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Currents Analysis of a Brushless Motor with Inverter Faults—Part I: Parameters of Entropy Functions and Open-Circuit Faults Detection

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Abstract: In the field of signal processing, it is interesting to explore signal irregularities. Indeed, entropy approaches are efficient to quantify the complexity of a time series; their ability to analyze and provide information related to signal complexity justifies their growing interest. Unfortunately, many entropies exist, each requiring setting parameter values, such as the data length N , the embedding dimension m , the time lag τ , the tolerance r and the scale s for the entropy calculation. Our aim is to determine a methodology to choose the suitable entropy and the suitable parameter values. Therefore, this paper focuses on the effects of their variation. For illustration purposes, a brushless motor with a three-phase inverter is investigated to discover unique faults, and then multiple permanent open-circuit faults. Starting from the brushless inverter under healthy and faulty conditions, the various possible switching faults are discussed. The occurrence of faults in an inverter leads to atypical characteristics of phase currents, which can increase the complexity in the brushless response. Thus, the performance of many entropies and multiscale entropies is discussed to evaluate the complexity of the phase currents. Herein, we introduce a mathematical model to help select the appropriate entropy functions with proper parameter values, for detecting open-circuit faults. Moreover, this mathematical model enables to pick up many usual entropies and multiscale entropies (bubble, phase, slope and conditional entropy) that can best detect faults, for up to four switches. Simulations are then carried out to select the best entropy functions able to differentiate healthy from open-circuit faulty conditions of the inverter.

Keywords: open-circuit; inverter; brushless motor; entropy; multiscale; fault detection



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1. Introduction

One of the most powerful tools to assess the dynamical characteristics of time series is entropy. Entropy used in several kinds of applications is able to account for vibrations of rotary machines [1] (electric machines), to detect battery faults [2] (short-circuit and open-circuit faults), to reveal important information about seismically active zones [3] (electroseismic time series), to measure financial risks [4] (economic sciences), to categorize softwood species under uniform and gradual cross-sectional structures [5] (biology) and to categorize benign and malignant tissues of different subjects [5] (biomedical).

Various entropy measures have been established over the past two decades. Pincus [6] proposed the approximation entropy $ApEn$, which calculates the complexity of data and measures the frequency of similar patterns of data in a time series. However, $ApEn$ also has some disadvantages: due to self-matching, the bias of $ApEn$ is important for small time series and depends on the entropy parameters. To avoid self-matching, Richman [6] defined the sample entropy $SampEn$. Since the introduction of $ApEn$ [6], other entropies have been proposed, such as Kolmogorov entropy $K2En$, conditional entropy $CondEn$, dispersion

entropy *DispEn*, cosine similarity entropy *CoSiEn*, bubble entropy *BubbEn*, fuzzy entropy *FuzzEn*, increment entropy *IncrEn*, phase entropy *PhasEn*, slope entropy *PhasEn*, entropy of entropy *EnofEn*, attention entropy *AttEn* and several other multiscale entropies.

Entropy is now widely applied to analyze signals in various fields having universal applications. A combination of wavelet transformation and entropy is proposed and applied in power grid fault detection [7]. Wavelet transform is commonly used to extract characteristic quantities, and to analyze transient signals, while entropy is ideal for the measurement of uncertainty. The approximate entropy features of a multiwavelet transform [8] combined with an artificial neural network recognizes transmission line faults. The multi-level wavelet Shannon entropy was proposed to locate single-sensor fault [9]. Guan [10] developed a precise diagnosis method of structural faults of rotating machinery based on a combination of empirical mode decomposition, *SampEn* and deep belief network. Entropy measures [11] are used in machine fault diagnosis. In [12], the variational mode decomposition energy entropy for each phase current cycle is calculated to accurately diagnose the arc fault: the noise component is removed according to the permutation entropy. [13] proposed to diagnose multi-circuit faults of three-phase motors. This method only needs to collect phase currents to diagnose multi-circuit points accurately: it improves the independence of diagnosis. Based on signal feature extraction, a combination of the empirical mode decomposition entropy and index energy methods is adopted in [14] to extract the Draft Tube's dynamic feature information for a water turbine. Open-circuit fault diagnosis of a multilevel inverter [15] uses the fast fault detection algorithm based on two sample techniques and the fault localization algorithm using the entropy of wavelet packets as a feature. The authors in [16] presented a fast feature extraction technique including wavelet packet decomposition, an entropy of wavelet packets for fault detection and classification of IGBT-based converters.

Open-circuit fault diagnosis methods can be divided into voltage-based methods and current-based methods, according to different fault characteristics. Voltage-based methods [17,18] can be implemented with external hardware or modeled. Recently, current-type methods based on current waveform analysis have attracted much attention [19–21].

An effective open-circuit fault diagnosis using the phase current performance of a brushless motor or inverters is shown in [22]. Other practical current-based diagnostic algorithms are addressed in [19,23,24]: they identify the reference current errors and the average absolute value of currents. Then, the average value of the current error and the average absolute value of the motor phase current are used to realize the diagnostic variable. A fast approach based on the amplitude of the d-q axis referential currents is proposed by [21]. The development of intelligent algorithms, such as fuzzy logic [25], sliding mode observer [26], neural networks [27], machine learning [28], an optimized support vector machine method [29] and wavelet transform [30], which allows to detect and identify faulty switches.

A mathematical model of healthy and faulty conditions is developed by [31]: it detects an open-circuit in interleaved boost converters with the Filippov method. The stable range of the load variation is extended using an original fault-tolerant strategy based on this model. In [32], one or a maximum of two open-circuit faults are detected by entropy functions. Seven entropies are investigated, but only sample and fuzzy entropies are able to differentiate healthy from open-circuit faulty conditions of the AC-DC-AC converter considered in [32].

We now propose a fault-detection method for a brushless motor with a three-phase inverter. The occurrence of faults in an inverter leads to atypical characteristics of phase currents, specific to the drive circuit. Usual and multiscale entropies are then used to detect multiple open-circuit faults. In this paper, we broaden the spectrum of investigation to 52 entropies, to evaluate their ability to differentiate healthy states from open-circuit faulty conditions. This is why we herein introduce a mathematical model to select the appropriate entropy functions with an appropriate parameter combination for open-circuit faults detection. The entropy calculation has several parameters, such as data length N ,

embedding dimension m , time lag τ , tolerance r and scale s . However, the dependence of the entropy effectiveness on the choice of parameters used for the phase currents analysis has not yet been investigated for a brushless motor. Moreover, using this mathematical model, we are able to pick up many usual entropies and multiscale entropies (bubble, phase, slope and conditional entropy) that can better detect faults for up to four switches. Our goal herein is to be able to select the appropriate entropy.

The paper is organized as follows. The usual entropies and multiscale entropies are introduced in Section 2. Sections 3 and 4 present the brushless motor and the dataset we used of output currents under healthy state, with one, two, three and four open-circuit faults. Then, Section 5 illustrates the evaluation of the different entropies under variation of the data length, embedding dimension, time lag, tolerance and scale. We end with a Conclusion in Section 7.

2. Entropy Methods

- Sample entropy *SampEn* and approximate entropy *ApEn* are the most commonly used measures for analyzing time series. For a time series $\{x_i\}_{i=1}^N$ with a given embedding dimension m , tolerance r and time lag τ , the embedding vector $x_i^m = [x_i, x_{i+\tau}, \dots, x_{i+(m-1)\tau}]$ is constructed. The number of vectors x_i^m and x_j^m , close to each other, in Chebyshev distance:

$$\text{ChebDist}_{i,j}^m = \max_{k=1,m} \{|x_i^m[k] - x_j^m[k]|\} \leq r \quad (1)$$

is expressed by the number $P_i^m(r)$. This number is used to calculate the local probability of occurrence of similar patterns:

$$B_i^m(r) = \frac{1}{N - m + 1} P_i^m(r). \quad (2)$$

The global probability of the occurrence of similar patterns is:

$$B^m(r) = \frac{1}{N - m + 1} \sum_{i=1}^{N-m+1} B_i^m(r) \quad (3)$$

with a tolerance r . For $m + 1$:

$$B^{m+1}(r) = \frac{1}{N - m} \sum_{i=1}^{N-m} B_i^{m+1}(r). \quad (4)$$

The approximation entropy is:

$$\text{ApEn}(m, \tau, r, N) = \ln \frac{B^m(r)}{B^{m+1}(r)}. \quad (5)$$

- Kolmogorov entropy [33]—*K2En* is defined as the probability of a trajectory crossing a region of the phase space: suppose that there is an attractor in phase space and that the trajectory $\{x_i\}_{i=1}^N$ is in the basin of attraction. *K2En* defines the probability distribution of each trajectory, calculated from the state space, and computes the limit of Shannon entropy. The state of the system is now measured at intervals of time. The time series $\{x_i\}_{i=1}^N$ is divided into a finite partition $\alpha = \{C_1, C_2, \dots, C_k\}$, according to $C_k = [x(i\tau), x((i+1)\tau), \dots, x((i+k-1)\tau)]$. The Shannon Entropy of such a partition is given by:

$$K(\tau, k) = - \sum_{C \in \alpha} p(C) \cdot \log p(C). \quad (6)$$

$K2En$ is then defined by:

$$K2En = - \sup_{\alpha \text{ finite partition}} \lim_{N \rightarrow \infty} \frac{1}{N} \sum_{n=0}^{N-1} (K_{n+1}(\tau, k) - K_n(\tau, k)). \quad (7)$$

- Conditional entropy [34]— $CondEn$ quantifies the variation of information necessary to specify a new state in a one-dimensional incremented phase space. Small Shannon entropy values are obtained when a pattern appears several times. $CondEn$ uses the normalization:

$$x(i) = \frac{X(i) - av[X]}{std[X]}, \quad (8)$$

where $av[X]$ is the series' mean and $std[X]$ is the standard deviation of the series. From the normalized series, the vector $x_L(i) = [x(i), x(i-1), \dots, x(i-L+1)]$ of L consecutive pattern is constructed in L dimensional phase space. With a variation in the Shannon entropy of $x_L(i)$, the $CondEn$ is obtained as:

$$CondEn(L) = - \sum_L p_L \cdot \log p_L + \sum_{L-1} p_{L-1} \cdot \log p_{L-1}. \quad (9)$$

- Dispersion entropy [35,36]— $DispEn$ focuses on the class sequence that maps the elements of time series into positive integers. According to the mapping rule of dispersion entropy, the same dispersion pattern results from multiple forms of sample vectors. The time series $\{x_i\}_{i=1}^N$ is reduced with the standard distribution function to normalized series $y_j^m = [y_j, y_{j+\tau}, \dots, y_{j+(m-1)\tau}]$:

$$y_i = \frac{1}{\sigma\sqrt{2\pi}} \int_{-\inf}^{x_i} \exp \frac{-(s-\mu)^2}{2\sigma^2} ds \quad (10)$$

where $y_i \in (0, 1)$. The phase space is restructured in c class number as $z_i^c = \text{round}(c \cdot y_i + 0.5)$ and $z_j^{m,c} = [z_j^c, z_{j+\tau}^c, \dots, z_{j+(m-1)\tau}^c]$. Each z_i^c corresponds to the dispersion pattern v . The frequency of v can be deduced as:

$$p = \frac{\text{Number}\{j | j \leq n - (m-1)\tau, v\}}{n - (m-1)\tau} \quad (11)$$

where $\text{Number}\{j | j \leq n - (m-1)\tau, v\}$ is the number of dispersion patterns v corresponding to $z_j^{m,c}$. Dispersion entropy can be defined according to information entropy theory:

$$DispEn(m, c, \tau) = - \sum_{v=1}^{c^m} p \cdot \log(p). \quad (12)$$

- Cosine similarity entropy [37]— $CoSiEn$ evaluates the angle between two embedding vectors instead of the Chebyshev distance. The global probability of occurrence of similar patterns using the local probability of occurrence of similar patterns is used to estimate entropy. The angular distance for all pairwise embedding vectors is:

$$AngDist_{i,j}^m = \frac{1}{\pi} \cos^{-1} \left(\frac{x_i^m \cdot x_j^m}{|x_i^m| \cdot |x_j^m|} \right), i \neq j, \quad (13)$$

where $x_i^m = [x_i, x_{i+\tau}, \dots, x_{i+(m-1)\tau}]$ is the embedding vector of $\{x_i\}_{i=1}^N$. When $AngDist_{i,j}^m \leq r$, the number of similar patterns $P_i^m(r)$ is obtained. The local and global probabilities of occurrence are:

$$B_i^m(r) = \frac{1}{N-m-1} P_i^m(r) \quad \text{and} \quad B^m(r) = \frac{1}{N-m} \sum_{i=1}^{N-m} B_i^m(r). \quad (14)$$

Finally, cosine similarity entropy is defined by:

$$CoSiEn(m, \tau, r, N) = -B^m(r) \cdot \log_2 B^m(r) - (1 - B^m(r)) \cdot \log_2(1 - B^m(r)). \quad (15)$$

- Bubble entropy [38,39]—*BubbEn* reduces the significance of the parameters employed to obtain an estimated entropy. Based on permutation entropy, the *BubbEn* vectors are ranked in the embedding space. The bubble sort algorithm is used for the ordering procedure and counts the number of swaps performed for each vector. More coarse-grained distributions are created and then compute the entropy of this distribution. *BubbEn* reduces the dependence on input parameters (such as N and m) by counting the number of sample swaps necessary to achieve the ordered subsequences instead of counting order patterns. *BubbEn* embeds a given time series $\{x_i\}_{i=1}^N$ into an m dimensional space, producing a series of vectors of size $N - m + 1$: $X_1, X_2, \dots, X_N$, where $X_i = (x_i, x_{i+1}, \dots, x_{i+m-1})$. The number of swaps required for sorting is counted for each vector X_i . The probability p_i of having i swaps is used to evaluate Renyi entropy:

$$B_2^m(x) = -\log \sum_{i=0}^{\frac{m(m-1)}{2}} p_i^2. \quad (16)$$

Increasing by one the embedding dimension m , the procedure is repeated to obtain a new entropy value B_2^{m+1} . Finally, *BubbEntropy* is obtained as for *ApEntropy*:

$$BubbEn(x, m, N) = \frac{B_2^{m+1} - B_2^m}{\log \frac{m+1}{m-1}}. \quad (17)$$

- Fuzzy entropy [40,41]—*FuzzEn* employs the fuzzy membership functions as triangular, trapezoidal, bell-shaped, Z-shaped, Gaussian, constant-Gaussian and exponential functions. *FuzzEn* has less dependence on N and uses the same step as in the *SampEn* approach. Firstly, the zero-mean embedding vectors (centered using their own means) are constructed $q_i^m = x_i^m - \mu_i^m$, where:

$$x_i^m = [x_i, x_{i+\tau}, \dots, x_{i+(m-1)\tau}] \quad \text{and} \quad \mu_i^m = \frac{1}{m} \sum_{k=1}^m x_i^m[k]. \quad (18)$$

FuzzEn calculates the $S_i^m(r, \eta)$ fuzzy similarity:

$$S_i^m(r, \eta) = e^{(ChebDist_{i,j}^m)^\eta / r} \quad (19)$$

obtained from a fuzzy membership function, where η is the order of the Gaussian function. The Chebyshev distance is:

$$ChebDist_{i,j}^m = \max_{k=\overline{1,m}} \{q_i^m[k] - q_j^m[k]\}, i \neq j. \quad (20)$$

As in the *SampEn* approach, the local and global probabilities of occurrence are computed, obtaining a subsequent fuzzy entropy:

$$FuzzEn(m, \tau, r, N) = \ln \frac{B^m(r)}{B^{m+1}(r)}. \quad (21)$$

- Increment entropy [42]: the *IncrEn* approach (similar to the permutation entropy) encodes the time series in the form of symbol sequences. For a time series $\{x_i\}_{i=1}^N$, an increment series $v(i) = x(i+1) - x(i)$, ($1 \leq i \leq N$) is constructed and then divided into vectors of m length $V(l) = [v(l), \dots, v(l+m-1)]$, $1 \leq l \leq N - m$. Each element

in each vector is mapped to a word consisting of the sign $s_k = \text{sgn}(v(j))$ and the size q_k , which is:

$$q_k = \min(q, \left\lfloor \frac{v(i) \cdot q}{\text{std}(v(i))} \right\rfloor). \quad (22)$$

However, the sign indicates the direction of the volatility between the corresponding neighboring elements in the original time series. The pattern vector w is a combination of all corresponding s_k and q_k pairs. The relative frequency of each word w_n is defined as $P(w_n) = Q(w_n)/(N - m)$, where $Q(w_n)$ is the total number of instances of the n th word. Finally, *IncrEn* is defined as:

$$\text{IncrEn} = -\frac{1}{m-1} \sum_{n=1}^{(2q+1)^m} P(w_n) \log P(w_n). \quad (23)$$

- *PhasEntropy* [43] quantifies the distribution of the time series $\{x_i\}$ in a two-dimensional phase space. First, the time-delayed time series $Y[n]$ and $X[n]$ are calculated as follows:

$$Y[n] = x[n+2] - x[n+1] \quad (24)$$

$$X[n] = x[n+1] - x[n] \quad (25)$$

The second-order difference plot of x is constructed as a scatter plot of $Y[n]$ against $X[n]$. The slope angle of $\theta[n]$ of each point $(X[n], Y[n])$ is measured from the origin $(0, 0)$. The plot is split into k sectors serving as a coarse-graining parameter. For each k , the sector slope angle $S_\theta[i]$ is the addition of the slope angle of points as follows:

$$S_\theta[i] = \sum_{j=1}^{N_i} \theta[n] \quad (26)$$

where $i = 1, 2, \dots, k$ and N_i is the points number of the i th sector. The probability distribution $p(i)$ of the sector is:

$$p(i) = \frac{S_\theta}{\sum_{j=1}^i S_\theta} \quad (27)$$

The estimation of the Shannon entropy of the probability distribution $p(i)$ leads to *PhasEn*, computed as:

$$\text{PhasEn} = -\frac{1}{\log(k)} \sum_{i=1}^k p(i) \cdot \log p(i). \quad (28)$$

- Slope entropy [44]—*SlopEn* includes amplitude information in a symbolic representation of the input time series $\{x_i\}_{i=1}^N$. Thus, each subsequence of length m drawn from $\{x_i\}_{i=1}^N$, can be transformed into another subsequence of length $m - 1$ with the differences of $x_i - x_{i-1}$. In order to find the corresponding symbols, a threshold is added to these differences. Then, *SlopEn* uses 0, 1 and 2 symbols with positive and negative versions of the last two. Each symbol covers a range of slopes for the segment joining two consecutive samples of the input data. The frequency of each pattern found is mapped into a value using a Shannon entropy approach: it is applied with the factor corresponding to the number of slope patterns found.

- Entropy of entropy [45]—*EnofEn*: the time series $\{x_i\}_{i=1}^N$ is divided into consecutive non-overlapping windows w_j^τ of length τ : $w_j^\tau = \{x_{(j-1)\tau+1}, \dots, x_{(j-1)\tau+\tau}\}$. The probability p_{jk} for the interval x_i over w_j^τ to occur in state k is:

$$p_{jk} = \frac{\text{total number of } x_i \text{ over } w_j^\tau \text{ in state } k}{\tau}. \quad (29)$$

Shannon entropy is used now to characterize the system state inside each window. Consequently:

$$y_j^\tau = \sum_{k=1} p_{jk} \cdot \log p_{jk}. \quad (30)$$

In the second step, the probability p_l for the interval y_j to occur in state l is:

$$p_l = \frac{\text{total number of } y_j^\tau \text{ in level } l}{N/\tau}. \quad (31)$$

Shannon entropy is used for the second time instead of the Sample entropy, to characterize the degree of the state change.

$$EnofEn(\tau) = - \sum_{l=1} p_l \cdot \log p_l. \quad (32)$$

- Attention entropy [46]—*AttEn*; traditional entropy methods focus on the frequency distribution of all the observations in a time-series, while attention entropy only uses the key patterns. Instead of counting the frequency of all observations, it analyzes the frequency distribution of the intervals between the key patterns in a time-series. The last calculus is the Shannon entropy of intervals. The advantages of attention entropy are that it does not need any parameter to tune, is robust to the time-series length and requires only a linear time to compute.
- Multiscale entropy [5,47,48]—*MSEn* extends entropy to multiple time scales by calculating the entropy values for each coarse-grained time series. The multiple time scales are constructed from the original time series $\{x_1, x_2, \dots, x_N\}$ of length N by averaging the data points within non-overlapping windows of increasing length. The coarse-grained time series $\{y^{(s)}\}$ is:

$$\mathbf{y}_j^{(s)} = \frac{1}{\tau} \sum_{i=(j-1)s+1}^{js} \mathbf{x}_i, \quad 1 \leq j \leq [N/s]. \quad (33)$$

MSEn is:

$$MSEn(m, r, s) = -\ln \frac{A_s^m(r)}{B_s^m(r)} \quad (34)$$

where $A_s^m(r)$ and $B_s^m(r)$ represent the probability that two sequences match for $m + 1$ points and m points, respectively, calculated from the coarse-grained time series at the scale factor s . Multiscale entropy reduces the accuracy of entropy estimation and is often undefined as the data length becomes shorter with an increase in scale s . This is true in the case of *SampEn*, which is sensitive to parameters (data length N , embedding dimension m , time lag τ , tolerance r) of short signals. To avoid this, many variants of the traditional multiscale entropy method, such as composite multiscale entropy [49,50] and refined multiscale entropy [51,52], are proposed. In the classical multiscale entropy method, there is only one coarse-grained time series derived from a non-overlapping coarse-grained procedure at scale s . However, s is the number of coarse-grained time series in the composite multiscale entropy method. The sliding windows of all coarse-grained procedures overlap. The mean of entropy values for all coarse-grained time series is defined as the composite multiscale entropy value at the

scale s to improve the multiscale entropy accuracy. At a scale factor s , the $cMSEn$ is defined as:

$$cMSEn(m, r, s) = \frac{1}{s} \sum_{k=1}^s \left(-\ln \frac{n_{k,s}^{m+1}}{n_{k,s}^m} \right), \quad (35)$$

where $n_{k,s}^m$ is the total number of m -dimensional matched vector pairs and is calculated from the k th coarse-grained time series at a scale factor s .

The refined multiscale entropy [51,52], based on the multiscale entropy approach, applies different entropies as a function of time scale in order to perform a multiscale irregularity assessment. $rMSEn$ prevents the influence of the reduced variance on the complexity evaluation and removes the fast temporal scales. Thus, an $rMSEn$ method improves the coarse-grained process.

3. System Description

Many industrial applications require precise regulation of the speed of the drive motors. A brushless motor operates under various speed and load conditions and the knowledge of some physical parameters (speed, torque, current) for proper speed regulation is essential. Figure 1 shows a system implementation for brushless motor control as a Permanent Magnet Synchronous Machine in Matlab/Simulink. A three-phase inverter is used to feed the motor phases, thereby injecting currents in the coils to create the necessary magnetic fields for three phases. The three-phase inverter is modeled as an universal bridge in Matlab, with three arms and MOSFET/ Diode as power electronic devices (T_i and B_i , $i = a, b, c$), controlled by pulse width modulation.

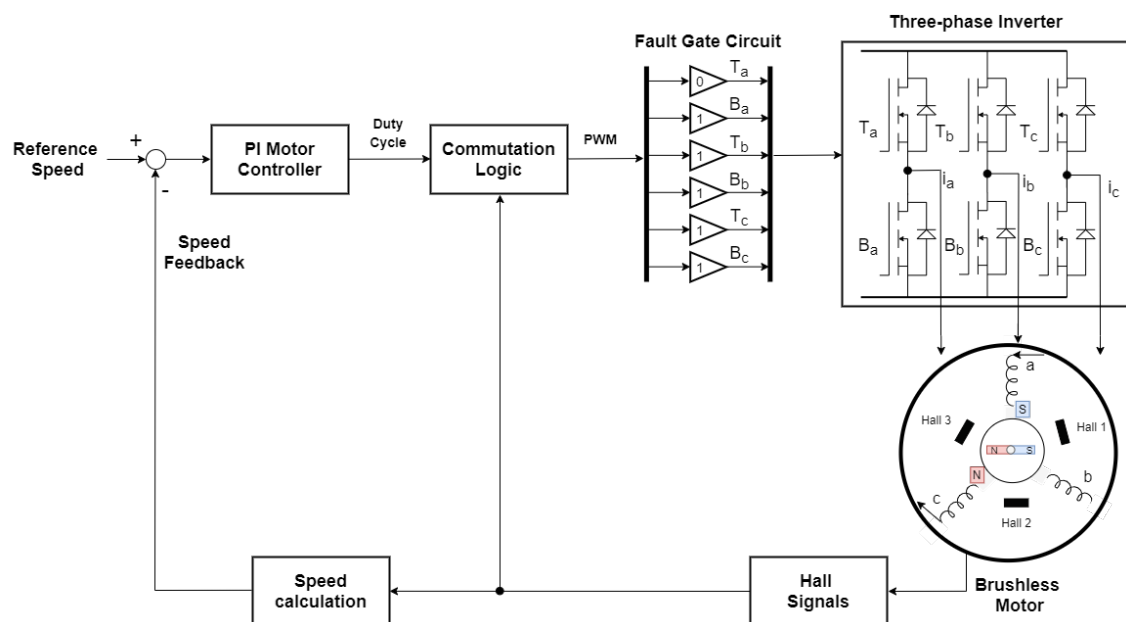


Figure 1. Power circuit structure of a brushless motor.

A simplified model of stator consists of three coils arranged in a , b and c directions. To ensure the brushless motor movement, the a , b and c stator windings are powered according to the rotor's position. The rotor magnetic field position is detected by three Hall sensors (placed every 120°) and provides the corresponding winding excitation through the commutation logic circuit. Table 1 summarizes the main specifications of this brushless machine.

In permanent magnet synchronous motors, a physical phenomenon can appear: the electromagnetic torque oscillations. These oscillations are named the Cogging effect and are taken in consideration by [53,54]. The Cogging phenomenon is the interaction of the magnetic field produced by the permanent magnet rotor with the stator teeth. This interaction can be reduced by the physical modification of the rotor and stator internal

structure. Another modality to reduce the phenomenon is the control technique introducing this knowledge directly in the controller design, as in [53,54]. Cogging torque is a significant problem for high-precision applications where position control is required. In order to simplify the analysis, the previously mentioned Cogging phenomenon can be neglected.

The brushless motor design and the analysis of various control techniques are discussed in [55], where double closed loops (speed and current) are considered. The current loop is used to improve the dynamic performance of the controlled system. Wu [56] used only one speed control loop as [57]. Nga [58] assumed that the current control loop is ideal, meaning that the transfer function of the closed current control loop is equal to 1. In the cascaded control structure, the inner loops are designed to achieve fast response and outer loop is designed to achieve optimum regulation and stability.

The inner loop also keeps the torque output below a safe limit. Moreover, the controller should be developed in such a manner that it produces less torque ripple. Torque ripple is developed from motor control through inefficient commutation strategies and internal gate control schemes. Ideally, the torque ripple is constant due to the in-phase back electromotive force and quasi-square wave stator current. In this paper, we consider the dynamics of the current control loop much faster than that of the speed control loop in order to decouple both dynamics. Satisfying this condition, the reference value of the inner loop, which is the output of the outer controller can be considered nearly constant (a simple current limit closed control loop). To achieve the regulation objective, we are interested by the steady-state phase currents and not by their dynamic performances. This paper proposes a simple control structure using only the speed control loop.

The outer loop helps to control the speed of the motor. The speed feedback comes from the Hall sensor positions. The three-phase control technique for brushless motor uses a proportional integral (PI) controller. The controller receives the error signal and generates the control signal to regulate the speed response (referred to the target speed). The PI controls the duty cycle of the PWM pulses to maintain the desired speed. The proportional and integral gains of the controller are described in Table 1. The inner loop synchronizes the inverter gate states of the brushless motor and stator winding excitation as in Table 2. With this table, the commutation logic can easily control the commutation. The fault gate circuit is implemented by gains destined to each MOSFET. The gain is zero for an open-circuit fault, and one if not faulty.

Both single-switch and multi-switch open-circuit faults are classified and studied.

- One open-circuit fault may occur in the switch: T_a or B_a of the first phase a , T_b or B_b of the second phase b , T_c or B_c of the phase c .
- Open-circuit phase fault can be detected in T_a and B_a , T_b and B_b or T_c and B_c .
- If two upper MOSs faults are detected, the two open-circuit faults can be T_a and T_b , T_a and T_c or T_b and T_c . The two open-circuit faults, B_a and B_b , B_a and B_c or B_b and B_c , are the symmetrical faults of the lower arms.
- The cases of two open-circuit faults on the upper and lower arms are T_a and B_b , T_a and B_c , T_b and B_a , T_b and B_c , T_c and B_a and T_c and B_b .
- The brushless motor is still running even in three fault cases: T_a, B_a, T_b ; T_a, B_a, B_b ; T_a, B_a, T_c ; T_a, B_a, B_c ; T_b, B_b, T_a ; T_b, B_b, B_a ; T_b, B_b, T_c ; T_b, B_b, B_c ; T_c, B_c, T_a ; T_c, B_c, B_a ; T_c, B_c, T_b ; T_c, B_c, B_b ; T_a, B_b, T_c ; T_a, B_b, B_c ; T_a, T_b, B_c ; B_a, B_b, T_c ; B_a, T_b, B_c ; B_a, T_b, T_c .
- If the upper and lower arms are affected by multiple open-circuits, the open-circuit faults can be: T_a, B_a, T_b, B_c ; T_a, B_a, B_b, T_c ; T_a, T_b, B_b, B_c ; B_a, T_b, B_b, T_c ; T_a, B_b, T_c, B_c ; B_a, T_b, T_c, B_c .

With no loss of generality, this work focuses on the open-circuit fault on the first switch T_a of the first phase a . Two open switch faults are also considered: on the second switch B_a of the first phase and on the first switch T_b of the second phase; then, two open-circuit faults on the first phases T_a, B_a , followed by the case T_b, T_c . The cases of multiple open-circuits are: B_a, B_b, T_c , then B_a, T_b, B_b and finally B_a, T_b, B_b, T_c .

Table 1. Mean specifications of the brushless machine.

Specification	Parameter	Value
Brushless motor	Stator phase resistance	2.8Ω
	Stator phase inductance	$8.5 \cdot 10^{-3} \text{ H}$
	Flux linkage	0.175
	Inertia	$0.8 \cdot 10^{-3} \text{ kg/m}^2$
	Viscous damping	0.001 Nms
	Pole pairs	4
Speed controller	Rotor flux position	90°
	Proportional	0.015
	Integral	16
	Min output	−500
	Max output	500

Table 2. Truth table of Hall effect sensors and gate state of the brushless motor.

Hall 1	Hall 2	Hall 3	T_a	B_a	T_b	B_b	T_c	B_c
1	0	1	1	0	0	0	0	1
0	0	1	0	1	0	0	1	0
0	1	1	0	0	0	1	1	0
0	1	0	0	0	1	0	0	1
1	1	0	0	1	1	0	0	0
1	0	0	1	0	0	1	0	0

4. Datasets

Each inverter phase has two arms, i.e., the upper arm and the lower arm, whose currents are denoted as i_a , i_b and i_c . The three-phase currents of the brushless motor are recorded as a one-dimensional time series.

Let us observe the current of phase a under normal operating conditions (i.e., without any fault on the switches T_a , B_a , T_b , B_b , T_c or B_c of the inverter). Figure 2a shows this time-series data, sampled with sampling time $T = 5 \mu\text{s}$ and composed of $N = 6000$ samples. The currents of phase b and c are similar to phase a 's current. Under healthy conditions, Table 3 (first line) shows the zero average of the phase currents.

Then, an open-circuit fault occurs in phase a on the T_a switch. The output currents of phases a , b and c corresponding to an open-circuit fault are shown in Figures 2b and 3a,b. When an open-circuit fault occurs in phase a , the positive phase current gets distorted and that phase average current becomes negative; it is positive for the two others. The DC side of phase a output current can be observed in Table 3 (line 2). The current amplitude of phases b and c change; their means change too. Similarly, when an open-circuit fault occurs in phase a on switch B_a , the negative phase current gets distorted and the average current of that phase becomes positive when it is negative for the two others.

Considering a phase fault in switches T_a and B_a , the phase current waveforms are illustrated in Figures 4a,b and 5a. Consequently to these faults, the mean of the phase current i_a has a very low amplitude. The currents of the other phases recover the alternating waveforms. Line 8 of Table 3 presents the current means.

For instance, when two upper open-circuit faults simultaneously occur in T_a and T_b , the currents in the upper half-bridges are only able to flow in T_c . Figures 5b and 6a,b show the abnormal distortions of the currents of phases a , b and c , which differ from normal operating conditions. During this process, the open-circuit faults degrade the system's performances, but do not cause a shutdown.

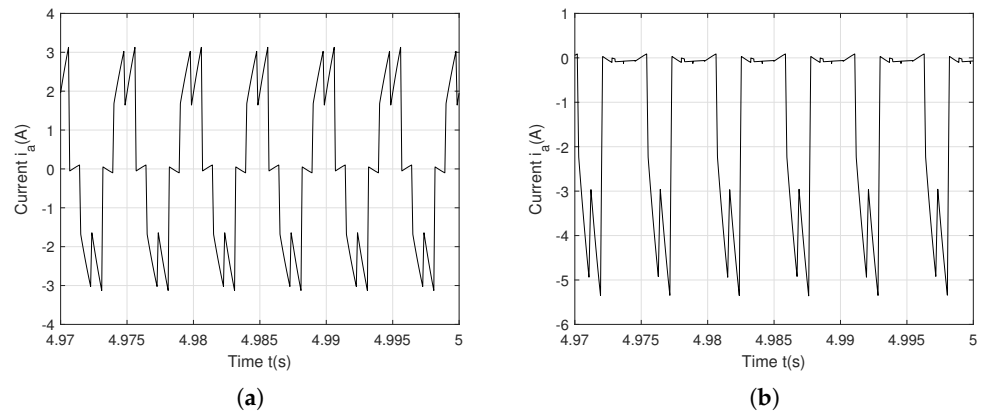


Figure 2. (a) Current i_a during a no-fault case; (b) Current i_a during open-circuit faults on T_a .

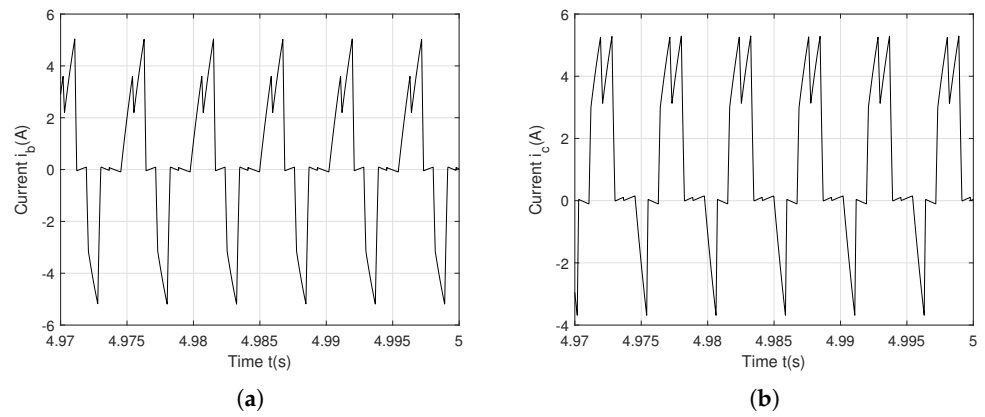


Figure 3. (a) Current i_b during open-circuit faults on T_a ; (b) Current i_c during open-circuit faults on T_a .

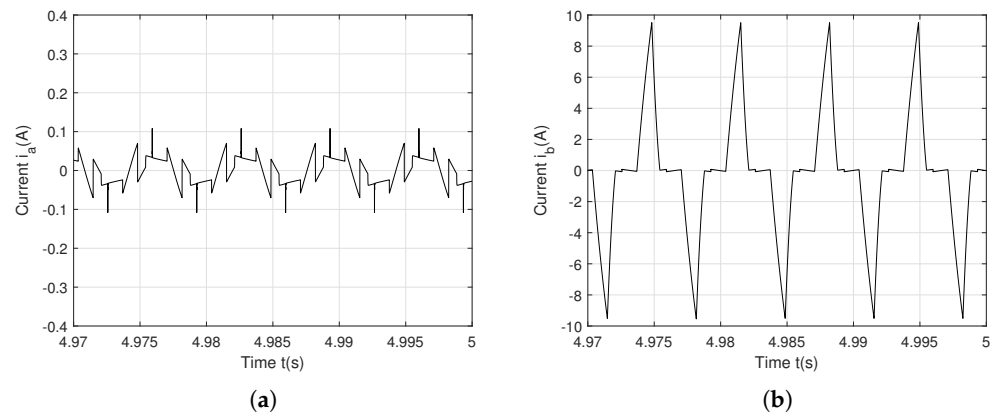


Figure 4. (a) Current i_a during open-circuit faults on T_a and B_a ; (b) Current i_b during open-circuit faults on T_a and B_a .

Table 3. Current means of phases a , b and c with no-fault, one open-circuit fault, two open-circuit faults, three open-circuit faults and four open-circuit faults on the switches for a couple = 3 Nm and a reference speed = 3000 tr/min.

No.	Open-Circuit Fault	i_a Current Mean	i_b Current Mean	i_c Current Mean	$xyzw$
1.	No fault	0.00033	−0.00001	−0.00034	
2.	T_a	−1.4164	0.2167	1.1994	abac
3.	T_b	1.2017	−1.4161	0.2144	abbc
4.	T_c	0.2885	1.1260	−1.4145	acbc
5.	B_a	1.4158	−0.2652	−1.1506	abac
6.	B_b	−1.1234	1.2713	−0.1479	abbc
7.	B_c	−0.2702	−1.1422	1.4125	acbc
8.	T_a, B_a	0.0006	0.2708	−0.2714	abac
9.	T_b, B_b	−0.2761	0.0007	0.2754	abbc
10.	T_c, B_c	−0.173	0.1757	−0.0027	acbc
11.	T_a, T_b	−0.8987	−1.6516	2.5503	acbc
12.	T_b, T_c	2.465	−0.8106	−1.6545	abac
13.	T_a, T_c	−1.6474	2.5753	−0.9278	abbc
14.	B_a, B_b	0.9219	1.6456	−2.5675	acbc
15.	B_b, B_c	−2.4387	0.9258	1.5129	abac
16.	B_a, B_c	1.6466	−2.5087	0.8621	abbc
17.	T_a, B_b	−1.7775	1.3916	0.3858	acbc
18.	T_a, B_c	−1.3516	−0.4263	1.7779	abbc
19.	T_b, B_a	1.9577	−1.5853	−0.3724	acbc
20.	T_b, B_c	0.5589	−1.8893	1.3304	abac
21.	T_c, B_a	1.5627	0.5331	−2.0958	abbc
22.	T_c, B_b	−0.6330	2.0175	−1.3846	abac
23.	T_a, B_a, T_b	0.0004	−2.6371	2.6367	acbc
24.	T_a, B_a, B_b	0.0044	2.9920	−2.9964	acbc
25.	T_a, B_a, T_c	0.0025	2.4690	−2.4715	abbc
26.	T_a, B_a, B_c	−0.0032	−2.8272	2.8304	abbc
27.	T_b, B_b, T_a	−2.9702	0.0025	2.9678	acbc
28.	T_b, B_b, B_a	2.3538	0.0007	−2.3546	acbc
29.	T_b, B_b, T_c	2.9561	−0.0022	−2.9538	abac
30.	T_b, B_b, B_c	−2.3683	−0.0019	2.3702	abac
31.	T_c, B_c, T_a	−2.5577	2.5564	0.0014	abbc
32.	T_c, B_c, B_a	2.2754	−2.2745	−0.0009	abbc
33.	T_c, B_c, T_b	2.6707	−2.6692	−0.0015	abac
34.	T_c, B_c, B_b	−2.9748	2.9760	−0.0012	abac
35.	T_a, B_b, T_c	−1.6465	2.4144	−0.7679	abac
36.	T_a, B_b, B_c	−2.5268	0.9357	1.5911	abac
37.	T_a, T_b, B_c	−0.7666	−1.6462	2.4128	abac
38.	B_a, B_b, T_c	0.9229	1.6451	−2.5680	abac
39.	B_a, T_b, B_c	1.6455	−2.5318	0.8864	abac
40.	B_a, T_b, T_c	2.3986	−0.7597	−1.6389	abac
41.	T_a, B_a, T_b, B_c	0.0016	−2.6055	2.6038	abac
42.	T_a, B_a, B_b, T_c	0.0041	3.0170	−3.0211	abac
43.	T_a, T_b, B_b, B_c	−2.8549	0.0023	2.8526	abac
44.	B_a, T_b, B_b, T_c	2.6972	−0.0011	−2.6961	abac
45.	T_a, B_b, T_c, B_c	−2.4336	2.4316	0.002	abac
46.	B_a, T_b, T_c, B_c	2.3253	−2.3255	0.0001	abac

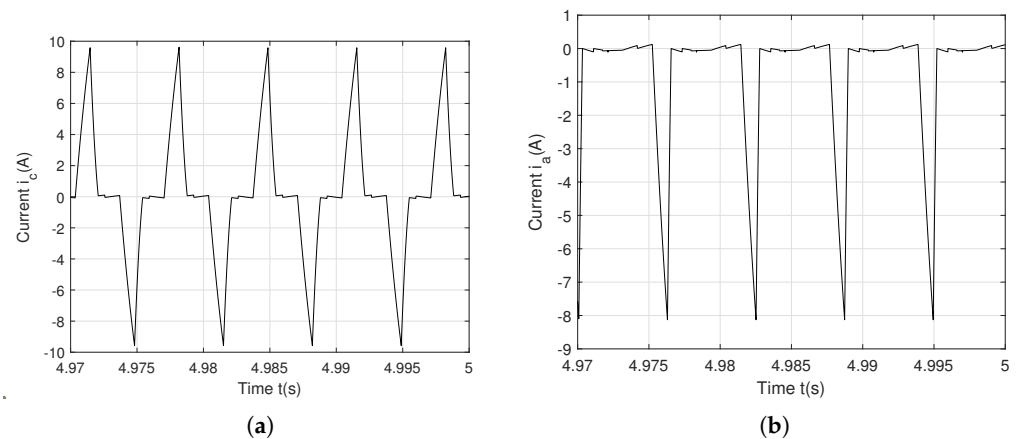


Figure 5. (a) Current i_c during open–circuit faults on T_a and B_a ; (b) Current i_a during open–circuit faults on T_a and T_b .

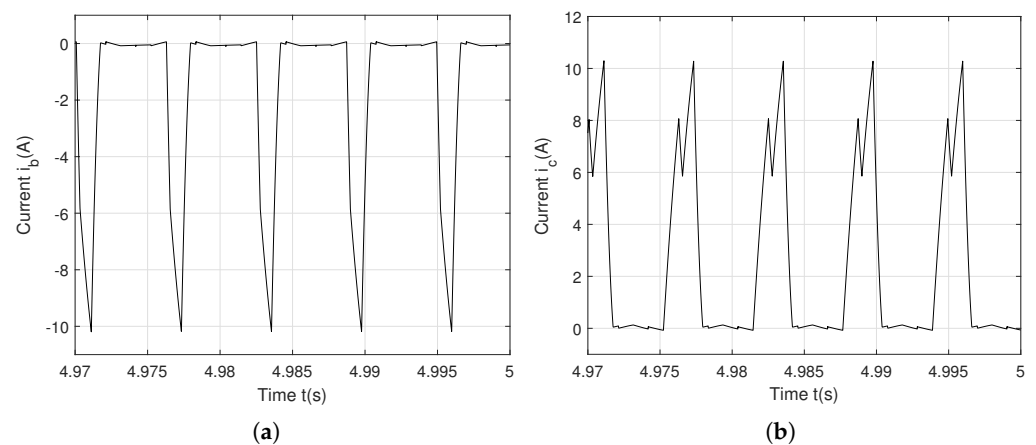


Figure 6. (a) Current i_b during open–circuit faults on T_a and T_b ; (b) Current i_c during open–circuit faults on T_a and T_b .

If two open-circuit faults occur in T_a and B_b , the phase a current remains positive and the phase b current remains negative, as shown in Figure 7a,b. The other phase current (i_c) is also affected with unbalance during these fault conditions, as shown in Figure 8a.

Considering three faults in T_a , B_a , T_b , the phase a current is near zero and the phase b current during the positive cycle is eliminated as shown in Figures 8b and 9a. Consequently, the phase c current only remains during the positive cycles, as shown in Figure 9b.

Similarly, the effects of B_a , T_b and B_c faults on the phase currents are easy to find out. When the lower switch B_a is faulty, the current i_a flows only T_a , having a positive mean (Figure 10a). With T_b fault, the positive cycle of phase current i_b vanishes, as shown in Figure 10b. Figure 11a shows i_c : when the open-circuit fault of B_c occurs, current i_c has a positive waveform.

In the case of multiple open-circuit faults in several switches (B_a , T_b , B_b , T_c), phase current waveforms are seriously affected as shown in Figures 11b and 12a,b: phase b current is near zero according to phase fault, while phase a current and phase c current have a positive mean and a negative mean, respectively.

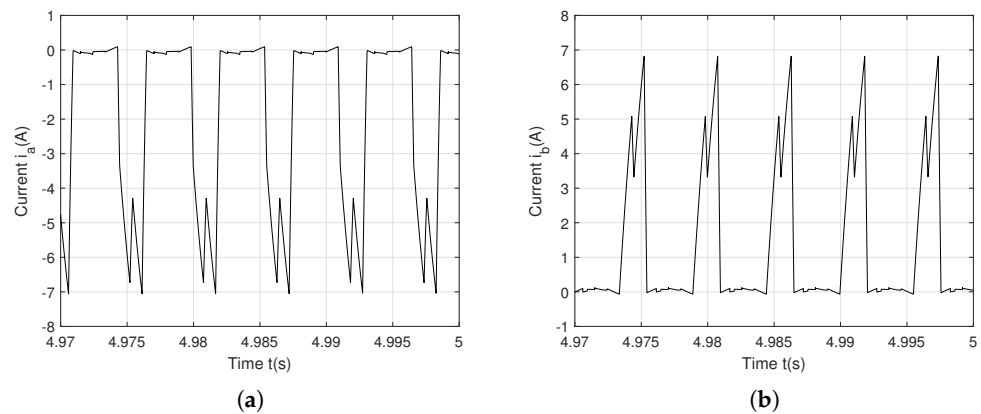


Figure 7. (a) Current i_a during open-circuit faults on T_a and B_b ; (b) Current i_b during open-circuit faults on T_a and B_b .

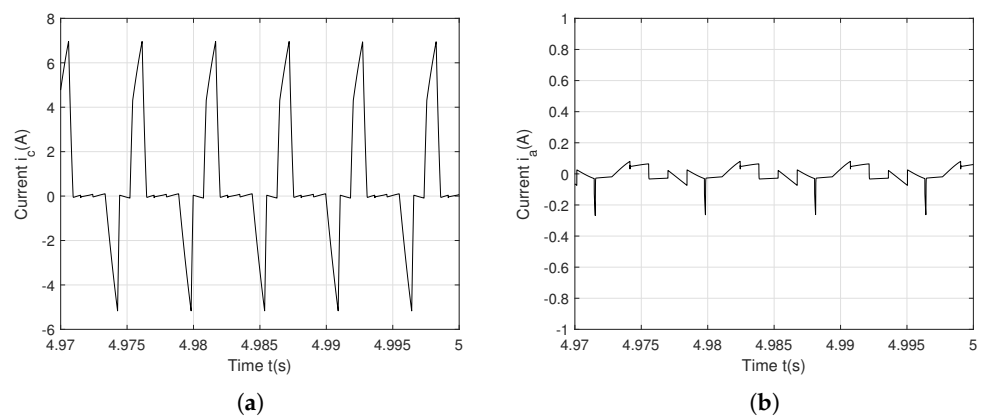


Figure 8. (a) Current i_c during open-circuit faults on T_a and B_b ; (b) Current i_a during open-circuit faults on T_a , B_a and T_b .

The faults are divided into eight categories: no fault, 6 single-switch faults, 3 double-switch faults in the same bridge arm, 3 two upper-switch faults and 3 two lower-switch faults, 6 double faults from crossed half-bridges, 12 triple-switch faults with phase failure, 6 triple-switch faults in different bridge arms and, finally, 6 multiple faults with phase failure. For a typical three-phase inverter, there are 45 possible open-circuit faults, as shown in Table 3. For these cases, the mean of the phase currents are calculated and shown in Table 3.

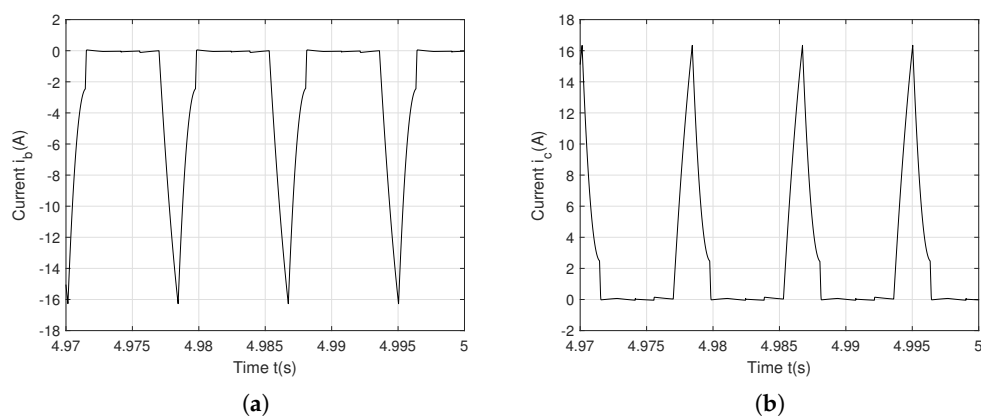


Figure 9. (a) Current i_b during open-circuit faults on T_a , B_a and T_b ; (b) Current i_c during open-circuit faults on T_a , B_a and T_b .

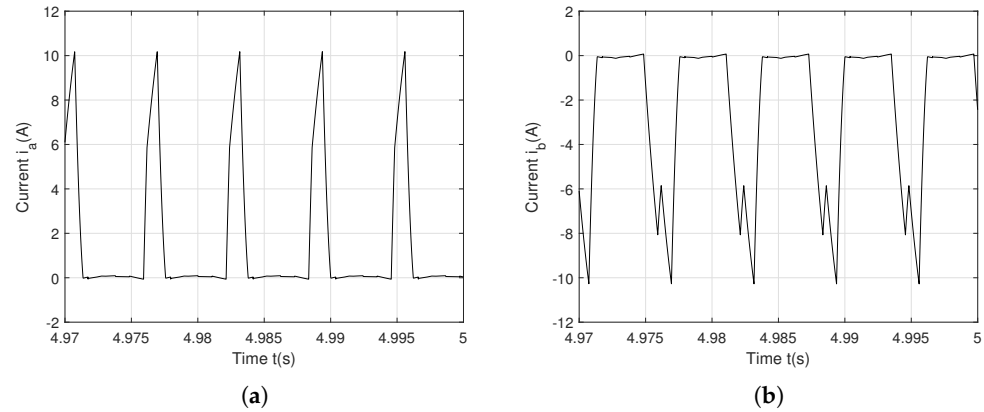


Figure 10. (a) Current i_a during open-circuit faults on B_a , T_b and B_c ; (b) Current i_b during open-circuit faults on B_a , T_b and B_c .

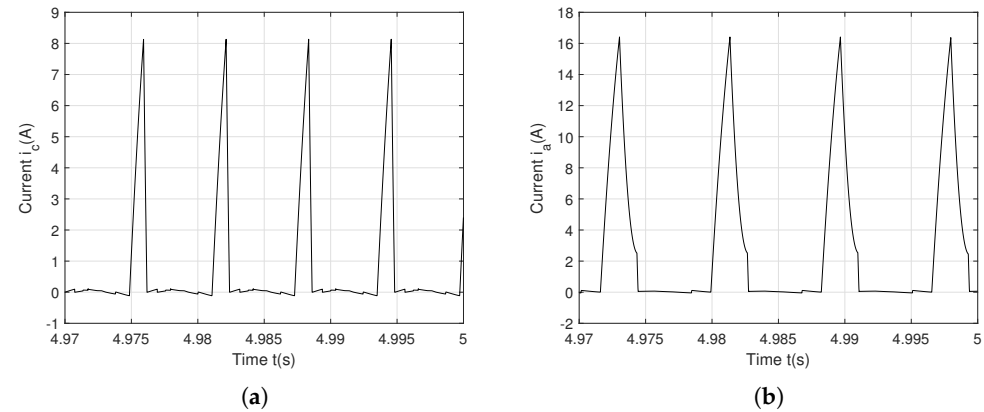


Figure 11. (a) Current i_c during open-circuit faults on B_a , T_b and B_c ; (b) Current i_a during open-circuit faults on B_a , T_b , B_b and T_c .

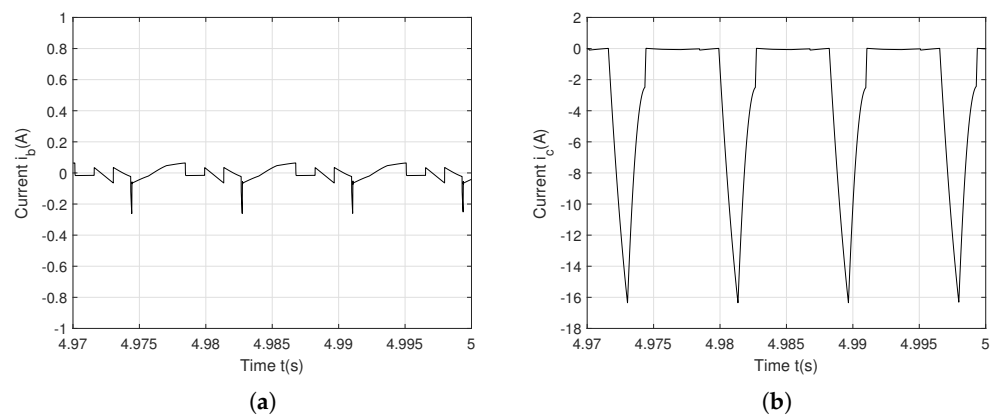


Figure 12. (a) Current i_b during open-circuit faults on B_a , T_b , B_b and T_c ; (b) Current i_c during open-circuit faults on B_a , T_b , B_b and T_c .

For the first fault case (T_a), the signs of the phase currents (i_a , i_b and i_c) are negative, positive and positive. Positive, negative and negative values are found, respectively, on lines 15 (B_b and B_c faults), 17 (T_a and B_c faults) and 36 (T_a , B_b and B_c faults). If a phase is faulty, for example phase b , the line 9 of Table 3 presents a negative, zero and positive mean values. However, negative, zero and positive mean values can also be on the other fault cases: line 27 (T_b , B_b and T_a faults), line 30 (T_b , B_b and B_c faults) and line 43 (T_a , T_b , B_b and

B_c faults). For the last example with negative, negative and positive mean current values, there are four fault cases: line 7 (B_c fault), line 11 (T_a and T_b faults), line 18 (T_a and B_c faults) and line 37 (T_a , T_b and B_c faults).

5. Selection of Entropy Functions

In this part, entropy is employed to characterize the complexity of signals in the open-circuit case, such as the healthy and faulty waveforms, as in Figures 2a–12b. Phase currents are directly used as information. A fault is detected, based on the average current. When the fault occurs in the inverter, the current waveforms vary. *MSEn*, *cMSEn* and *rMSEn* algorithms can use *SampEn*, *K2En*, *CondEn*, *DispEn*, *CoSiEn*, *BubbEn*, *ApEn*, *FuzzEn*, *IncrEn*, *PhasEn*, *SlopEn* and *EnofEn* approaches or *AttEn*, giving 52 entropy functions to evaluate the signals complexity. For the ease of comparison, the entropy of phases a , b and c when one open-circuit fault occurs on T_a , is divided by the entropy of phase a under healthy conditions. Similarly, the entropy of phases a , b and c when multiple open-circuit faults occur on T_i and B_i $i = a, b, c$, is divided by the entropy of phase a under healthy conditions.

5.1. One Open-Circuit Fault on T_a on the Phase a

This study investigates the efficiency of different entropies with several parameters, such as data length $N = 6000$ samples, embedding dimension $m = 2$, time delay $\tau = 1$, tolerance $r = 0.2$ and scale $s = 3$. The entropies of the 6000 samples are shown in Figure 13. The *BubbEn* entropy of phase a samples (represented in red), where the open-circuit fault occurs, has larger value than the entropy of phases b and c (represented in black). Incontestably, they are clearly separated. Even the entropy of phase a is lower than the entropy of phases b and c for *SampEn*, *K2En*, *DispEn*, *ApEn*, *SlopEn* and *AttEn*. The separation of the three phases a , b and c is shown in Figure 13: phases b and c have an entropy very close to each other, and different from that of phase a . Each of these entropies is able to detect the faulty phase. Figure 13 represents the larger difference between the entropy of phase a ; the entropy of phases b and c is given by *BubbEn*.

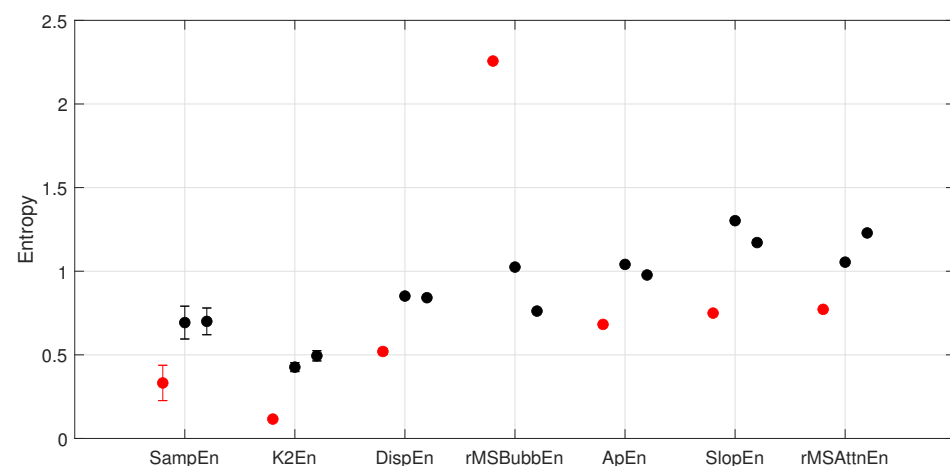


Figure 13. Entropy evaluation using *SampEn* (mean of four sample entropies), *K2En* (mean of four Kolmogorov entropies), *DispEn* (mean of four dispersion entropies), *rMSBubbEn*, *ApEn*, *SlopEn* (mean of four slope entropies) and *rMSAttEn* for one open-circuit fault on T_a : phase a entropy with an open-circuit fault in red and phases b and c entropies in black.

Many values represented in Figure 13 are an average of two, three or four entropies. Relevant values of *SampEn*, *MSSampEn*, *cMSSampEn* and *rMSSampEn* are averaged to give a mean entropy of phases a , b and c . In the same way, for slope entropy, the same entropy value is obtained with *SlopEn*, *MSSlopEn*, *cMSSlopEn* and *rMSSlopEn* functions. With dispersion entropy also, for *DispEn*, *MSDispEn*, *cMSDispEn* and *rMSDispEn*, the same value is obtained. *K2En*, *MSK2En*, *cMSK2En* and *rMSK2En* give similar entropy val-

ues. For bubble entropy, a pertinent value is obtained only with *rMSBubbEn*: unfortunately, *BubbEn*, *MSBubbEn* and *cMSBubbEn* do not distinguish the open-circuit fault on phase *a* from phases *b* and *c*. Figure 13 presents the approximation entropy using only *ApEn*. The other values of *MSApEn*, *cMSApEn* and *rMSApEn* do not distinguish the open-circuit fault on phase *a*. A relevant value of attention entropy is obtained with *rMSAttEn*. For the other entropies, such as *CondEn*, *CoSiEn*, *FuzzEn*, *IncrEn*, *PhasEn* and *EnofEn*, the distance between faulty phase *a* and phases *b* or *c* is nearly zero: the open-circuit fault is not detected.

The optimal entropy should be searched from all possible combinations, according to the following rules:

$$\max \left(\text{distance}_{j=1}^{52} \left| \text{entropy}_{\text{phase}-a} - \text{entropy}_{\text{phase}-b} \right| \right) \quad (36)$$

and

$$\max \left(\text{distance}_{j=1}^{52} \left| \text{entropy}_{\text{phase}-a} - \text{entropy}_{\text{phase}-c} \right| \right). \quad (37)$$

The objective is to maximise the distance between the phase *a* entropy, where the open-circuit fault occurs and the entropy of phases *b* and *c*. For a typical brushless motor, 52 possible open-circuit faults can be diagnosed using Equations (36) and (37) according to the principle shown in Table 4. Normally, the entropy is able to detect the faulty phase: it is denoted with '✓'. Otherwise, if the open-circuit fault is not detected (the distance between faulty phase *a* and phases *b* or *c* is nearly zero), it is pointed out by '✗'. The neutral mark '-' is employed if the distance between phase *a* and phases *b* or *c* is not zero but not enough to detect the open-circuit fault. However, the distance is only an approximate measure on the characteristic plot.

Table 4. Several entropies' fault-detection capability with one open-circuit fault, two open-circuit faults, three open-circuit faults and four open-circuit switches faults for a couple = 3 Nm and a reference speed = 3000 tr/min.

Entropies	T_a	$B_a T_b$	$T_a B_a$	$T_b T_c$	$B_a B_b T_c$	$B_a T_b B_b$	$B_a T_b B_b T_c$
<i>SampEn</i>	✓	✗	✓	✓	✗	✗	✗
<i>MSSampEn</i>	✓	✗	✓	✗	✗	✗	✗
<i>cMSSampEn</i>	✓	✗	✓	✗	✗	✗	✗
<i>rMSSampEn</i>	✓	✓	✓	✗	✗	✗	✗
<i>K2En</i>	✓	✗	✓	✓	✗	✗	✗
<i>MSK2En</i>	✓	✗	✓	✓	✗	✗	✗
<i>cMSK2En</i>	✓	✗	✓	✓	✗	✗	✗
<i>rMSK2En</i>	✓	✗	✓	✓	✗	✗	✗
<i>CondEn</i>	-	✗	-	✓	-	✗	✓
<i>MSCondEn</i>	✗	✗	-	✗	-	✗	✓
<i>cMSCondEn</i>	✗	✗	-	✗	-	✗	✓
<i>rMSCondEn</i>	✗	✗	-	✗	-	✗	-
<i>DispEn</i>	✓	✗	-	✓	✗	✗	✗
<i>MSDispEn</i>	✓	✗	-	✓	✗	✗	✗
<i>cMSDispEn</i>	✓	✗	-	✓	✗	✗	✗
<i>rMSDispEn</i>	✓	✗	-	✓	✗	✗	✗
<i>CoSiEn</i>	-	✓	✗	✗	✗	✗	✗
<i>MSCoSiEn</i>	-	-	✗	✗	✗	✗	✗
<i>cMSCoSiEn</i>	-	✓	✗	✗	✗	✗	✗
<i>rMSCoSiEn</i>	-	✓	✗	✗	✗	✗	✗
<i>BubbEn</i>	✗	✗	-	✗	✓	✗	✗
<i>MSBubbEn</i>	✗	✗	-	✗	✓	✗	✗
<i>cMSBubbEn</i>	✗	✗	-	✗	✓	✗	✗
<i>rMSBubbEn</i>	✓	-	✓	✓	-	✗	✗

Table 4. Cont.

Entropies	T_a	$B_a T_b$	$T_a B_a$	$T_b T_c$	$B_a B_b T_c$	$B_a T_b B_b$	$B_a T_b B_b T_c$
$ApEn$	✓	✗	-	-	✗	✗	✗
$MSApEn$	✗	✗	✓	✗	✗	✗	✗
$cMSApEn$	✗	✗	✓	✗	✗	✗	✗
$rMSApEn$	✗	✗	✓	✗	✗	✗	✗
$FuzzEn$	-	✓	✓	✗	✗	✗	✗
$MSFuzzEn$	✗	✓	✓	✗	✗	✗	✗
$cMSFuzzEn$	✗	✓	✓	✗	✗	✗	✗
$rMSFuzzEn$	✗	✓	✓	✗	✗	✗	✗
$IncrEn$	✗	✗	✗	✗	✓	✓	✓
$MSIncrEn$	✗	✗	✗	✗	✓	✓	✓
$cMSIncrEn$	✗	✗	✗	✗	✓	✓	✓
$rMSIncrEn$	-	✗	✗	✗	-	✗	-
$PhasEn$	✗	-	✗	-	✗	✓	✗
$MSPhasEn$	✗	-	✗	-	✗	✓	✗
$cMSPhasEn$	✗	-	✗	-	✗	✓	✗
$rMSPhasEn$	✗	-	✗	-	✗	✗	✗
$SlopEn$	✓	✓	✓	✗	✗	✗	✗
$MSSlopEn$	✓	✓	✓	✗	✗	✗	✗
$cMSSlopEn$	✓	✓	✓	✗	✗	✗	✗
$rMSSlopEn$	✓	✓	✓	✗	✗	✗	✗
$EnofEn$	-	✓	✗	✗	✗	✗	✗
$MSEnEn$	-	✓	✗	✗	✗	✗	✗
$cMSEnEn$	-	✓	✗	✗	✗	✗	✗
$rMSEn$	✗	✓	✗	✗	✗	✗	✗
$AttEn$	✗	✗	✗	✗	✗	✗	✗
$MSAttEn$	✗	✗	✗	✗	✗	✗	✗
$cMSAttEn$	✗	✗	✗	✗	✗	✗	✗
$rMSAttEn$	✓	-	✗	-	✗	✗	✗

5.2. Two Open-Circuit Faults on B_a —Phase a and on T_b —Phase b

The embedding dimension m , data length N , time delay τ and the choice of tolerance r remain unchanged. Figure 14 shows the performance of several entropies with two open-circuit faults: on B_a —phase a and on T_b —phase b. The entropies of faulty phases a and b are in red, the entropy of phase c is in black.

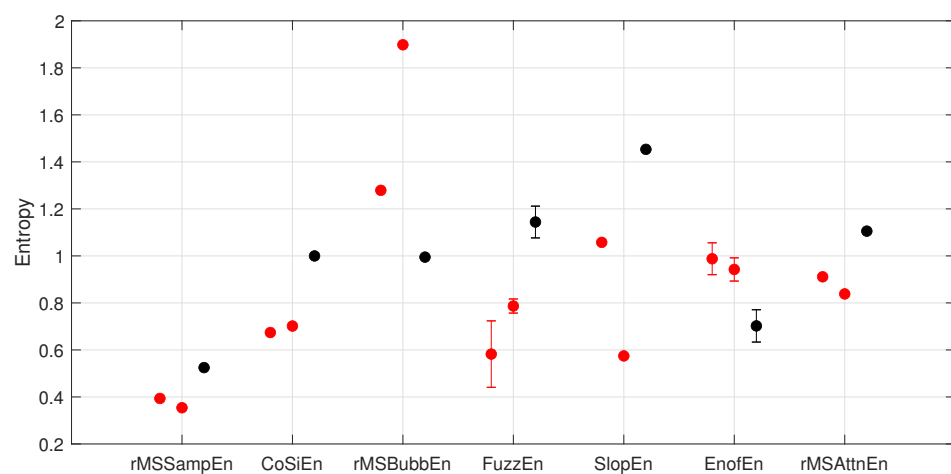


Figure 14. $rMSSampEn$, $Cosien$, $FuzzEn$, $EnofEn$, $ApEn$, $rMSSlopEn$ and $rMSAttEn$ for one open-circuit fault on B_a and T_b : entropy of faulty phases a and b in red and phase c in black.

The optimal entropy should be searched from all possible combinations, according to the following rules:

$$\max \left(\text{distance}_{j=1}^{52} | \text{entropy}_{\text{phase}-a} - \text{entropy}_{\text{phase}-c} | \right) \quad (38)$$

and

$$\max \left(\text{distance}_{j=1}^{52} | \text{entropy}_{\text{phase}-b} - \text{entropy}_{\text{phase}-c} | \right). \quad (39)$$

The objective is to maximise the distance between the entropy of phase *a* and this of phase *c*, as distance between the entropy of phase *b* and phase *c*. Relevant results are obtained with *rMSSampEn*, *CoSiEn*, *FuzzEn*, *EnofEn* and *rMSAttEn*. For following explanations, *SlopEn* and *rMSBubbEn* are also represented even if they do not distinguish as well the open-circuits on phases *a* and *b*.

5.3. Two Open-Circuit Faults on T_a and on B_a —Phase *a*

The entropy parameters are unchanged. We investigate a phase fault: on T_a and on B_a —phase *a*. Figure 15 shows the investigation of different entropies: the phase *a* entropy with open-circuit is in red, the entropies of phases *b* and *c* are in black. The largest distance between phase *a* entropy and those of phases *b* and *c* are obtained with *SampEn*, *ApEn* and *rMSBubbEn*. The entropies are selected using Equations (36) and (37). The values of *SampEn*, *ApEn* are for the particular form of the phase current i_a . As shown in Figure 4a, this current has a regular shape with a very small amplitude.

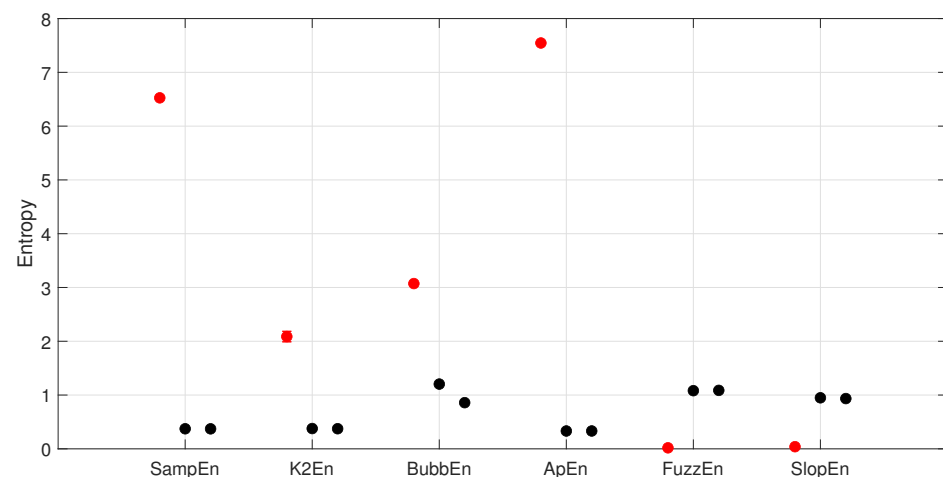


Figure 15. *SampEn*, *K2En*, *ApEn*, *FuzzEn* and *SlopEn* for two open—circuit faults on T_a and B_a : phase *a* entropy with open—circuit fault in red and phases *b* and *c* entropies in black.

5.4. Two Open-Circuit Faults on T_b —Phase *b* and on T_c —Phase *c*

The two open-circuit faults considered in this subsection are on T_b —phase *b* and on T_c —phase *c*. Figure 16 shows the different entropies: the entropy of phase *a* is in black, phases *b* and *c* entropies are in red. The biggest distance between the phase *a* entropy and those of phases *b* and *c* is obtained with *rMSBubbEn*. The entropies are selected using Equations (36) and (37). For the following explanations, *SlopEn* is also represented even if it does not distinguish as well the open-circuits on phases *b* and *c* compared with phase *a*.

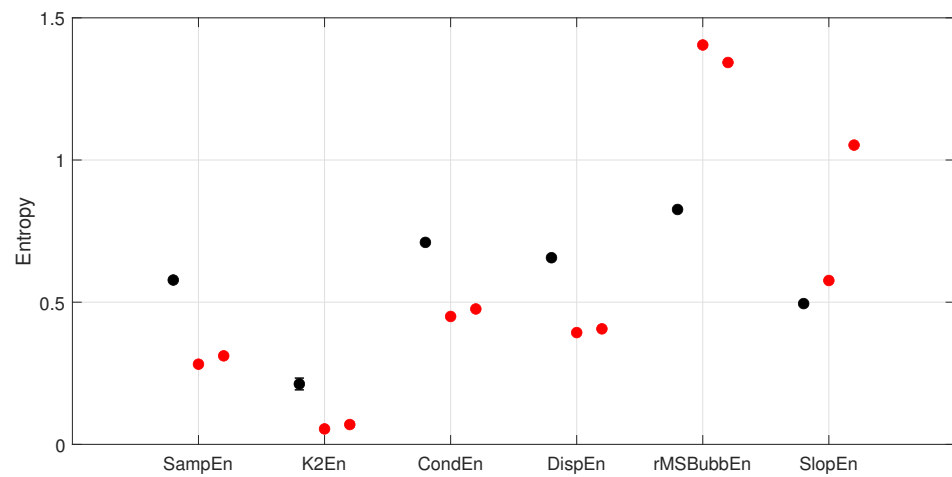


Figure 16. *SampEn*, *K2En*, *CondEn*, *DispEn*, *rMSBubbEn* and *SlopEn* for two open-circuit faults on T_b and T_c : phase a entropy in black and phases b and c entropies with open-circuits in red.

5.5. Three Open-Circuit Faults on B_a —Phase a , T_b —Phase b and on T_c —Phase c

Three open-circuit faults occur on B_a —phase a , on T_b —phase b and T_c —phase c . Figure 17 shows the entropies of phases a , b and c with open-circuit faults, in red. The optimal entropy should be searched from all possible combinations, according to the following rules:

$$\min \left(\text{distance}_{j=1}^{52} \left| \text{entropy}_{\text{phase}-a} - \text{entropy}_{\text{phase}-c} \right| \right) \quad (40)$$

and

$$\min \left(\text{distance}_{j=1}^{52} \left| \text{entropy}_{\text{phase}-b} - \text{entropy}_{\text{phase}-c} \right| \right). \quad (41)$$

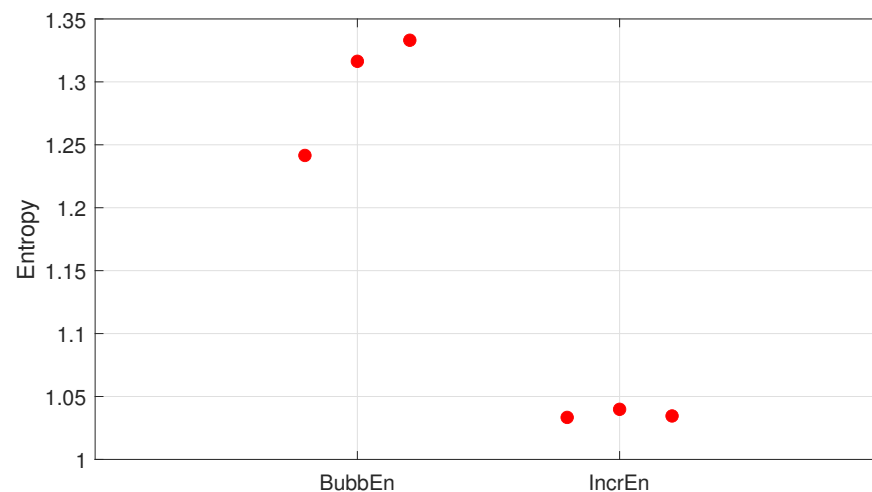


Figure 17. *BubbEn* and *IncrEn* with three open-circuit faults on B_a , T_b and T_c : phase a , b and c entropies in red.

According to Equations (40) and (41), Figure 17 presents *BubbEn* and *IncrEn*. The entropies of phases a , b and c are very closed.

5.6. Three Open-Circuit Faults on B_a —Phase a , T_b and B_b —Phase b

Three open-circuit faults occur on B_a —phase a , on T_b and B_b —phase b . As we can see in Figure 18, the entropies of phases a and b with open-circuit faults is represented in red, and the entropy of phase c is in black. The optimal entropy should be searched from all possible combinations, according to Equations (38) and (39). This time, only *PhasEn* is able to detect the phases where the open-circuit faults occur. For example, this is not the case with *SlopEn*. Phase a entropy is too close to phase c entropy.

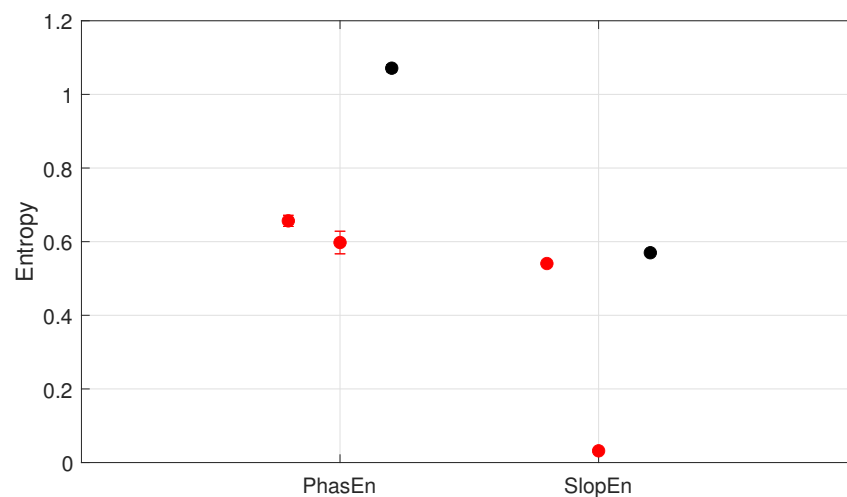


Figure 18. *PhasEn* and *SlopEn* for three open-circuit faults on B_a , T_b and B_b : phases a and b entropies with open-circuit faults in red and entropy of phase c in black.

5.7. Four Open-Circuit Faults on B_a —Phase a , T_b and B_b —Phase b and T_c —Phase c

Four open-circuit faults occur on B_a —phase a , on T_b and B_b —phase b and T_c —phase c . Figure 19 shows the entropies of phases a , b and c with open-circuit faults, in red according to Equations (40) and (41). Once again, *IncrEn* presents very good results.

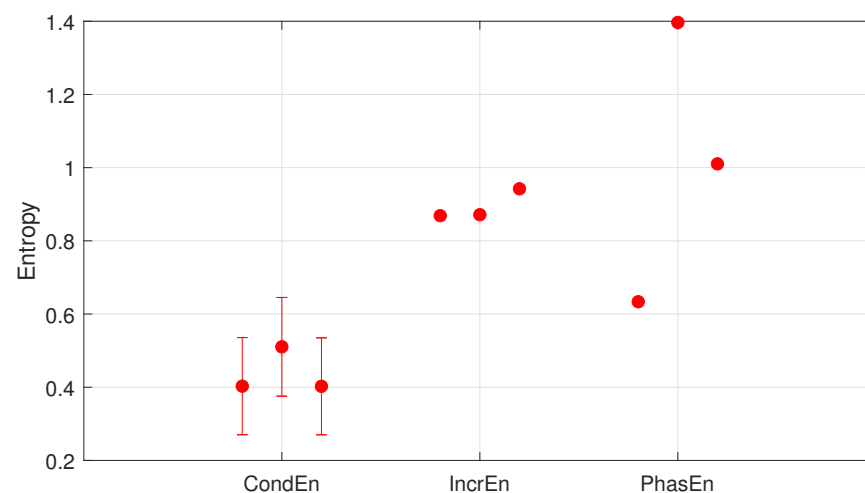


Figure 19. *CondEn*, *IncrEn* and *PhaseEn* for four open-circuit faults on B_a , T_b , B_b and T_c : entropies of phase a , b and c with open-circuit faults in red.

6. Optimization of Parameters L , m , r , τ and s

The parameters, data length N , embedding dimension m , time lag τ and tolerance r , are discussed in the next subsections. The calculated values of entropy depend on the parameters as embedded dimension m and tolerance r . The scale s may also affect the

performance of our fault detection method. Finding an optimum set is a major challenge. The parameter optimization is carried out by the maximization of the distance:

$$\max \left(\text{distance}_{j=1}^{52} \left| \text{entropy}(L, m, r, \tau, s)_{\text{phase}-x} - \text{entropy}(L, m, r, \tau, s)_{\text{phase}-y} \right| \right) \quad (42)$$

and

$$\max \left(\text{distance}_{j=1}^{52} \left| \text{entropy}(L, m, r, \tau, s)_{\text{phase}-z} - \text{entropy}(L, m, r, \tau, s)_{\text{phase}-w} \right| \right). \quad (43)$$

in the cases of single or two open-circuit faults and three open-circuit faults (two faults on the same phase). For three and four open-circuit faults on the three phases, the parameter optimization is carried out by the minimization of the distance:

$$\min \left(\text{distance}_{j=1}^{52} \left| \text{entropy}(L, m, r, \tau, s)_{\text{phase}-x} - \text{entropy}(L, m, r, \tau, s)_{\text{phase}-y} \right| \right) \quad (44)$$

and

$$\min \left(\text{distance}_{j=1}^{52} \left| \text{entropy}(L, m, r, \tau, s)_{\text{phase}-z} - \text{entropy}(L, m, r, \tau, s)_{\text{phase}-w} \right| \right). \quad (45)$$

All x , y , z and w cases are presented in Table 3. There are five main parameters for the entropy methods, including length L , embedding dimension m , threshold r , time delay τ and scale s . The optimal combination of L , m , r , τ and s should be searched. In order to check the incidence of the parameters variation on the entropy, we present *DispEn*, *rMSBubbEn* and *rMSAttnEn* with one open-circuit on T_a (Figure 13). The values of *CoSiEn* and *EnofEn* are evaluated if two open-circuits occur on B_a and T_b (Figure 14). *rMSSampEn*, *K2En*, *MSApEn*, *FuzzEn* and *SlopEn* are studied considering the phase fault as in Figure 15. Then, we examine *CondEn* with two other open-circuit faults: T_b and T_c , as in Figure 14. If there are three open-circuit faults on B_a , T_b and T_c , *IncrEn* is evaluated (Figure 17). The last entropy, *PhasEn*, is considered with three open-circuit faults B_a , T_b and B_b , as in Figure 18.

6.1. Varied Data Length (L)

Figure 20 show the analysis for the data length L . The parameter we used are: $m = 2$, $\tau = 1$, $r = 0.2$ and $s = 2$.

When changing from 1000 samples to 6000 samples, the data lengths are: $L_1 = 1000$ points; then, the length increases up to $L_2 = 2000$ samples, approximately two periods of the signal, followed by $L_3 = 3000$ points; $L_4 = 4000$ represents four signal periods; then, 5000 points are saved of L_5 data; and, finally, $L_6 = 6000$ samples, i.e., six signal periods, as in Figures 2b–12b.

rMSSampEn, *K2En*, *CondEn*, *DispEn*, *CoSiEn*, *rMSBubbEn*, *MSApEn*, *FuzzEn*, *PhasEn*, *SlopEn*, *EnofEn* and *rMSAttnEn* are performed with a specifier open-circuit fault. Then, the distance between the healthy phase (represented by a red curve) and the open-circuit phases (represented by a black curve) is maximal, except for one case: the distance between the three red curves is minimal for *IncrEn*, performed with three open-circuit faults B_a , T_b and T_c .

Figure 20a shows *rMSSampEn* as function of the data length. In Figure 20a, *rMSSampEn*, increases for L_1 – L_2 in the sample range (1000, 2000), decreases for $[L_2$ – $L_3]$ in the sample range (2000, 3000) and is followed by an increase in the range L_3 – L_4 in the sample range (3000, 4000). Then, it slowly decreases to a constant value for L_6 . *K2En*, *rMSBubbEn* are unchanged as L increases, keeping a constant entropy value as in Figure 20b,f. In Figure 20c, *CondEn* increases, decreases and increases slowly, keeping a constant distance between the entropies curves. *DispEn* of the healthy phase gradually decreases when the data length increases, as shown in Figure 20d. For *DispEn*, it is appropriate to choose L_1 because the

entropy values are length independent. To ensure a large difference between phases *a* and *b* entropies and phase *c* entropy (Figure 20e), it is appropriate to choose L_6 for *CoSiEn*.

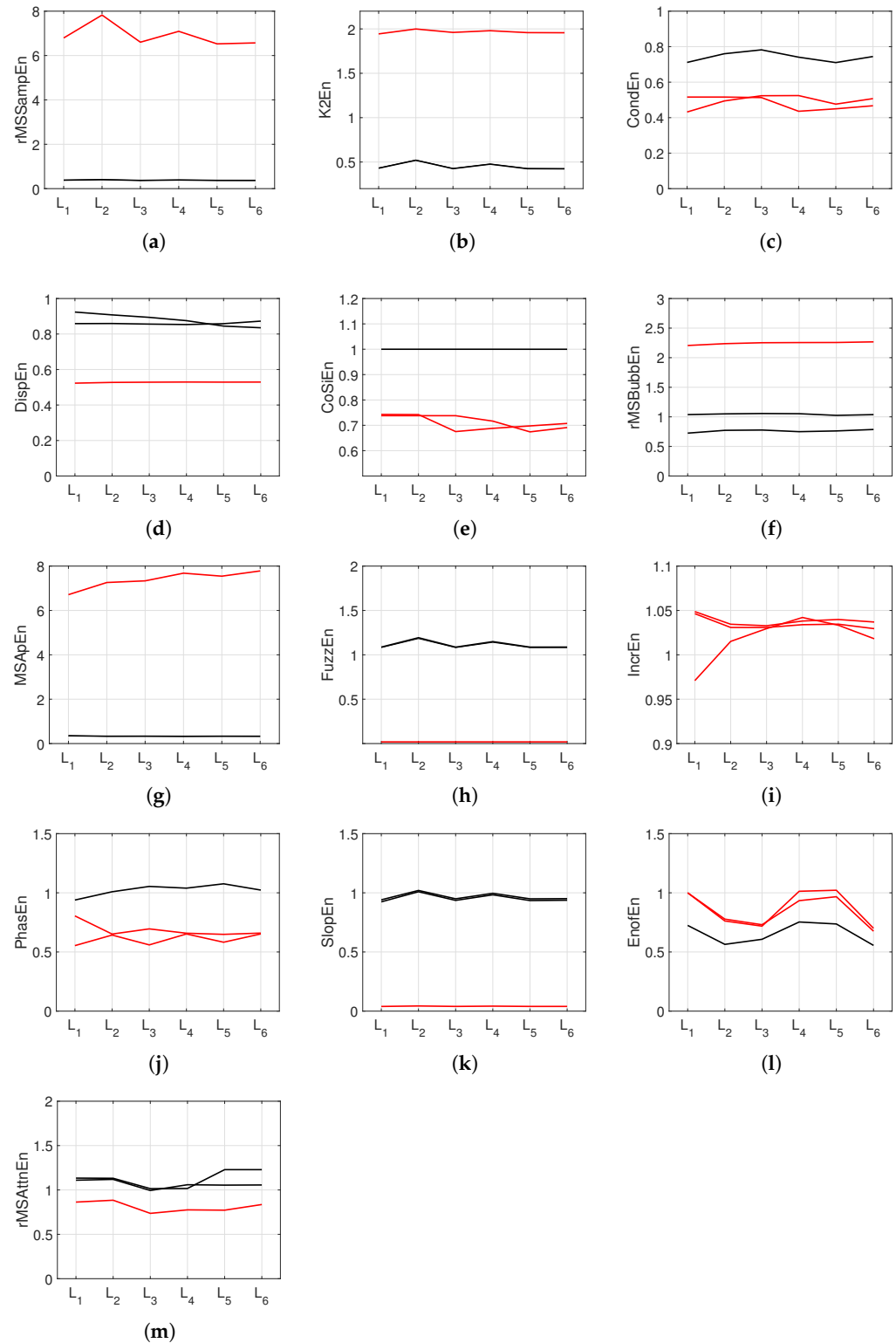


Figure 20. Entropies computed with (a) $rMSSampEn$, (b) $K2En$, (c) $CondEn$, (d) $DispEn$, (e) $CoSiEn$, (f) $rMSBubbEn$, (g) $MSApEn$, (h) $FuzzEn$, (i) $IncrEn$, (j) $PhasEn$, (k) $SlopEn$, (l) $EnofEn$ and (m) $rMSAttEn$ for the data length L : healthy phase represented by a black curve and the open-circuit phase represented by a red curve.

In Figure 20g, $MSApEn$ increases slowly for $[L_1-L_6]$ in the sample range (1000, 6000). With regards to the entropy shape, a large length of data ensures a maximum distance between the healthy and faulty phases. Figure 20h,k show $FuzzEn$ and $SlopEn$. After an insignificant variation, the entropies are nearly constant when L is in the range $[L_5, L_6]$. A suitable value of data length is L_3 for $IncrEn$: the distance between the three entropies is minimal. A maximal distance between the healthy phase (red curve) and the open-circuit phases (black curve) of $PhasEn$ is for L_6 , as in Figure 20j. The results of $EnofEn$ and $rMSAttnEn$ are shown in Figure 20l,m. Even if these entropies vary (increase or decrease), the distance between the healthy and faulty phases is constant. It seems better to choose L_5 as the data length.

6.2. Varied Embedding Dimension (m)

Let us change m from 2 to 8 to study the effect of m on these approaches ($rMSSampEn$, $K2En$, $CondEn$, $DispEn$, $CoSiEn$, $rMSBubbEn$, $MSApEn$, $FuzzEn$, $IncrEn$ and $SlopEn$) as in Figures 21a–j. The functions $PhasEn$, $EnofEn$ and $AttnEn$ do not have an embedding dimension m .

Results of $SampEn$, $rMSBubbEn$ and $ApEn$ are shown in Figure 21a,f,g. These entropies decrease faster, ensuring a large difference between phase a entropy and phases b and c entropies for $m = 2$. $K2En$, $CondEn$, $FuzzEn$ and $CoSiEn$ are constant when m is in the range $[2, 8]$, as in Figure 21b,c,e,h. In Figure 21d, $DispEn$ gradually decreases when the embedding dimension m increases, keeping a constant difference between the entropy of phase a and the entropies of phases b and c , as in Figure 21d.

Figure 21i shows the entropies $IncrEn$ of phases a , b and c (in red), which are very close to each other. $m = 2$ is chosen in order to minimise the distance between these entropies. For the last entropy, $SlopEn$ (Figure 21j): the entropies of the healthy phases b and c decrease when m increases; the entropy of the open-circuit phase a increases when m increases. It is appropriate to choose $m = 2$ for $SlopEn$.

6.3. Varied Time Lag (τ)

Here, we deepen the influence of another indicator, such as time lag τ on some entropies. Time lag τ varies from 1 to 7. We already illustrated the influence of data length L and embedding dimension m on the entropy; let us now examine the performance of $rMSSampEn$, $K2En$, $CondEn$, $DispEn$, $CoSiEn$, $rMSBubbEn$, $MSApEn$, $FuzzEn$, $IncrEn$, $PhasEn$, $SlopEn$ and $EnofEn$ with the variation of time lag τ . The function $AttnEn$ does not require a time lag τ . The data length L , embedding dimension m , scale s and tolerance r were fixed at $N = 6000$, $m = 2$, $s = 2$ and $r = 0.2$ in the following analysis.

Figure 22a,f,g, show the impact of different values of τ on $rMSSampEn$, $rMSBubbEn$ and $rMSApEn$: a steep decrease of these entropies of phase a and a nearly constant value for phases b and c can be observed when τ increases. The major difference between the curves is for a smaller $\tau = 1$. We find that the difference between the $CondEn$, $DispEn$, $CoSiEn$, $PhasEn$ and $EnofEn$ of healthy phase and open-circuit phase is nearly constant, suggesting correlation, as plotted in Figure 22c–e,j,l.

In Figure 22b the shape of $rMSK2En$ in function of τ , decreases at the beginning of the interval $\tau = [1, 2]$, followed by a slow increase for $\tau = [2, 4]$, ending with an abrupt increase of open-circuit phase entropy. Figure suggests that $\tau = 7$ suits well for the calculation of $rMSK2En$. $FuzzEn$ entropy of phases a and b is shown in Figure 22h: only larger time-lag entropies have a relevant significance. For τ equals to 1, $FuzzEn$ is 1.1, and exceeds 1.7 for $\tau = 7$.

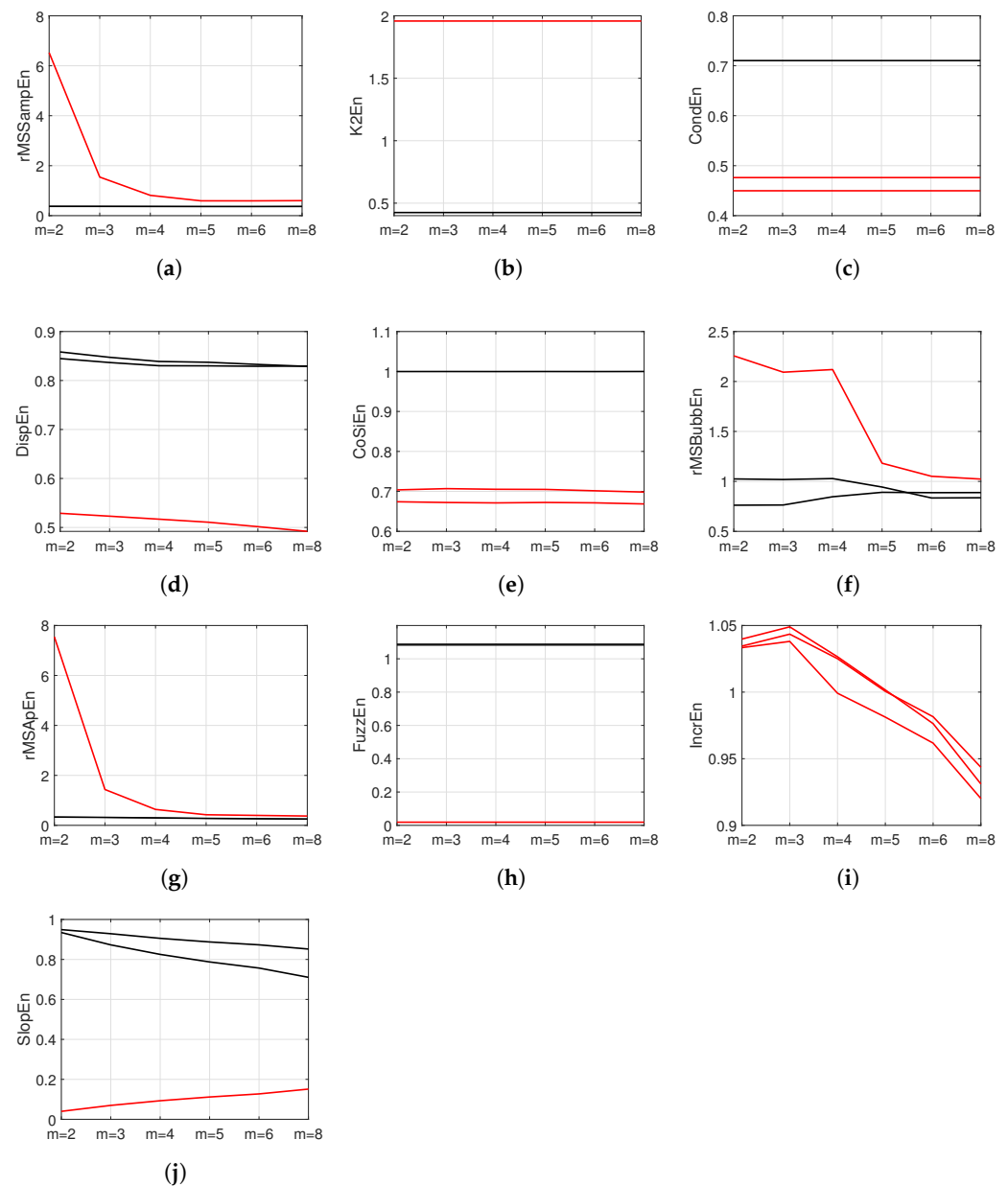


Figure 21. Entropies computed with (a) $rMSSampEn$, (b) $K2En$, (c) $CondEn$, (d) $DispEn$, (e) $CoSiEn$, (f) $rMSBubbEn$, (g) $rMSApEn$, (h) $FuzzEn$, (i) $IncrEn$ and (j) $SlopEn$ for the embedding dimension m : healthy phase represented by a black curve and the open-circuit phase represented by a red curve.

Figure 22i shows the entropies $IncrEn$ of phases a , b and c , which are very close to each other. $\tau = 1$ is chosen in order to minimize the distance between these entropies. $SlopEn$ presents a peak for $\tau = 3$: the difference between $FuzzEn$ of phase a and of phase b is then maximal. However, as the time-lag increases, the difference between black and red curves become smaller. Only a lower time-lag ($\tau = 3$) entropy has a relevant significance, as in Figure 22k.

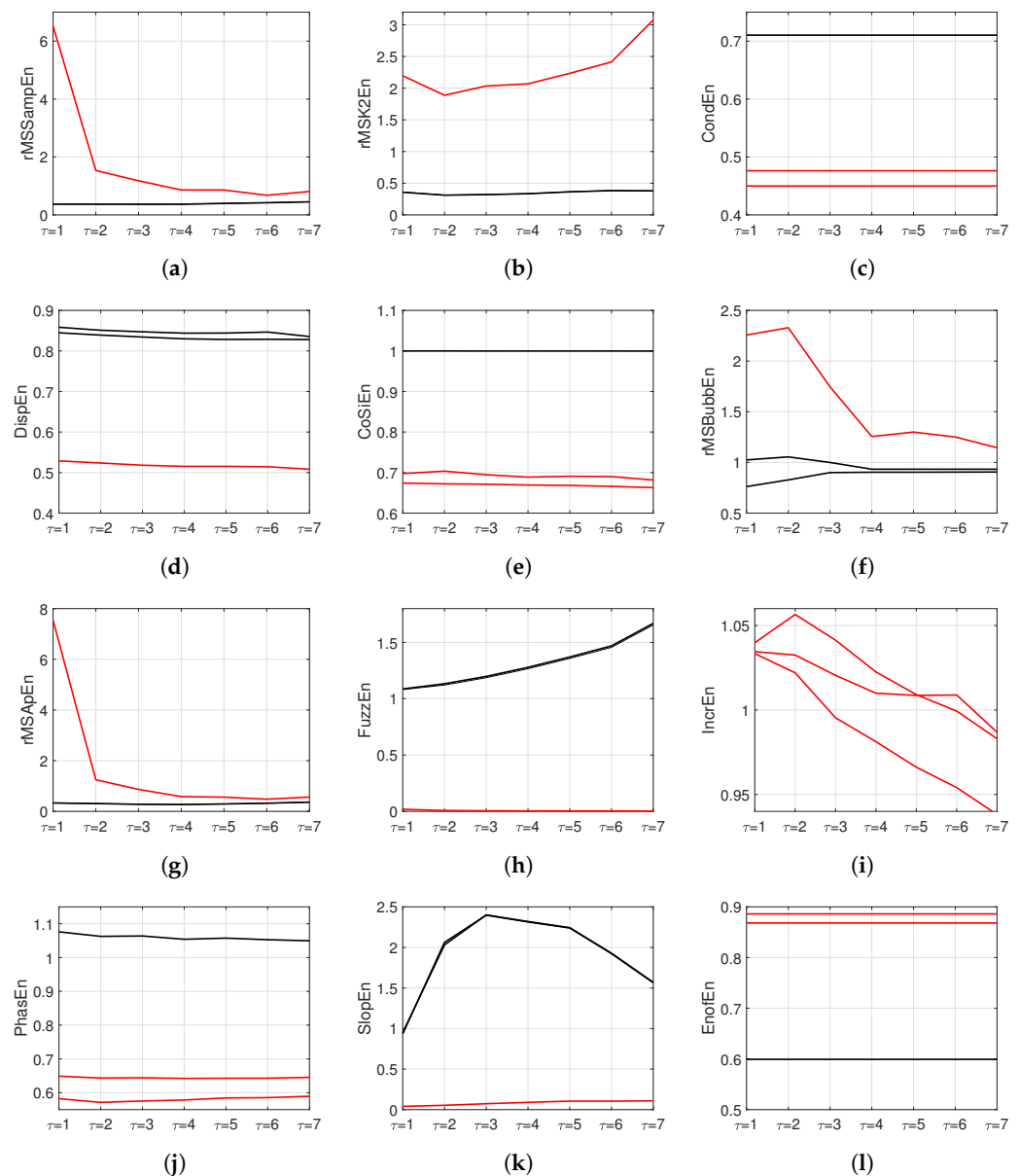


Figure 22. Entropies computed with (a) $rMSSampEn$, (b) $rMSK2En$, (c) $CondEn$, (d) $DispEn$, (e) $CoSiEn$, (f) $rMSBubbEn$, (g) $rMSApEn$, (h) $FuzzEn$, (i) $IncrEn$, (j) $PhasEn$, (k) $SlopEn$ and (l) $EnofEn$ for the time lag τ : healthy phase represented by a black curve and the open-circuit phase represented by a red curve.

6.4. Varied Tolerance (r)

The analysis of the tolerance r , changing from 0.2 to 0.7, was only performed on $rMSSampEn$, $rMSK2En$, $CoSiEn$, $rMSApEn$ and $FuzzEn$. The data length, time lag and embedding dimension are $N = 6000$, $\tau = 2$, $s = 2$ and $m = 2$.

Figure 23a,c present the impact of several r values on, respectively, $rMSSampEn$ and $rMSApEn$. The increase of r results in a monotone increase of $rMSSampEn$ and $rMSApEn$ of faulty phase a (Figure 23a) except for the constant values for $r = [0.4, 0.5]$. $rMSSampEn$ and $rMSApEn$ both of phase b , with no-fault, are nearly constant. The largest difference between the two curves is for a large r . The figures suggest that $r = 0.7$ is suitable for the calculation of $rMSSampEn$ and $rMSApEn$ values. Figure 23b shows $rMSK2En$: the entropy of the healthy phases b and c increases when the embedding dimension m increases; the entropy of the open-circuit phase a decreases when the embedding dimension m increases.

It is appropriate to choose $r = 0.2$ for $rMSK2En$. For the last entropy, the difference between phases a and $bFuzzEn$ is nearly constant, as plotted in Figure 23d. The entropy $FuzzEn$ is valid for any value of r .

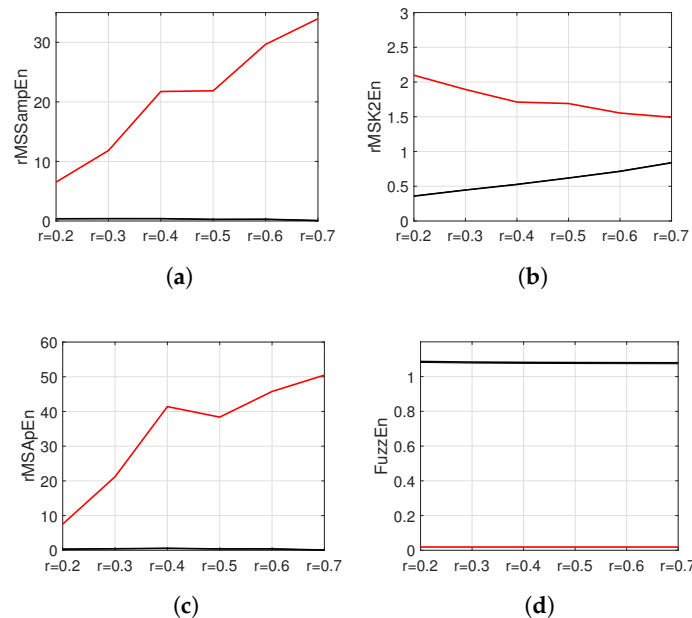


Figure 23. Entropies computed with (a) $rMSSampEn$, (b) $rMSK2En$, (c) $rMSApEn$ and (d) $FuzzEn$ for the tolerance r : healthy phase represented by a black curve and the open-circuit phase represented by a red curve.

6.5. Varied Scale (s)

Figure 24a–l illustrate the performance of all entropies: $rMSSampEn$, $K2En$, $CondEn$, $DispEn$, $CoSiEn$, $rMSBubbEn$, $rMSApEn$, $FuzzEn$, $IncrEn$, $PhasEn$, $SlopEn$, $EnofEn$ and $rMSAttEn$. To investigate the effects of scale s on these entropies, we used: $L = 6000$ points, $m = 2$, $\tau = 1$ and $r = 0.2$.

Figure 24a shows $rMSSampEn$ as a functions of scale. The entropy of the open-circuit phase a decreases for $s = [1, 2]$, is nearly constant in the range $s = [3, 7]$, followed by an increase in the range of $s = [7, 9]$, ending with a decrease for $s = [9, 10]$. In the meantime, the entropy of the healthy phase is nearly constant for all ranges of s . The scale $s = 2$ is appropriate. As for $rMSSampEn$, $rMSK2En$ is nearly constant for a healthy case. After a very slow variation, $rMSK2En$ of the open-circuit phase a increases in the range $s = [5, 9]$, decreasing at the end for the last scale. To ensure a large difference between phase a entropy and phases b and c entropies, it is appropriate to choose $s = 9$ for $rMSK2En$, as in Figure 24b.

In Figure 24c–e,h,j, $CondEn$, $DispEn$, $CoSiEn$, $FuzzEn$ and $PhasEn$ are represented. The differences between the healthy phase entropy and the open-circuit phase entropy are nearly constant over the range $s = [2, 10]$.

Results of $rMSBubbEn$ are shown in Figure 24f. The entropy of phase a decreases gradually with an increase of s . Meanwhile, entropy of phase b undergoes slight variations. The first scale $s = 2$ gives the largest distance between the entropies of phases a and b . The same result is obtained for $rMSApEn$, as in Figure 24g. At the end of the s interval, the two curves merge and the open-circuit fault on phase a cannot be detected any more. Only a lower scale ($s = 2$) entropy has relevant significance, as in Figure 24g. Scale $s = 4$ or 5 gives the smallest distance between the faulty phases a , b and c for $IncrEn$, as shown in Figure 24i.

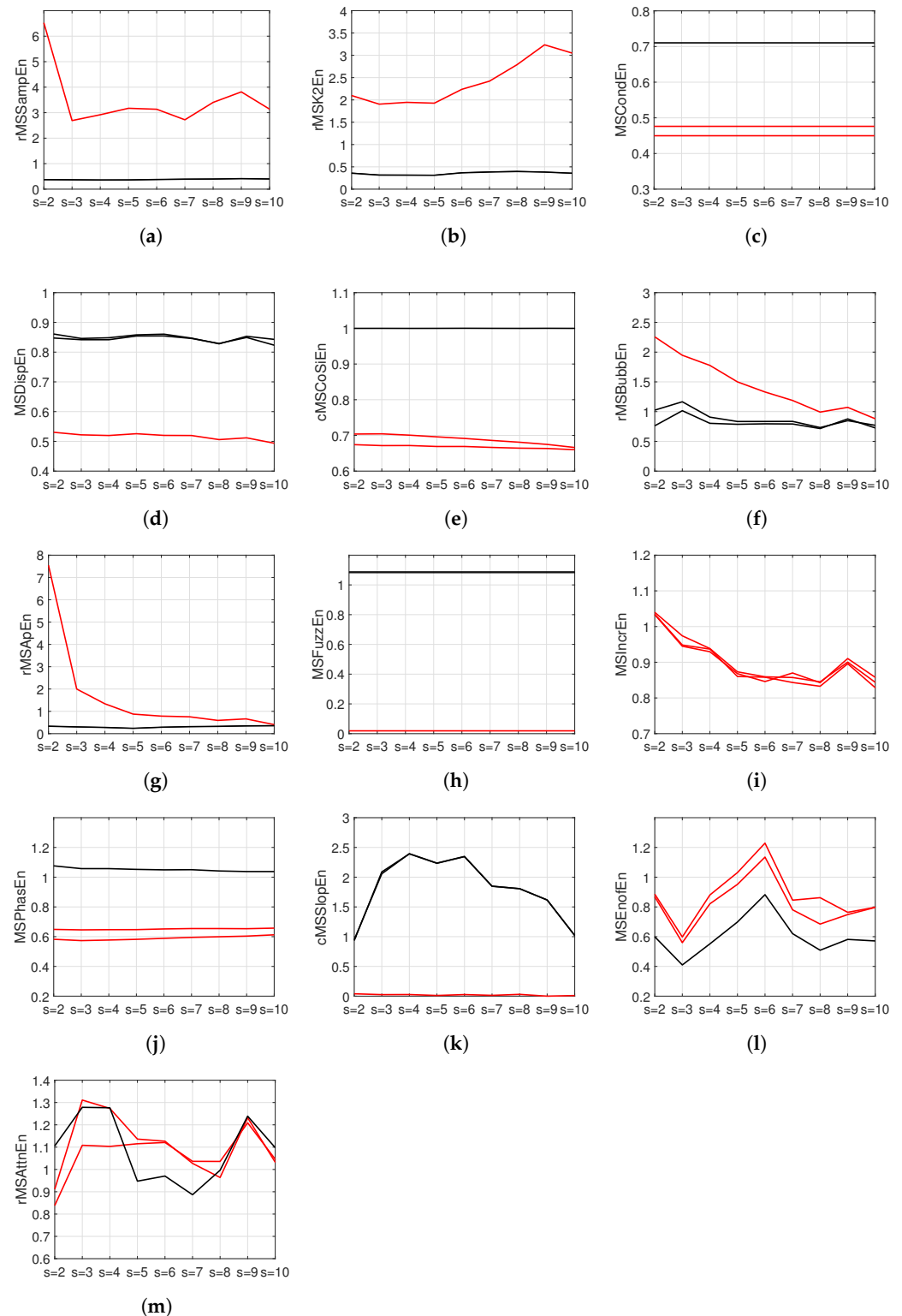


Figure 24. Entropies computed with (a) $rMSSampEn$, (b) $rMSK2En$, (c) $MSCondEn$, (d) $MSDispEn$, (e) $cMSCoSiEn$, (f) $rMSBubbEn$, (g) $rMSApEn$, (h) $MSFuzzEn$, (i) $MSIncrEn$, (j) $MSPhasEn$, (k) $cMSSlopEn$, (l) $MSeNoEn$ and (m) $rMSAttEn$ for the scale s : healthy phase represented by a black curve and the open-circuit phase represented by a red curve.

$cMSSlopEn$ entropy of phases a and b is shown in Figure 24k: only lower scale entropies show a relevant significance. For $s = 2$, $cMSSlopEn$ is 1, exceeding 2.4 for $s = 4$. Furthermore, the scale analysis reveals additional entropy information not previously

observed at scale $s = 2$. $cMSSlopEn$ clearly presents two peaks for $s = 4$ and 6 : the difference between phase a and phase b $cMSSlopEn$ is maximal for $s = 4$. However, the difference between the black and red curves becomes smaller as the scale increases.

The results of $MSEnofEn$ are shown in Figure 24l. Even if these entropies vary (increase or decrease), the distance between the healthy and faulty phases is constant. It seems better to choose the scale $s = 2$.

Figure 24m shows that $rMSAttnEn$ with repeated up and down, where phase a entropy and phases b and c entropies are interlaced. As long as the two curves (phase a entropy and other phases entropy) merge, the phase a open-circuit fault cannot be detected. Only lower scale ($s = 2$) and middle scale ($s = 5, 6$ or 7) entropies have relevant significance.

6.6. New Setting of Parameters

Parameters are now set to: $N = 2000$, $m = 2$, $\tau = 1$, $r = 0.7$, $s = 2$ for $rMSSampEn$; $N = 2000$, $m = 2$, $\tau = 7$, $r = 0.2$, $s = 9$ for $K2En$; $N = 2000$, $m = 2$, $\tau = 1$, $s = 2$ for $CondEn$; $N = 5000$, $m = 8$, $\tau = 7$, $s = 9$ for $DispEn$; $N = 5000$, $m = 2$, $\tau = 1$, $r = 0.2$, $s = 10$ for $CoSiEn$; $N = 2000$, $m = 2$, $\tau = 1$, $s = 2$ for $rMSBubbEn$; $N = 6000$, $m = 2$, $\tau = 1$, $r = 0.7$, $s = 2$ for $rMSApEn$; $N = 2000$, $m = 2$, $\tau = 7$, $r = 0.2$, $s = 2$ for $FuzzEn$; $N = 3000$, $m = 2$, $\tau = 1$, $s = 2$ for $IncrEn$; $N = 2000$, $\tau = 1$ and $s = 2$ for $PhasEn$; $N = 2000$, $m = 2$, $\tau = 3$, $s = 4$ for $SlopEn$; $N = 5000$, $\tau = 1$ and $s = 4$ for $EnofEn$; $N = 3000$ and $s = 6$ for $rMSAttnEn$. These new settings of parameters are able to increase the distance between faulty and non-faulty phases or to decrease this distance in the $IncrEn$ case. Some entropy functions will be applied to distinguish the healthy state and an open-circuit faulty state and to fault classification, considering the new setting parameters.

7. Conclusions

In this paper, we provide a systematic overview of many known entropy measures, highlighting their applicability to inverter fault detection. Several usual entropies (sample entropy, Kolmogorov entropy, dispersion entropy, cosine entropy, bubble entropy, approximation entropy, fuzzy entropy, incremental entropy, phase entropy, slope entropy, entropy of entropy, attention entropy) and multiscale entropies (and also refined multiscale entropy, composite multiscale entropy) are proposed to quantify the complexity of the brushless motor currents. Their roles in fault detection are summarized into the entropy distance between a healthy phase and an open-circuit faulty phase. Moreover, this paper reveals the great ability of some entropies to distinguish between a healthy and an open-circuit faulty phase. Finally, the simulation results show that these entropies are able to detect and locate the arms of the bridge with one, two, three or even four open-circuit faults.

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