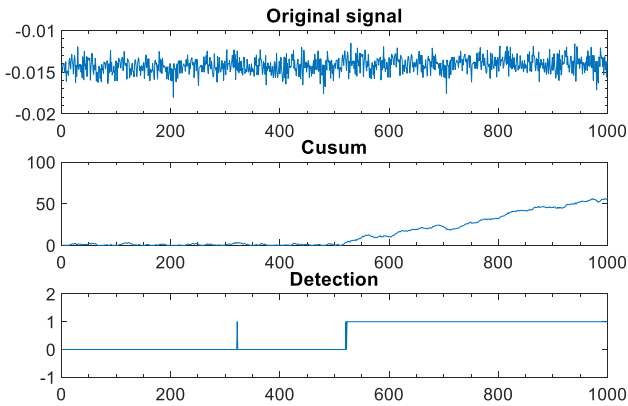


Fig. 9. 100µs Fault Detection results with CUSUM Mean with skewness

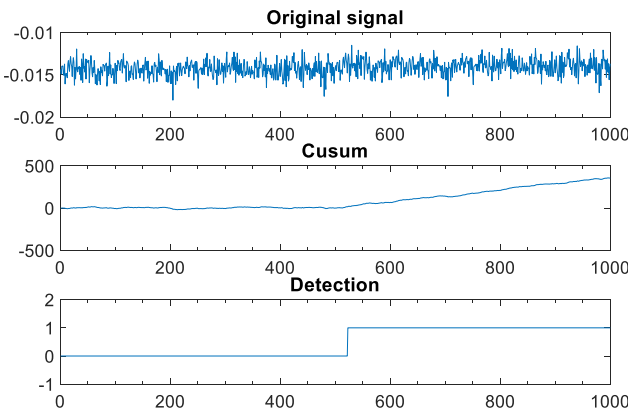


Fig. 10. 100µs Fault Detection results with CUSUM Variance with skewness

The same types of good results are obtained using the CUSUM for the Kurtosis realisations.

IV. CONCLUSION

This paper deals with open switch fault detection and diagnosis in three-level NPC inverter for electrical drives. Two statistical techniques have been proposed for the FDD

methodology and then evaluated. At first, a solution based on the extraction and analysis of the first four statistical moments of the current flowing in the windings of the machine is proposed. With this method, the fault is detected with a probability of detection higher than 80% when the rotating speed is higher than the tier of the nominal speed. However, the performances are degraded at lower speed and for lower SNR (high noise levels). Then at second we have used the CUSUM for mean and variance variations to improve the detection. Better performances are obtained for the detection of the incipient faults in low speed and high noisy conditions.

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