



## Faults detection approach using PCA and SOM algorithm in PMSG-WT system

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### Abstract

In this paper, a new approach for faults detection in observable data system wind turbine - permanent magnet synchronous generator (WT-PMSG), the studying objective, illustrate the combination (SOM-PCA) to build Multi-local-PCA models faults detection in system (WT-PMSG), the performance of the method suggested to faults detection in system data, finding good results in simulation experiment.

### Keywords

Permanent magnet synchronous generator (PMSG); Diagnostic; Self Organized Map (SOM); Principal Component Analysis (PCA); Multi-PCA

### Introduction

Wind energy is becoming an important consideration in the planning and development of the modern electric system. In the past decade, grew output of wind energy strongly, and was faster than the combination of all other forms of electrical energy, in this scientific boom, and the remarkable growth in wind turbines, in 2010 the wind energy industry installed more turbines than all previous years combined.

The wind energy tends to be one of the perfect renewable energy options, this is due to a number of factors, including the fact that wind stations are much quicker in design, construction, pollution, least expensive and permission than traditional stations [1].

Recently, the main objective of the wind energy is to be more economically, with increase profits and reduce costs, including costs associated with the maintenance of wind turbines, which it exploit the important weight of the costs [2,3].

The faults detection and isolation in wind turbines at an early stage is very important for the procedures maintenance and protection of the costly systems against faults, because these procedures can reduce outage time and can prevent errors greater can lead to damage in system.

Faults detection in WT-PMSG (Wind Turbine - Permanent Magnet Synchronous Generator) is a theme concerned by the research community, these methods are generally based on data exploration and analysis techniques, compression, data space transformation representation and neural network models.

In recent years, SOM (Self Organized Map) is one of the famous multivariate classification techniques used in fault detection. the idea is to define the projection of process data on a lower dimensional variable space, and extracting information without loss of useful information far noises, to greatly simplify the process monitoring procedure and acquire easily the faults detection steps after comparison between similar ideal systems. Where, the principal advantage of this method is in depending on historical and operational data without need for a thorough knowledge of the complicated process. The advantage of this technique can be in the remedy the problem posed by nonlinear relations in observable data, without need for a thorough knowledge of the complicated process, this method counter to old techniques, such as PCA (Principal Component Analysis) [4], we propose a new nonlinear process monitoring technique based on SOM Algorithm and PCA to solve the problem posed by nonlinear relation in observable data.

## **Material and method**

### ***Wind turbine modelling***

The power extracted from the wind by a wind turbine is given by [5-7] the following formula:

$$P_{wt} = \frac{1}{2} \rho \pi R_p^2 V_w^3 C_p \quad (1)$$

where  $R_p$  is the blade radius of the wind turbine,  $V_w$  is the wind speed,  $\rho$  is the air density, and  $C_p$  is the power coefficient.

The torque that can be recovered on the turbine shaft is calculated by [6, 8] the following formula:

$$\Gamma_e(\Omega, \lambda) = \frac{1}{2} \rho \pi R_p^3 V_w^2 C_T(\lambda) \quad (2)$$

where the torque coefficient  $C_T(\lambda)$  can be approximated by the following sixth order polynomial function [6] as following:

$$C_T(\lambda) = a_0 + a_1 \lambda + a_2 \lambda^2 + a_3 \lambda^3 + a_4 \lambda^4 + a_5 \lambda^5 + a_6 \lambda^6 \quad (3)$$

The tip speed ratio is defined as:

$$\lambda = \frac{\Omega R}{V_w} \quad (4)$$

where,  $\Omega$  is the mechanical angular velocity of the turbine rotor.

The  $C_p$  equations is given by:

$$C_p = \lambda C_T(\lambda) \quad (5)$$

### ***Synchronous generator modelling***

This paper presents the model of permanent magnet synchronous generator based on wind energy conversion system. We use the park model. Then, the PMSG model is given as follows [8]:

$$v_d = R_s i_d + L_q \frac{di_d}{dt} - \omega_r L_q i_q \quad (6)$$

$$v_q = R_s i_q + L_q \frac{di_q}{dt} + L_d \omega_r i_d + \omega_r \sqrt{\frac{3}{2}} \Phi \quad (7)$$

$$\Gamma_{em} = p((L_d - L_q) i_d i_q + \omega_r \sqrt{\frac{3}{2}} \Phi i_q) \quad (8)$$

where  $v_d$ ,  $v_q$ ,  $i_d$ ,  $i_q$  are respectively the magnitudes of stator voltages and currents on the axes d, q, also,  $\Gamma_{em}$  is the torque of PMSG,  $\Phi$  is the rms of the flux generated by the rotor and which passes through the armature windings,  $L_q$  is q axis inductance,  $L_d$  is d axis inductance,

$R_s$  is the resistance of a stator phase,  $\omega_r$  is the pulsation of the rotor field, which is related to the rotation speed of the rotor  $\Omega$  by  $\omega_r = p\Omega$ , and  $p$  is the quantity of poles pair.

The dynamic equations are given by:

$$\frac{d\omega_r}{dt} = \frac{1}{J}(\Gamma_{em} - \Gamma_e - F_r\omega_r) \quad (9)$$

$$\frac{d\theta_r}{dt} = \omega_r \quad (10)$$

where  $J$  is the inertia of rotor,  $F_r$  is the friction of rotor and rotor angular  $\theta_r$ .

Synchronous generators play an important position due to their widely use in the field of wind energy. Hence, faults detection in synchronous generators is decisive to the reliability of wind turbines [9]. To help the preventive maintenance of these generators, the most important step is the early detection of defects, and without a stop or interruption in their operation.

**Table 1.** Simulation parameters PMSG WT System

Parameters PMSG WT		
$R_p$	3	[m]
$V_w$	9	[m/s]
$\rho$	1.25	[kg/m <sup>3</sup> ]
$L_d$	0.0273	[H]
$L_q$	0.0213	[H]
$R_s$	0.75	[Ω]
$p$	3	
$J$	0.2	[kg.m <sup>2</sup> ]

### ***Principal Component Analysis (PCA)***

PCA is a data analysis method based on a simple transformation of collected data (observations without fault), stored in a reduced and normalized matrix  $X \in \mathfrak{R}^{n \times m}$ , to produce statistically independent score variables, stored in  $T \in \mathfrak{R}^{n \times m}$  [10-12].

$$X = TP^T \quad (11)$$

where,  $T$  and  $P$  are known as are the matrix of the principals components (PCs) and eigenvectors, respectively, from the spectral decomposition of the covariance matrix  $\Sigma$  of  $X$  :

$$\Sigma = P\Lambda P^T \quad (12)$$

$$PP^T = I_m \quad (13)$$

where  $\Lambda$  is the diagonal matrix composed of  $m$  eigenvalues in descending order.

By projecting the original information onto a lower dimensional space  $l < m$ ,  $X$  can be

decomposed as the following equation:

$$X = \hat{X} + E \quad (14)$$

where,

$$\hat{X} = \hat{T}\hat{P}^T \text{ and } E = \tilde{T}\tilde{P}^T \quad (15)$$

and

$$X = [\hat{T} \quad \tilde{T}] [\hat{P} \quad \tilde{P}]^T \quad (16)$$

With

$$\hat{X} = X \hat{P} \hat{P}^T \quad (17)$$

the residual matrix  $E$  can be as following :

$$E = X - \hat{X} = X (I - \hat{P} \hat{P}^T) \quad (18)$$

where  $\hat{T} \in \mathfrak{R}^{n \times \ell}$  and  $\hat{P} \in \mathfrak{R}^{m \times \ell}$  are the matrix of the principal components and eigenvectors, respectively of the main sub-space,  $\tilde{T} \in \mathfrak{R}^{n \times (m-\ell)}$  and  $\tilde{P} \in \mathfrak{R}^{m \times (m-\ell)}$  are the matrix of the principal components and eigenvectors, respectively of the residual sub-space.

The number of proper principal components  $\ell$  can be determined by different methods, such as, the accumulated contributions of the principal components, VNR (unreconstructed variable) or cross validation [12].

### ***Faults detection by PCA***

Process monitoring is based on the two statistics called  $T^2$  and  $SPE$  respectively [12].

The Hotelling  $T^2$  statistic, based on the first  $\ell$  PCs, is defined as:

$$T^2 = X \hat{P} \Lambda^{-1} \hat{P}^T X^T \quad (19)$$

The confidence limit for  $T^2$  at significance level  $(1-\alpha)$  are related to the  $F$ -distribution is as follows:

$$T_{\alpha}^2 = \frac{\ell(n^2 - 1)}{n(n - \ell)} F_{\alpha}(\alpha, n - \alpha) \quad (20)$$

The squared prediction error  $SPE$  or  $Q$  statistic indicates the correspondence of each sample to the model, measured by the projection of the vector samples in the residual subspace. The prediction from the PCA model is given by [12]:

$$SPE = \|e\|^2 = e^T(k)e(k) \quad (21)$$

The process is considered in normal situation if:

$$SPE \leq \delta_\alpha^2 \quad (22)$$

where  $\delta_\alpha^2$  is the detection threshold of *SPE* significance  $\alpha$  level.

$$\delta_\alpha^2 = \theta_1 \left[ 1 + \frac{c_\alpha h_0 \sqrt{2\theta_2}}{\theta_1} + \frac{\theta_2 h_0 (h_0 - 1)}{\theta_1} \right]^{1/h_0} \quad (23)$$

$$\theta_i = \sum_{j=\ell+1}^m \lambda_j^i \quad i = 1, 2, 3 \dots \quad (24)$$

$c_\alpha$  is the confidence limits for the  $(1-\alpha)$  percentile in a standard normal distribution. These confidence limits are calculated based on the assumptions that the measurements are time independent and multivariate normally distributed.

### ***Self-Organizing Maps (SOM)***

Self-organizing maps provide an alternative to PCA that is accommodating nonlinear relationships in the dataset [13, 14].

SOM is a method data analysis to complement traditional linear techniques without replacement, although it provides additional power for nonlinear datasets [14].

As SOM algorithm is a method of nonlinear projection, it effectively classify data into different clusters, without any explicit modeling of the system [13, 14].

The formation of SOM is iterative time process that converges to centroids of input vectors  $X$ , the index of the winner class is defined on the basis of the most widely used distance, the Euclidean distance between  $X$  and  $W$ , with calculation of the minimum distance [4, 14-16].

$$\|X - W_c\| = \min_i \{ \|X - W_i\| \} \quad (25)$$

where  $W_i$  is the winner prototype and  $i$  is the index of the winner class.

Through a similarity measure and update the values of the vectors of the winning prototype

$$\Delta W_i(t) = \begin{cases} \varepsilon(t)(x(t) - w_i(t)) & \text{if } i \in N_c \\ 0 & \text{if } i \notin N_c \end{cases} \quad (26)$$

$\varepsilon(t)$  is the learning rate and  $N_c$  the neighbors of class  $c$ .

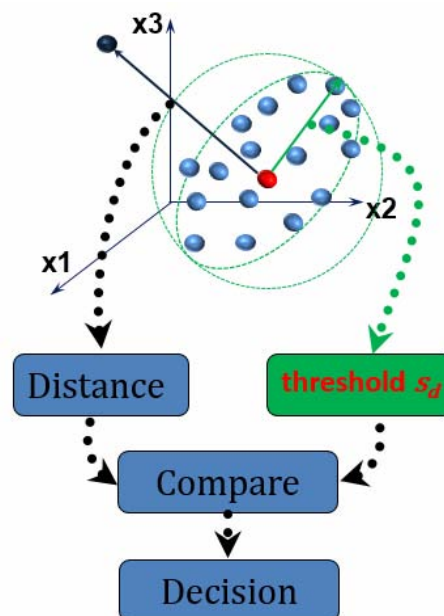
Equations of updated prototype can be as follow:

$$W_i(t+1) = \begin{cases} W_i(t) + \Delta W_i(t) & \text{if } i \in N_c \\ W_i(t) & \text{if } i \notin N_c \end{cases} \quad (27)$$

After define the optimized vector, the classification of the input data (without faults) is obtained in model saint, this classification can be characterized by the distances between the input data and their prototypes. On this concept the proposed method fault detection was been based.

### *SOM fault detection*

This paper presents the case of modeling used the SOM algorithm, where the input data corresponding to a normal data has been used to train the SOM. This data can be represented by normal model formed with different classes; this last is characterized by their prototypes and detection threshold. Once, the model is ready, it is exposed to the actual data from the system under unknown state. The data points are injected and classified onto the precedent model to describing the current state of the system. This information can be used for fault detection (Figure 1).



**Figure 1.** Fault detection with Kohonen (SOM) algorithm

For the detection of defective data, threshold is used; it is a distance  $D_i$  interval that defines the class containment of data.

This data is abnormal if the distance between the prototype of class and the data

exceeds the detection threshold.

$$S_d = \min_i \{ D_i \} \quad (28)$$

where

$$D_i = \| x_i - P_c \| \quad (29)$$

$P_c$  is the prototype of the class  $c$ .

The detection threshold is defined by the maximum distance can cover the class to contain data, consider the actual data from the system  $x_i(t)$

$$\text{If } D_i = \| x_i - P_c \| > S_d \quad (30)$$

$x_i$  is abnormal.

Else

$x_i$  is normal.

After determine the threshold detection, this method can used in real time, where  $x_i(t)$  can be a new data classified in  $c$ , and  $P_c$  is the prototype of the class  $c$ .

### ***Multi-models PCA approach***

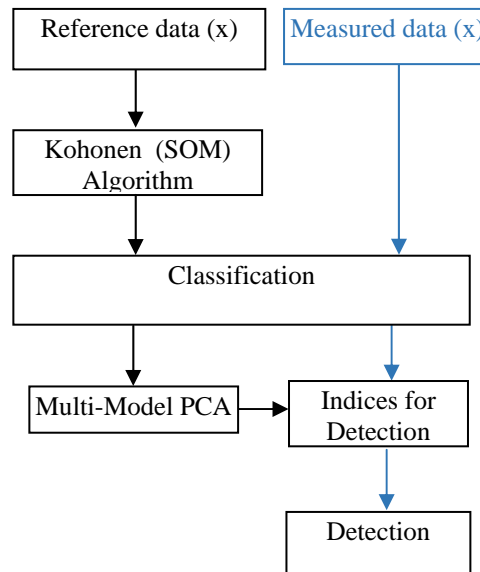
The nonlinear PCA is an extension of the linear PCA [17]. While this latter seeks to identify linear relationships between the variables of the process, the purpose of the non-linear PCA is to extract both linear relationships and analyze nonlinear data [18].

### ***Modeling with multi-models PCA***

We propose in this work, a nonlinear model can be combining several PCA-linear models. The idea of this approach is to understand the nonlinear behavior of a system by a set of local models (PCA-linear).

The concept of multi-model introduces the definition of the use of the PCA in different operating zones. To determine the different local models [4], the Kohonen algorithm (SOM) is used for the classification of data, each class data supply the PCA to determine the sub-model and subsequently detect anomalies by different indices detection study in Figure 2.





**Figure 2.** The sketch map of the fault detection

Also, the proposed method can be used in real time, with fixing the class corresponding to the new measure and examining its state if it is normal or defected.

### ***SOM-PCA fault detection algorithm***

**Step 1:** Obtain data  $X$  without fault

**Step 2:** Data Modelling

SOM data classification in  $i$  classes  $c_i$

- Fault detection indices  $D_i$  and threshold  $S_d$

PCA data model of  $c_i$

- Fault detection indices  $SPE$  and threshold  $\delta_\alpha^2$

**Step 3:** Obtain new data

**Step 4:** New Data test

Projection of new data in  $c_i$  classes using SOM

- Fault detection indices  $D_i$  and compare with threshold  $S_d$

PCA Fault detection

- Fault detection indices  $SPE$  and compare with threshold  $\delta_\alpha^2$

**Step 5:** Decision

If  $SPE < \delta_\alpha^2$   $x_i$  is normal else  $x_i$  is abnormal

$D_i < S_d$   $x_i$  is normal else  $x_i$  is abnormal.

### Results and discussion

The feasibility of the proposed method is evaluated using signals derived from the modeling the system wind turbine and PMSG outputs (currents in three phases) in normal case, and with created faults.

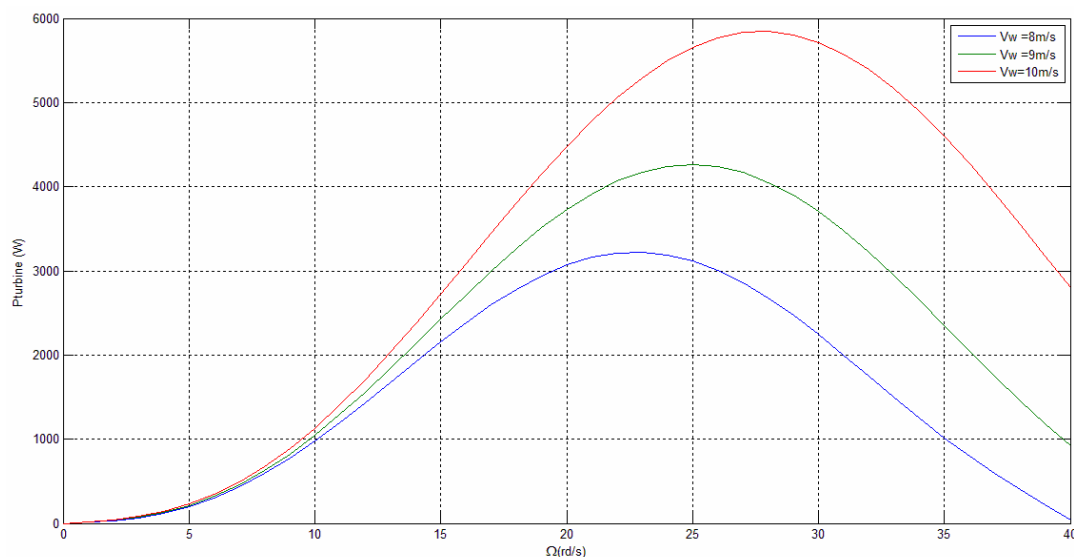
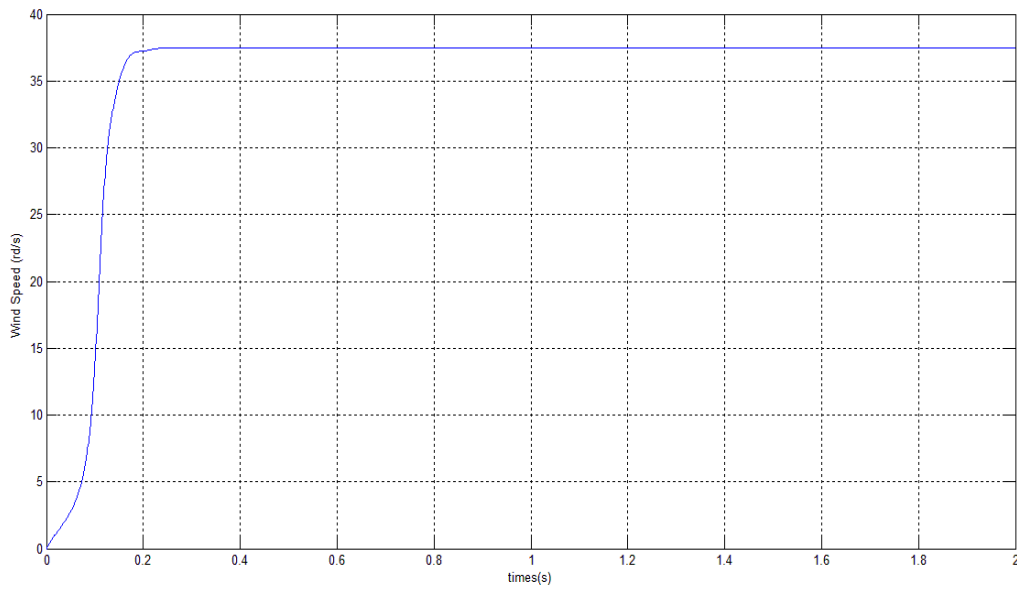


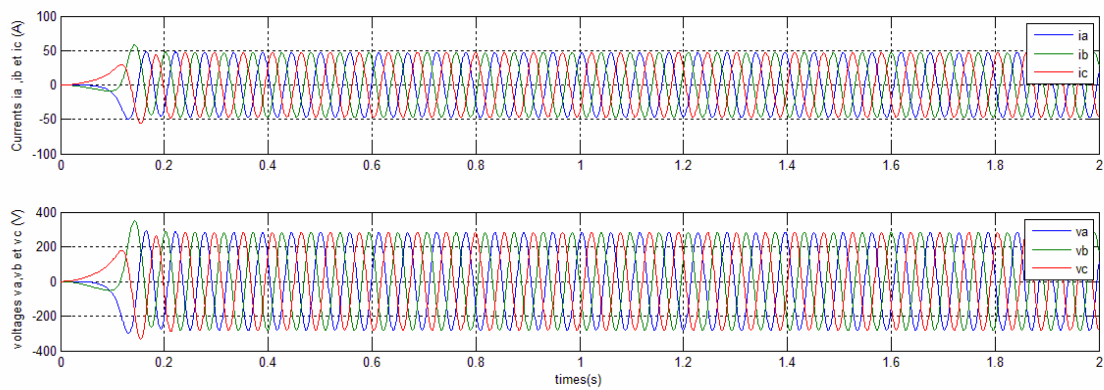
Figure 3. Wind Turbine Power coefficients versus tip speed ratio in different cases of wind speed



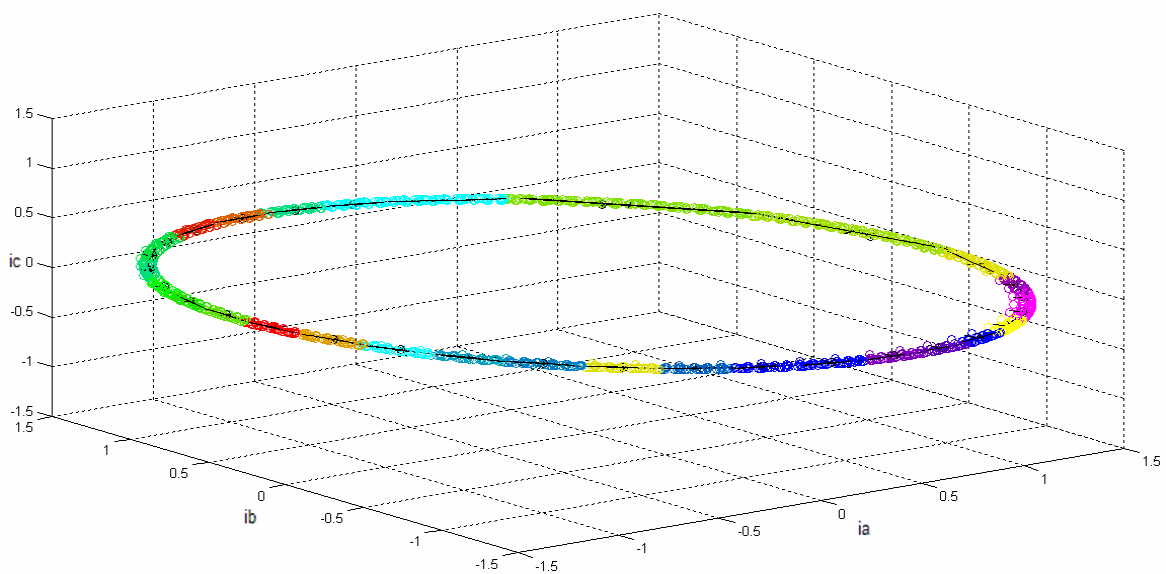
Figure 4. Power coefficients versus rotational speed in different cases of wind speed



*Figure 5. Time evolution of wind speed*



*Figure 6. Time evolution of currents and voltages without fault*



*Figure 7. Estimation of the curve using the SOM-PCA*

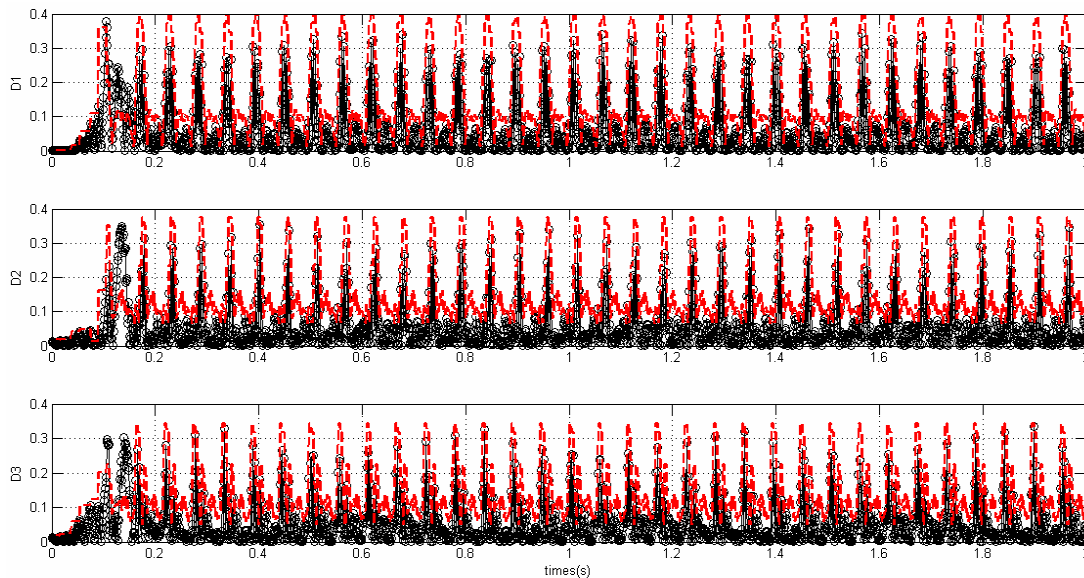


Figure 8. Time evolution of distances ( $D_i$ ) without fault

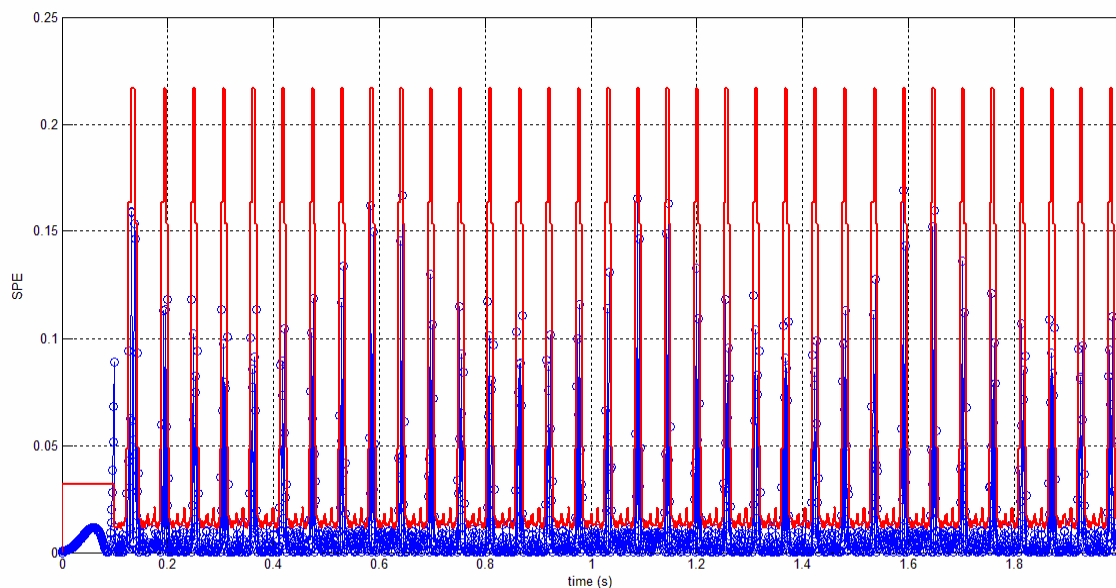


Figure 9. Time evolution of SPE without fault

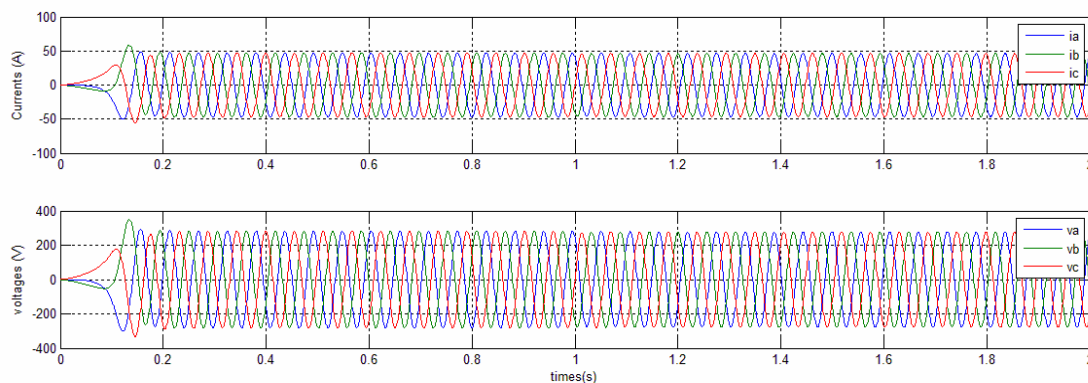
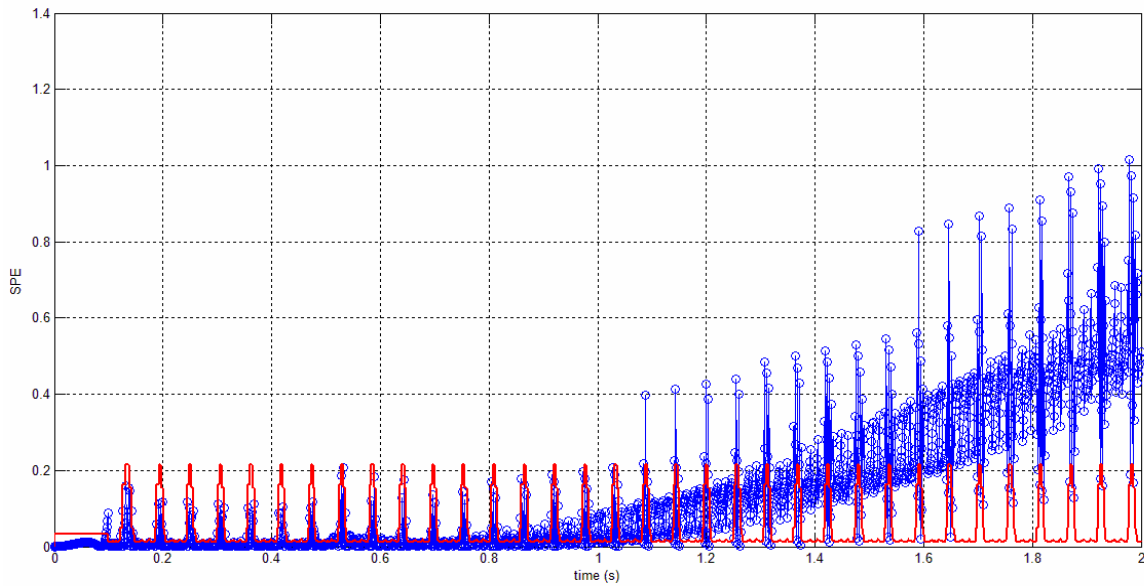
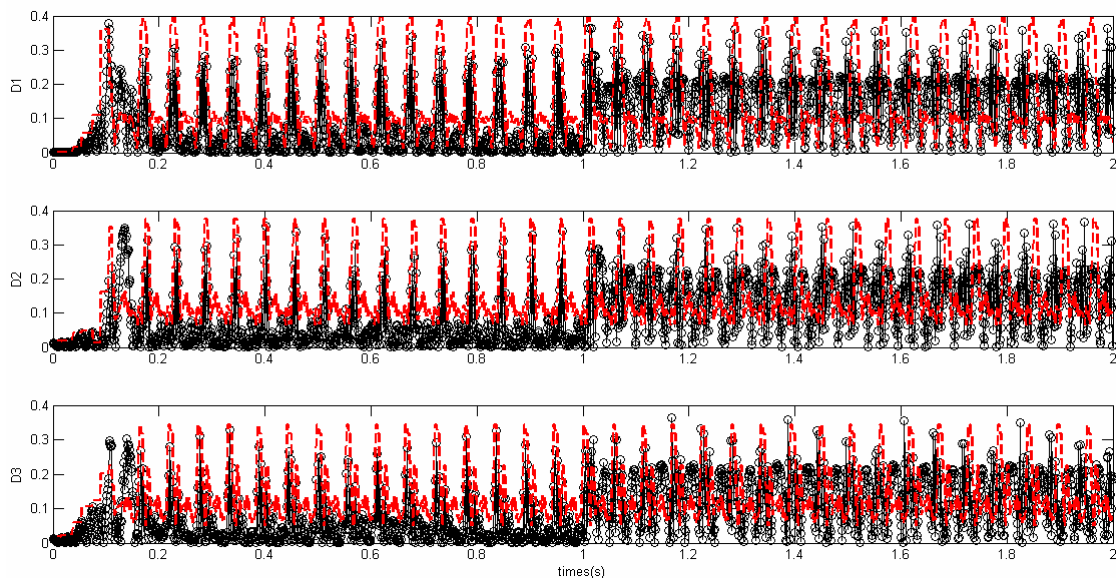


Figure 10. Time evolution of currents and voltages with fault



*Figure 11. Time evolution of SPE with fault*



*Figure 12. Time evolution of distances ( $D_i$ ) with faults*

### *Considered faults*

In this paper, the simulated defects on resistance due to an increase in temperature will be studied. Considered fault is increases by  $\gamma\Delta T_n$  of the stator resistance value  $R_S$ , the resistance versus the temperature is expressed as:

$$R_{ST} = R_S + \gamma\Delta T_n \quad (31)$$

$R_S$  is the resistance value at  $T_n = 25^\circ C$ ,  $\gamma$  is the temperature coefficient of the resistance and  $\Delta T_n$  is the temperature variation [19].

Three observable signals output (currents) used in simulation, to offer good graphical representation of Multi-model-local PCA in modeling performance (Figure 3 and 4).

In Figure 5 and 6 typical quantities of the turbine system without faults, as wind speed, voltage and current of wind generator, the estimated curve of the stationary regime of the measured data (currents) in normal conditions of simulation of the system WT-PMSG is presented in Figure 7. It can be observed different classes color, where estimated curve (models PCA) are showed with black color, and the values of SPE, representing the normal operating condition, are plotted as shown in Figure 8.

To show performances of the fault detection of the proposed approach, a fault is simulated at  $t = 1$  [sec], an increase to 15 % in  $R_s$  is applied to the system, the typical quantities of the turbine system with faults are showed in Figure 9 and 10, where little reduction in crest values of currents outputs, This fault is detected on the SPE and the distances as depicted in Figure 11 and 12.

### **Conclusion**

This paper presents a new approach for faults detection based on the combination of linear PCA and Kohonen (SOM) Algorithm used in system WT-PMSG in continuous time domain. From the presented results, it is definitely able to reveal the time of faults and gives excellent results.

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