Faults Detection and Diagnosis Approach Using PCA and SOM Algorithm in PMSG-WT System

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Abstract: - In this papers, a new approach for faults detection and diagnosis 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 and diagnostic in experimental data, finding good results in simulation experiment.

Key-Words: WT,PMSG , FDI, Diagnostic, SOM, PCA, Multi-PCA, FFT.

1 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].

Typically, wind farms installation studies do not provide all protection conditions. For this reason, the necessity of fault detection methods is caused in the wind energy field. Where the different possible faults in these systems can cause fatigue and damage in all components [4,5], the fundamental components wind turbine shown in Fig 1.

The WT maintenance statistics available shows that the frequency of faults by component are not equal [7,8] ''Fig 2'', where some components are more sensitive to faults, and others produce more downtime [4,5], where in recent years studies mention the three most contributor's components to damages in wind turbine are: rotor, blades, and electric generator.

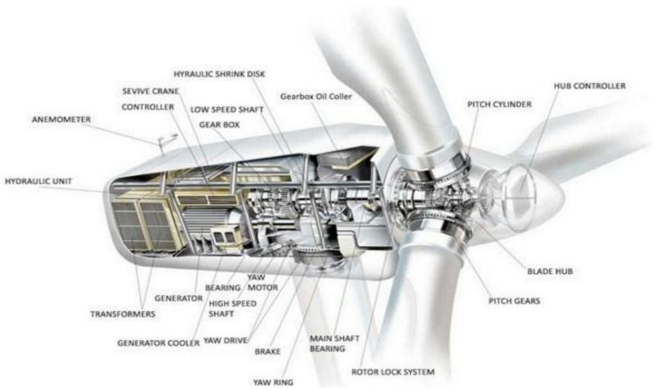

Fig 1. Wind turbine Components [6].

In literature, the diversity of WT components and their faults [4,6,7,8](damages of generator windings, short-circuit and over voltage of electronics components, transformer….etc) requires variety of fault detection methods such as the data analysis and vibration analysis.

The faults detection and diagnosis 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.

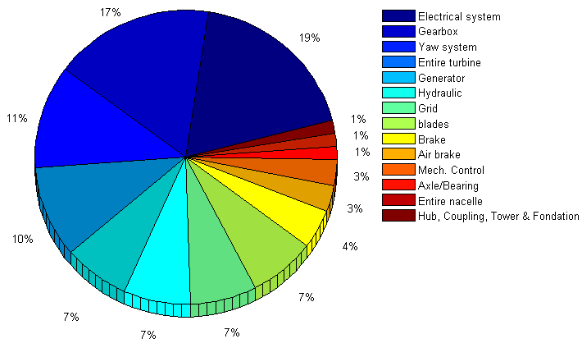

Fig 2. Failure rate of wind turbine components.

Faults detection in WT-PMSG 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 and PCA are 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 [9], we propose a new nonlinear process monitoring technique based on Self Organized Map (SOM) Algorithm and PCA to solve the problem posed by nonlinear relation in observable data and nonstationary data.

Generally, in this paper two studies are given to analyze system data. First, simulation study, explain the time domain detection techniques, second explain the frequency domain diagnosis techniques and classification vibration signals.

2 Wind turbine modelling

The power extracted from the wind by a wind turbine is given by [10-12] the following formula :

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

Where R_p is the blade radius of the wind turbine, V_w is the wind speed, ρ is the air density, and C_p is the power coefficient.

The torque that can be recovered on the turbine shaft is calculated by [11,13] the following formula:

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

Where the torque coefficient $C_T(\lambda)$ can be approximated by the following sixth order polynomial function [11] as following:

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

The tip speed ratio is defined as

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

Where, Ω is the mechanical angular velocity of the turbine rotor.

and the C_p equations is given by:

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

3 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 [13]:

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

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

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

Where v_d, v_q, i_d, i_q are respectively the magnitudes of stator voltages and currents on the axes d,q, also, Γ_{em} is the torque of PMSG, Φ 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 , ω_r is the pulsation of the rotor field, which is related to the rotation speed of the rotor Ω by $\omega_r = p\Omega$, and p is the quantity of poles pair.

The dynamic equations are given by:

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

$$\frac{d\theta_r}{dt} = \omega_r \tag{10}$$

Where J is the inertia of rotor, F_r is the friction of rotor and rotor angular θ_r.

Today, in the world of renewable energy, synchronous generators play an important position due to their widely use in the field of wind energy. Hence, faults detection in synchronous generators are decisive to the reliability of wind turbines [14]. 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.

4 Principal Component Analysis

PCA is a data analysis method based on a simple transformation of collected data (observations without fault), stored in a reduced and normalized matrix $X \in \Re^{n\times m}$, to produce statistically independent score variables, stored in $T \in \Re^{n\times m}$ [15-17].

$$X = TP^T \tag{11}$$

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 Σ of X :

$$\Sigma = P\Lambda P^T \tag{12}$$

$$PP^T = I_m \tag{13}$$

Where Λ is the diagonal matrix composed of m eigenvalues in descending order.

By projecting the original information onto a lower dimensional space $\ell < m$, X can be decomposed as the following equation:

$$X = \hat{X} + E \tag{14}$$

Where

$$\hat{X} = \hat{T}\hat{P}^T \text{ and } E = \tilde{T}\tilde{P}^T \tag{15}$$

And

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

With

$$\hat{X} = X\hat{P}\hat{P}^T$$

the residual matrix E can as following :

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

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

The number of proper principal components ℓ can be determined by different methods, such as, the accumulated contributions of the principal components, VNR (unreconstructed variable) or cross validation [17].

4.1 Faults Detection

Process monitoring is based on the two statistics called T^2 and SPE respectively [17].

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

$$T^2 = X\hat{P}\Lambda^{-1}\hat{P}^T X^T \tag{19}$$

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

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

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 [17]:

$$SPE = \|e\|^2 = e^T(k)e(k) \tag{21}$$

The process is considered in normal situation if:

$$SPE \le \delta_\alpha^2 \tag{22}$$

Where

δ_α^2 is the detection threshold of SPE significance α level.

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

$$\theta_i = \sum_{j=\ell+1}^{m} \lambda_j^i \qquad i = 1,2,3... \tag{24}$$

c_α are the confidence limits for the (1-α) 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. (17)

5 Self-Organizing Maps (SOM)

Self-organizing maps provide an alternative to PCA that is accommodating nonlinear relationships in the dataset [18, 19].

SOM is a method data analysis to complement traditional linear techniques without replacement, although it provides additional power for nonlinear datasets [19].
As SOM algorithm is a method of nonlinear projection, it effectively classify data into different clusters, without any explicit modeling of the system [18,19].

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[9, 19-21].

$$\|X - W_c\| = \min_i \{\|X - W_i\|\} \tag{25}$$

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

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

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

Equations of updated prototype can be as follow:

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

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.

5.1 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.

-Threshold S_d : 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.

$$S_d = \min_i \{D_i\} \tag{28}$$

Where

$$D_i = \| x_i - P_c \| \tag{29}$$

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 $x_i(t)$

$$\begin{aligned} &\text{If} \quad D_i = \| x_i - P_c \| > S_d \\ &\qquad x_i \text{ is abnormal.} \\ &\text{Else} \quad x_i \text{ is normal.} \end{aligned} \tag{30}$$

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.

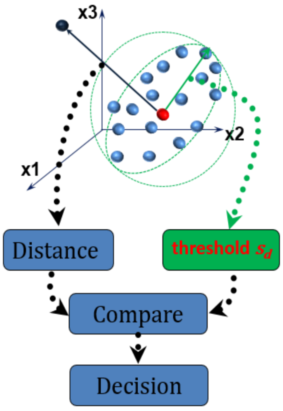

Fig 3. Fault detection (SOM) algorithm.

6 Multi-Models SOM-PCA

The nonlinear PCA is an extension of the linear PCA [22]. 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[23].

6.1 Multi-PCA Models

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 [9], 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 “Fig 2”. Also, the proposed method can used in real time, with fixing the class correspond the new measure and examine it state if it normal or defected.

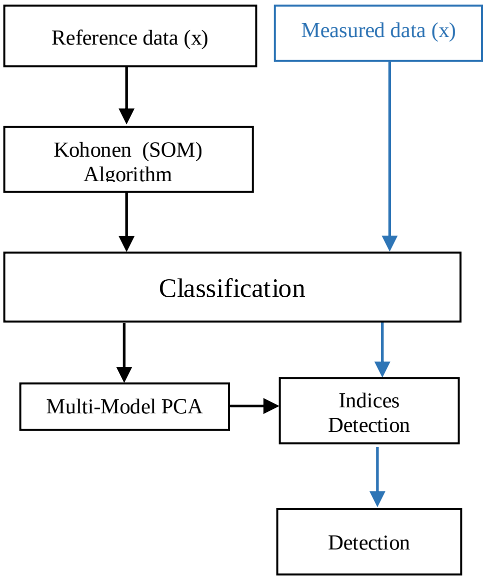

Fig 4. The sketch map of the fault detection.

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6.2 SOM-PCA FFT diagnosis

To assess the performance of the method previously proposed, with integration in bearing fault diagnosis, where SOM-PCA algorithm used to reduce the data size (without losing any important characteristic data), to modeling data, and calculate residuals, however, insurance the frequency domain analysis by FFT method, according to [24], extract the characteristics of a spectrum through the relative spectral entropy H_r and the gravity frequency F_c, and classification the nature of signal by SOM (defect identification) .

$$H(X) = -\sum \mu(X)\log(\mu(X)) \qquad (31)$$

Where X is the spectral sequence of the time series, and

$$\mu(X) = \frac{X}{\sum X} \qquad (32)$$

$$H_r(X) = H(X)/\log(N/2) \qquad (33)$$

Where N is the length of time series.

$$F_c(X) = \sum_{K=1}^{N/2} \frac{K}{N/2}\mu(X(K)) \qquad (34)$$

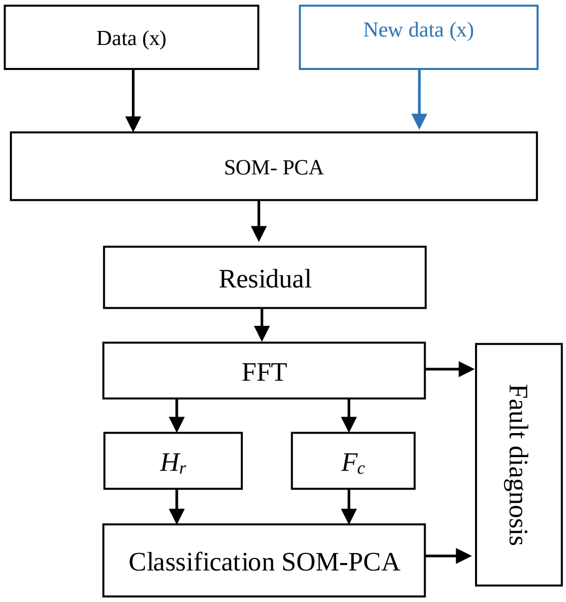

Fig 5. SOM-PCA FFT diagnosis.

7 Results and Discussion

7.1 Simulation study

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

Table 1. Simulation parameters PMSG WT System

Parameters PMSG WT		
R_p	3	[m]
V_w	9	[m/s]
ρ	1.25	[kg/m³]
L_d	0.0273	[H]
L_q	0.0213	[H]
R_s	0.75	[Ω]
p	3	
J	0.2	[kg.m²]

Considered faults

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 :

$$R_{ST} = R_S + \gamma\Delta T_n \tag{35}$$

R_S is the resistance value at $T_n = 25°C$, γ is the temperature coefficient of the resistance and ΔT_n is the temperature variation [25].

In this paper, three observable signals output (currents) used in simulation, to offer good graphical representation of Multi-SOM-PCA models in modeling performance Fig 10.

In "Fig 8 and 9" typical quantities of the turbine system without faults, as wind speed, voltage and

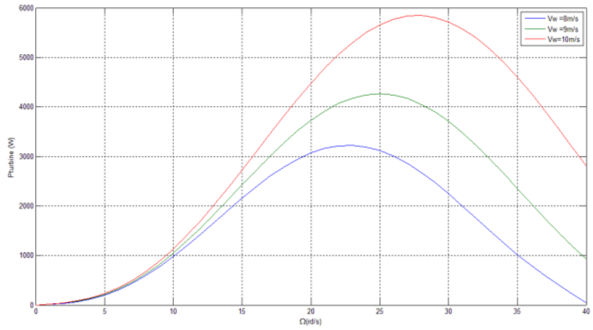

Fig 6. Wind Turbine Power coefficients versus tip speed ratio in different cases of wind speed.

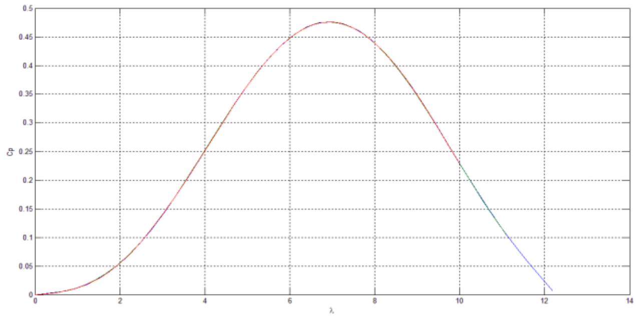

Fig 7. Power coefficients versus rotational speed in different cases of wind speed

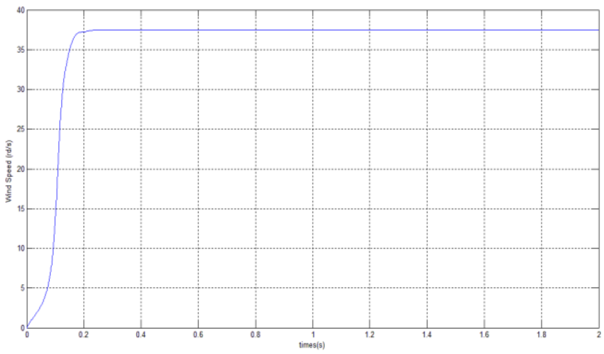

Fig 8. Time evolution wind speed.

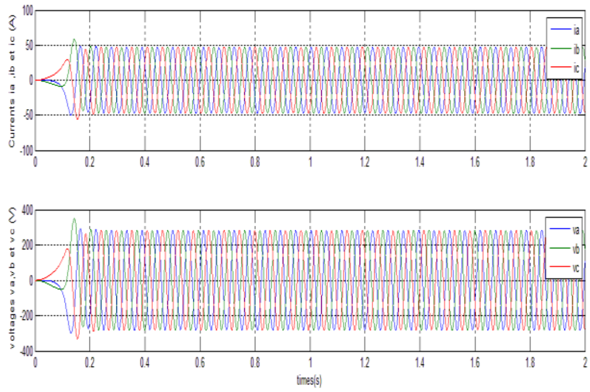

Fig 9. Time evolution currents and voltages without fault.

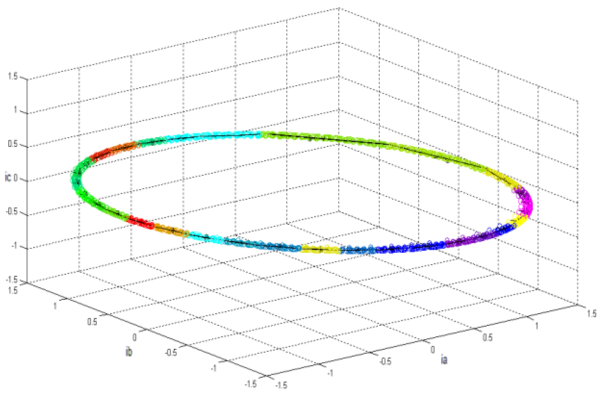

Fig 10. Estimation of the curve using the SOM-PCA

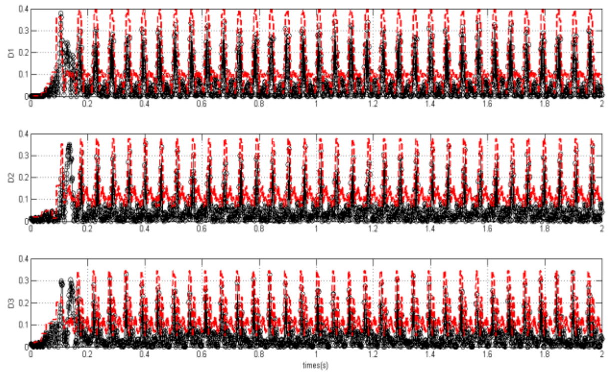

Fig 11. Time evolution of distances (D_i) without fault.

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 “Fig 10”. It can be observed different classes color, where estimated curve (models PCA) are showed with black color, and the values of D_i and SPE , representing the normal operating condition, are plotted as shown in “Fig 11 and 12”.

To show fault detection performances 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 “Fig 13”, where little reduction in crest values of currents outputs, This fault is detected on the SPE and the distances as depicted in “Fig 13 and 14’’ at t=1s.

7.2 Experimental study

In this study, 26 experimental signals (four signals types : normal, inner race fault, outer race fault and balls fault) from the Case Western bearing datacenter Reserve University (CWRU) [26] are used in approach evaluation; by relations in [27] the characteristic frequency of different cases signals are noticed in Table 2.

Table 2. Characteristic frequency of different cases signals

Sampling rate	**Signal type**	**characteristic frequency**	
12kHz	inner race fault f_i	162.1	[Hz]
	outer race fault f_u	107.3	[Hz]
	balls fault f_b	135.8	[Hz]
	Normal f_0	29.9	[Hz]

In “Fig 15” the spectrum of signals without fault, and show the difficulty to extract information, contrast, the ‘’ Fig 16’’ may clearly show a series of peaks f_0 the speed of rotation and it harmonics frequencies 2 f_0, and 3 f_0.

From ‘’Fig. 17, 18, 19’’ It is observed that the proposed method can identify easily the characteristic frequency of faults.

‘’Fig 20 ‘’ show the ability of the proposed method in automatic classification and diagnosis of fault, thereby forming a classification model for each new unknown signal.

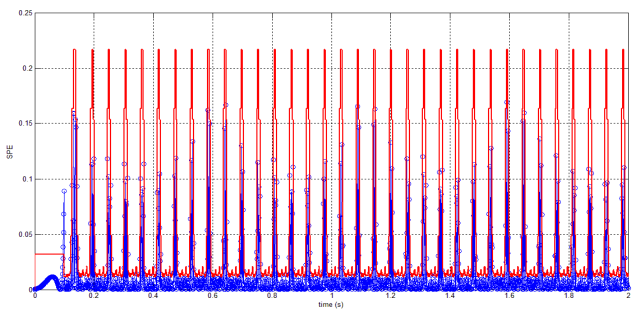

Fig 12. Time evolution of SPE without fault.

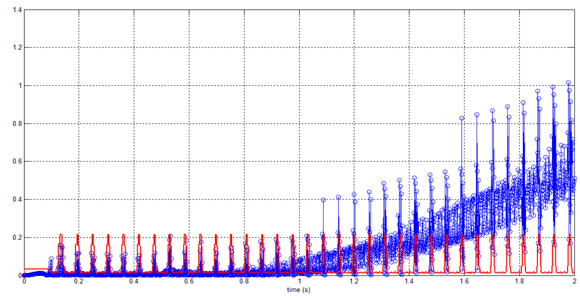

Fig 14. Time evolution of SPE with fault.

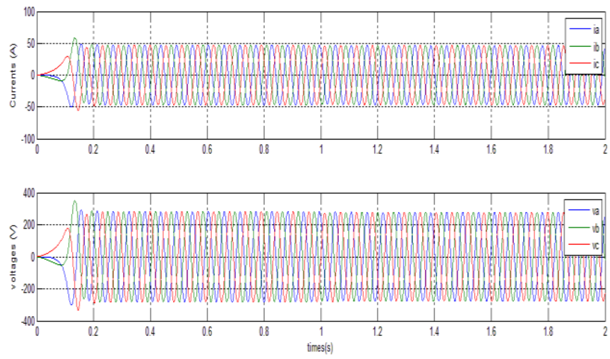

Fig 13. currents and voltages with fault.

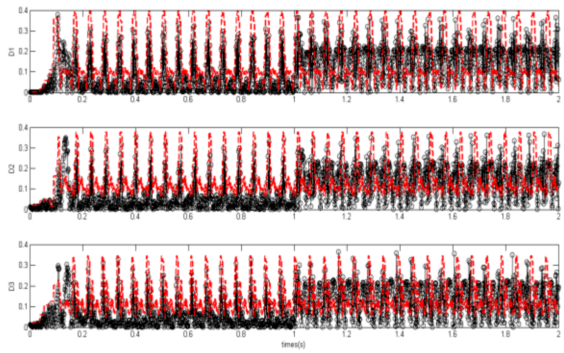

Fig 14. Distances (D_i) with faults.

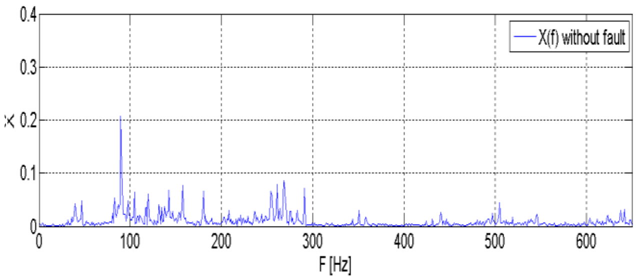

Fig 15. spectrum of signal without fault.

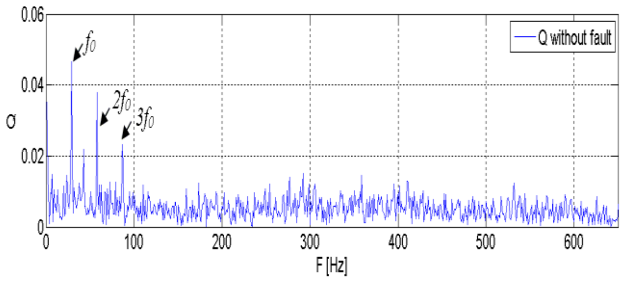

Fig 16. SPE spectrum without fault.

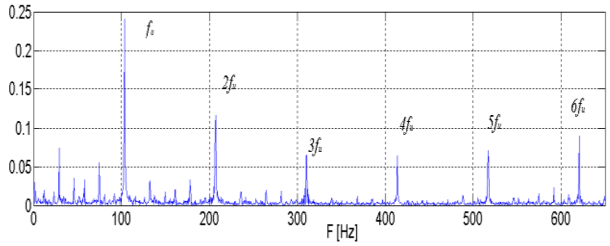

Fig 17. SPE spectrum with out-race fault.

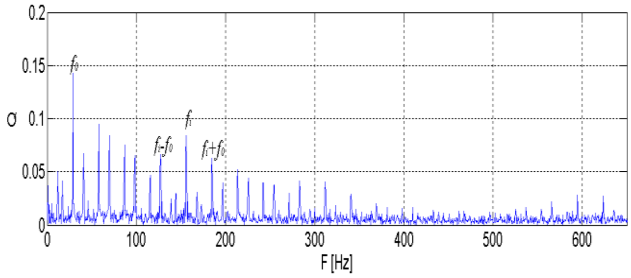

Fig 18. SPE spectrum with inner-race fault.

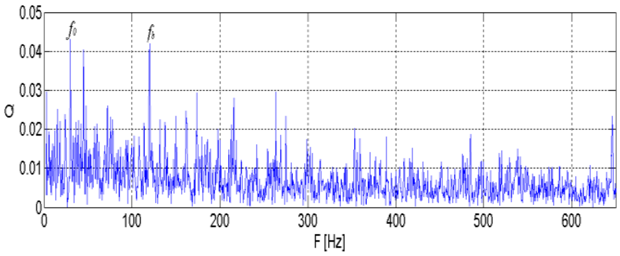

Fig 19. SPE spectrum of signal with ball fault.

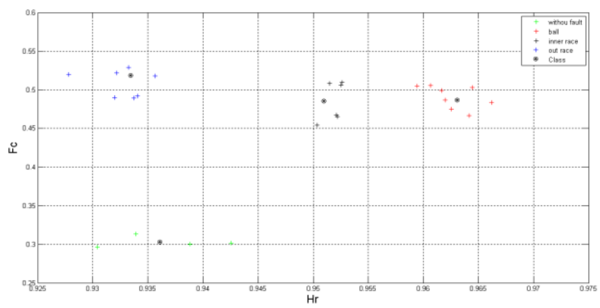

Fig 20. Fault diagnosis and classification using SOM-PCA.

8 Conclusion

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

9 acknowledge.

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References:

[1] Kimball R, a rational look at renewable energy and the implications of intermittent power. Ed 1.2, Deseret Power, South Jordan, USA, 11-2010.

[2] Amirat Y, Benbouzid M, Al-Ahmar E. A brief status on condition monitoring and fault diagnosis in wind energy conversion systems. Renew Sust Energ Rev 2009; 3(9): 2629–2636.

[3] Brandao RFM, Beleza-Carvalho JA, Barbosa FPM. Forecast of faults in a wind turbine gearbox. In: IEEE Proceedings of 9th International Conference ELEKTRO'2012, 21-22 May 2012; Rajeck Teplice, Slovakia. New York, NY, USA: IEEE. pp. 170 –173.

[4] J. R. Babu, S. V. Jithesh, ―Breakdown risks in wind energy turbines, Pravartak, the journal of Insurance and risk Management from National Insurance Academy, Pun, Volume III, Issue 3, April – June 2008.

[5] Pierre Tchakoua, René Wamkeue, Mohand Ouhrouche, Fouad Slaoui-Hasnaoui, Tommy Andy Tameghe, Gabriel Ekemb, Wind Turbine Condition Monitoring: State-of-the-Art Review, New Trends, and Future Challenges', Energies, April 2014 pp 2595-2630.

[6] Afrooz P, Ghavameddin N, Acoustic emission condition monitoring : an application for wind turbine fault detection, IJRET, 2013; 2(5) pp 907–918.

[7] Michael P, Bill C P L, Eden W M M; Review of offshore wind turbine failures and fault prognostic methods. Proceedings of the IEEE 2012 Prognostics and System Health Management Conference (PHM-2012 Beijing), pages 1–5, 2012.

[8] Hahn, B.; Durstewitz, M.; Rohrig, K. Reliability of Wind Turbines. In Wind Energy; Springer: Berlin/Heidelberg, Germany, 2007; pp. 329–332.

[9] Yang Y, Lu N, Wang F, Ma L, Chang Y. Statistical process monitoring using multiple PCA models. In: Proceedings of the American Control Conference IEEE 2002, 8-10 May 2002, Anchorage, Alaska, USA: IEEE, Vol 6, pp.5072 – 5073.

[10] Muyeen SM, Tamura J, Murata T. Stability Augmentation of a Grid-connected Wind Farm. Springer, London, 2009.

[11] Munteanu I, Bratcu A, Cutuluslis N, Ceanga E, Ceanga E, Optimal Control of Wind Energy Systems;Toward a Global Approach. Springer-Verlag, London Limited, 2008.

[12] Eisenhut C, Krug F, Schram C, Klockl B. Wind-Turbine Model for System Simulations Near Cut-In Wind Speed. IEEE T Energy Conver 2007; 22(2): 414 – 420.

[13] Pierre S, Nichita C, Brossard J, Jo CH. Concept development of real time emulators for offshore wind power (OWP) and tidal current power (TCP) hybrid system. In: IEEE 17th International Conference System Theory Control and Computing (ICSTCC'2013), 11-13 October 2013, Sinaia, România. New York, NY, USA: IEEE. pp. 416 - 421.

[14] Yang, W, Condition monitoring and fault diagnosis of a wind turbine synchronous generator drive train, IET Renew Pow Gen 2009; 3(2): 630–636.

[15] Dunia R, Qin SJ, Subspace approach to multidimensional fault identification and reconstruction. AIChEJ 1998; 44 (8): 1813–1831.

[16] Dunia R, Qin SJ, Edgar TF, Identification of faulty sensors using principal component analysis, AIChE J 1996; 42(10): 2797–2812.

[17] Ouni K, Dhouibi H, Nabli L, Hassani Messaoud. New monitoring method based principal component analysis and fuzzy clustering. Int J Phys Sci 2013; 8(18): 901–914.

[18] Kohonen T. Self-organizing maps. 3rd edition. NewYork, USA: Springer Series in Information Sciences, 30, 2001.

[19] Reusch DB, Alley R B, Hewitson BC, Relative performance of self-organizing maps and principal component analysis in pattern extraction from synthetic climatological data. Polar Geogr Geol 2005; 29, 3: 188–212.

[20] Yang BS, Han T, An J L. ART-KOHONEN neural network for fault diagnosis of rotating machinery. Mech Syst Signal Pr 2004; 18(3): 645–657.

[21] Saxena A, Saad A, Fault Diagnosis in Rotating Mechanical Systems Using Self-Organizing Maps. In: Artificial Neural Networks in Engineering Conference (ANNIE'2004), 7-10 November 2004, St. Louis, Missouri, USA.

[22] ZHU Q, LI C. Dimensionality Reduction with Input Training Neural Network and its Application in Chemical Process Modelling. Chinese J Chem Eng 2006; 14(5) 597–603.

[23] Verbeek, JJ, Vlassis N, Kröse BJA. A k-segments algorithm for finding principal curves. Pattern Recogn Lett 2002; 23(8): 1009–1017.

[24] Zhongqing Wei, Jinji Gao, Xin Zhong, Zhinong Jiang, Bo Ma, Incipient fault diagnosis of rolling element bearing based on wavelet packet transform and energy operator, WSEAS TRANSACTIONS on SYSTEMS, Issue 3, Volume 10, March 2011, pp 81-90.

[25] Ramahaleomiarantsoa JF, Sambatra EJR, Héraud N, Razafimahenina JM. Performances of the PCA Method in Electrical Machines Diagnosis Using Matlab. In: Katsikis V, editor. MATLAB – A Fundamental Tool for Scientific Computing and Engineering Applications – Chapitre 4. Rijeka, Croatia: InTech, 2012. 1. pp. 69–88.

[26] http://csegroups.case.edu/bearingdatacenter/pages/12k-drive-end-bearing-fault-data

[27] Jason R. Stack, Thomas G. Habetler and Ronald G. Harley, Fault Classification and Fault Signature Production for Rolling Element Bearings in Electric Machines, IEEE Transactions on Industry applications, Vol. 40, No. 3, pp. 735 -739, May/June 2004.