Condition Monitoring & Fault Diagnosis System for Offshore Wind Turbines

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Abstract— **Due to the technological development, the electronic power progress and economic stake, through the use of Wound Rotor Induction Motor (WRIM) has taken more and more places in different domains (transport, energy production, electric drive..,) thanks to their robustness, efficiency and lower costs. Despite the performed work researches and the improvement that has been brought, these machines still remain the potential seats of failures both in stator and rotor levels. Consequently, WRIM faults detection is currently one of the centers of interest of several researches of both academic and industrial laboratories. In fact, this article addresses this problem by the use of Principal Components Analysis (PCA) for faults detection in Offshore Wind Turbine Generator (OWTG). An accurate analytic modeling of healthy and faulted OWTG is suggested to perform the data matrix needed for PCA method. Tests were achieved using a numeric simulator on Matlab/Simulink software. Analysis of OWTG simulation proves the efficiency of PCA method. Several simulation results will be presented and discussed.**

Keywords- Diagnosis; Monitoring; OWTG modeling; Principal Components Analysis; Wind turbine

I. INTRODUCTION

The necessity for having reliable and less energy consumption electric machine is more important than ever and the trend continues to increase. Now, advances in engineering and science building lighter machines while having a considerable lifetime. Although researches and improvements have been carried out, these machines still remain the most potential of the stator and the rotor failures. The faults can be resulted by normal wear, poor design, poor assembly (misalignment), improper use or combination of these different causes. Indeed, for many years, faults detection in electrical machines has been the subject of reflection and research projects in various industrial and academic laboratories: wind turbines [1], the one half horsepower centrifugal water pump [2]...

Induction motors and synchronous machines were the most used on industry applications, and reliability researches were focused on these types of machines. Several detection and control exist and already used for the electrical machines monitoring.

The increasing demand in energy, the consequent depletion reserves of fossil fuels and the commitment of governments to reduce greenhouse gases effect required by peoples, encouraged the renewable energy development. Among the renewable energies, wind energy presents the highest growth in installed capacity and penetration in modern power systems. This is why reliability of wind turbines becomes an important topic in research and industry. The principal components studied in modern wind turbine are the rotor, the tower, the nacelle, the transmission mechanisms and generator. In particular, generators are followed because they have sensitive parts like power semiconductors and variable frequency drive technology. Some of modern wind turbines are equipped with a Wound Rotor Induction Generator (WRIG), which is used for variable speed generation; it has better energy capture than fixed speed generation. Besides, there are several other advantages of using variable speed generation such as mechanical stress reduction of turbine and acoustic noise reduction.

Variable speed wind turbine with WRIG introduces itself as a very attractive option for installations with a fast growing market demand. The fundamental feature of the WRIG is that the power processed by the power converter is only a fraction of the total wind turbine power, and therefore its size and cost are much smaller compared to a full size power converter [3].

First step of monitoring [4], [5] and [6] is the fault diagnosis. In this paper, the diagnosis approach is based on residues analysis of the electrical machine state variables by the use of Principal Components Analysis (PCA) method. The PCA is a statistical method used to monitor the system behaviour by reducing its size.

This article is organized as follows: Section 2 deals with OWTG modeling followed by the different types of stator and rotor OWTG faults. PCA principle and residues generation of fault detection will be presented in Section 3. The different proposed models and approaches have been implemented on the MATLAB/SIMULINK software. Results of several states variables of healthy and faulted OWTG are analyzed in Section 4. A brief summary and the innovative aspects of this paper are given in the end of the paper.

II. OWTG MODELING

In the diagnosis procedure, an accurate modeling of the machine is necessary. In this paper, three phases model based on magnetically coupled electrical circuits were chosen [7]. The aim of modeling is to highlight electrical faults influences on different state variables of the OWTG.

A. OWTG modeling

V_j, I_j and Φ_j (j : A, B, C for the stator phases et a, b, c, for the rotor phases) are respectively voltages, electrical currents and the magnetic flux of the stator and the rotor phases, θ is the angular position of the rotor relative to the stator. R_j and L_j are resistances and own inductances of the stator and the rotor phases.

Note voltages vector *($[V_S]$, $[V_R]$)*, currents vector *($[I_S]$, $[I_R]$)* and flux vector *($[\Phi_S]$, $[\Phi_R]$)* of the stator and the rotor:

$$[V_S]=\begin{bmatrix}V_A\\V_B\\V_C\end{bmatrix};\ [I_S]=\begin{bmatrix}I_A\\I_B\\I_C\end{bmatrix};\ [\phi_S]=\begin{bmatrix}\phi_A\\\phi_B\\\phi_C\end{bmatrix}$$

$$[V_R]=\begin{bmatrix}V_a\\V_b\\V_c\end{bmatrix};\ [I_R]=\begin{bmatrix}I_a\\I_b\\I_c\end{bmatrix};\ [\phi_R]=\begin{bmatrix}\phi_a\\\phi_b\\\phi_c\end{bmatrix}$$

Both stator and rotor three phases voltages and currents are according to the total magnetic flux by the following differential equation system [8], [9]. Stator and rotor voltages vectors expressions are given by:

$$[V_S]=[R_S][I_S]+\frac{d[\phi_S]}{dt} \tag{1}$$

$$[V_R]=[R_R][I_R]+\frac{d[\phi_R]}{dt} \tag{2}$$

$[R_S]$ and *$[R_R]$* are resistances matrix, *$[L_S]$* and *$[L_R]$* own inductances matrix. Equations (1) and (2) become:

$$[V_S]=[R_S][I_S]+\frac{d\{[L_S][I_S]\}}{dt}+\frac{d\{[M_{SR}][I_R]\}}{dt} \tag{3}$$

$$[V_R]=[R_R][I_R]+\frac{d\{[L_R][I_R]\}}{dt}+\frac{d\{[M_{RS}][I_S]\}}{dt} \tag{4}$$

The mechanical equations are:

$$J_t\frac{d\Omega}{dt}+f_v\Omega=C_{em}-C_r \tag{5}$$

$$\Omega=\frac{d\theta}{dt} \tag{6}$$

With

$$C_{em}=\frac{1}{2}[I]^t*\frac{d([L])}{d\theta}*[I] \tag{7}$$

J_t is the total inertia brought to the rotor shaft, Ω the shaft rotational speed, *$[I] = [I_A\ \ I_B\ \ I_C\ \ I_a\ \ I_b\ \ I_c]'$* is the current vector, f_v is the viscous friction torque, C_{em} is the electromagnetic torque, C_r is the load torque applied to the machine, θ is the angular position of the rotor with respect to the stator, and *$[L]$* is the inductance matrix of the machine. Introducing the cycle inductances of the stator and the rotor: $L_{RC}=\frac{3}{2}L_R$ and $L_{SC}=\frac{3}{2}L_S$ (L_S is the own inductance of the each phase of stator and L_R is the own inductance of the each phase of rotor), mutual inductances between stator and rotor coils M_{SR} and pole pair number p, inductance matrix of OWTG can be written as follow:

$$[L]=\begin{bmatrix}L_{SC}&0&0&M_{SR}f_1&M_{SR}f_2&M_{SR}f_3\\0&L_{SC}&0&M_{SR}f_3&M_{SR}f_1&M_{SR}f_2\\0&0&L_{SC}&M_{SR}f_2&M_{SR}f_3&M_{SR}f_1\\M_{SR}f_1&M_{SR}f_3&M_{SR}f_2&L_{RC}&0&0\\M_{SR}f_2&M_{SR}f_1&M_{SR}f_3&0&L_{RC}&0\\M_{SR}f_3&M_{SR}f_2&M_{SR}f_1&0&0&L_{RC}\end{bmatrix} \tag{8}$$

with

$$f1=\cos(p\theta)\,;\ f2=\cos(p\theta+\frac{2\pi}{3})\,;\ f3=\cos(p\theta-\frac{2\pi}{3})$$

In choosing stator and rotor currents, shaft rotational speed, angular position of the rotor relative to the stator as state variables, and differential equations system modeling the OWTG is given by:

$$[\dot{X}]=[A]^{-1}([U]-[B][X]) \tag{9}$$

With

$$[A]=\begin{bmatrix}[L]&0&0\\0&J_t&0\\0&0&1\end{bmatrix};\ [U]=\begin{bmatrix}[V]\\-C_r\\0\end{bmatrix};\ [V]=[V_A\ V_B\ V_C\ V_a\ V_b\ V_c]^t;$$

$$[B]=\begin{bmatrix}[R]+\Omega\frac{d[L]}{d\theta}&0&0\\-\frac{1}{2}[I]^t\frac{d[L]}{d\theta}&f_v&0\\0&-1&0\end{bmatrix};\ [X]=[I_A\ I_B\ I_C\ I_a\ I_b\ I_c\ \Omega\ \theta]^t;$$

This model of OWTG is used to simulate both healthy and faulted operation case of stator and rotor.

B. Considered faults

In this paper, defects on resistance due to an increase in temperature will be studied. Indeed, the resistance versus the temperature is expressed as:

$$R = R_0(1+\alpha\Delta T) \quad (10)$$

R_0 is the resistance value at T_0 = 25°C, α is the temperature coefficient of the resistance and ΔT is the temperature variation.

The model has been implemented on MATLAB/SIMULINK and allows us to obtain the matrix of state variables for PCA method application.

III. PCA Methodology

The PCA method is based on simple linear algebra. It can be used as exploring tool, analyzing data and models design. It is based on transformation of space data representation [10]. The new space dimension is smaller than the original one. It is classified as without model method and it can be considered as full identification method of physical systems [11]. The PCA method allows providing directly the redundancy relations between variables without identifying the state representation matrix of the system. This task is often difficult to achieve.

A. PCA method formulation

Note $x_i(j) = [x_1\ x_2\ x_3\ ...x_m]$ the measurements vector; « *i* » represents the measurement variables to be monitored (*i = 1 to m*) and « *j* » the number of measurements for each variable « *i* », *j = 1 to N.*

Measurements data matrix $(X_d \in R^{N*m})$ can be written as follows:

$$X_d = \begin{pmatrix} x_1(1) & \dots & x_m(1) \\ \dots & \dots & \dots \\ x_1(N) & \dots & x_m(N) \end{pmatrix} \quad (11)$$

The data matrix is described with a smallest new matrix, that is an orthogonal linear projection of a subspace of *m* dimension on a less dimension subspace *l (l<m).* This method consists in identifying PCA model respecting two steps [12], [13]:

- Determination on eigenvalues and eigenvectors of covariance matrix *R*.
- Determination of model structure, by identifying the components number « *l* » for PCA model.

B. Eigenvalues and eigenvectors determination

The first step is data normalization. The variables must be centered and reduced. Then, the new normalized matrix obtained is:

$$X = [X_1 ... X_m] \quad (12)$$

and the covariance matrix R is given by:

$$R = \frac{1}{N-1} X X^T \quad (13)$$

By decomposing R, (13) can be expressed as:

$$R = P \Lambda P^T \quad (14)$$

with

$$P P^T = P^T P = I_m \quad (15)$$

Λ is the diagonal matrix of the eigenvectors of *R* and their eigenvalues are ordered in descending order towards magnitude values ($\lambda_1 \geq \lambda_2 \geq ... \geq \lambda_m$).

Orthonormal projection matrix *P* formed by *m* eigenvectors associated with eigenvalues of the correlation matrix *R* is expressed as:

$$P = [p_1, p_2, ..., p_m] \quad (16)$$

p_i is the orthogonal eigenvectors corresponding to the eigenvalues λ_i . Then, the principal components matrix can be calculated by using:

$$T = XP \quad (17)$$

$$T \in \Re^{N*m}$$

C. Determination of the model structure

This step is very important for PCA construction. It allows to obtain the model structure, by calculating the components number "l". It is done using the following expression:

$$\left(\frac{\sum_{i=1}^{l} \lambda_i}{\sum_{k=1}^{m} \lambda_k} \right) * 100 \geq thc \text{ , } l<m \quad (18)$$

where *thc* is an user defined threshold expressed as percentage. Now, user should retain only the components number "l" which was associated in the first term of (18). By reordering the eigenvalues, the minimum numbers of components are retained while still reaching the minimum variance threshold [2].

By taking into account the number of components to be retained and by partitioning the principal component matrix *T*, eigenvectors matrix *P* and eigenvalues matrix Λ [14], the constructed PCA model is given by:

$$T = \left[T_p^{N*l}\, T_r^{N*(m-l)} \right] \quad (19)$$

$$P = \left[P_p^{N*l}\, P_r^{N*(m-l)} \right] \quad (20)$$

$$\Lambda = \begin{bmatrix} \Lambda^{l*l} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \Lambda^{(m-l)(m-l)} \end{bmatrix} \quad (21)$$

T_p and T_r are respectively the principal and residual parts of T, P_p and P_r are respectively the principal and residual parts of P. With this PCA model, centered and reduced matrix X can be written as:

$$X = P_p T_p^T + P_r T_r^T \tag{22}$$

By considering

$$X_p = P_p T_p^T = \sum_{i=1}^{l} P_i T_i^T \tag{23}$$

$$E = P_r T_r^T = \sum_{i=l+1}^{m} P_i T_i^T \tag{24}$$

The centered and reduced matrix data is given by:

$$X = X_p + E \tag{25}$$

X_p is the principal estimated matrix and E the residues matrix which represents information losses due to data matrix X reduction. It represents the difference between the exact and the approached representations of X. This matrix is associated with the lowest eigenvalues $\lambda_{l+1},...,\lambda_m$. In this case, data compression preserves the best information that it conveys.

IV. Application on Offshore Wind Turbine

A. Tests conditions

First tests were achieved using the numeric simulator (Matlab/Simulink). A full representation of a wind turbine with a WRIG was created, as shown next [15]:

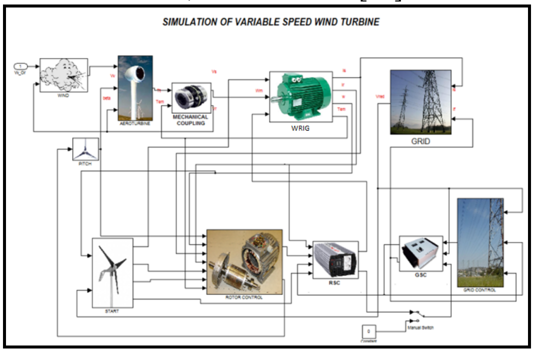

Figure 1. The general representation of a wind turbine using Matlab/Simulink

Nine state variables (m=9) have been chosen to be monitored and 10000 measures (N=10000) during 4 seconds are considered. OWTG faults are introduced from the time equal to 2 seconds (t=2s). The machine is coupled to a mechanical load torque (10 N.m) at t=0.8s. Considered faults are respectively, increases by 0.001%, 10% and 30% of the resistance value of both stator and rotor coils.

B. Results

Different tests have been performed towards the conditions mentioned earlier.

The following results are divided into two groups:

The first results group (Fig. 2 and Fig. 3) represents the real variations of different state variables of the OWTG (stator current and rotor current) versus time.

The second results group (Fig. 4 and Fig. 5) represents the simulation results of different state variables of the OWTG using PCA method. This last one is performed to treat state variables matrix. The principal aim is to generate the residual of its state variables and to compare the results from those obtained with the first group.

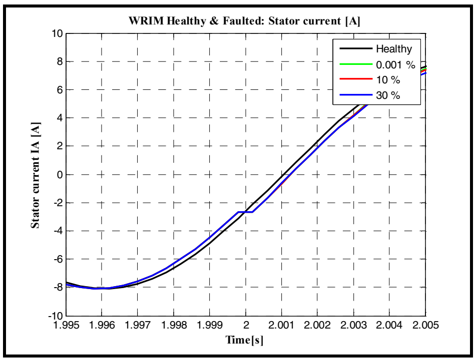

Figure 2. Variations versus time of the stator current of the healthy and faulted OWTG

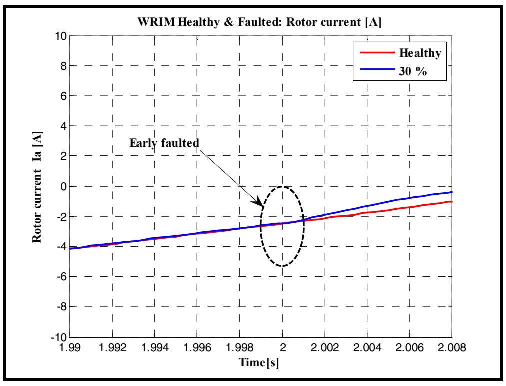

Figure 3. Variations versus time of the rotor current of the healthy and faulted OWTG

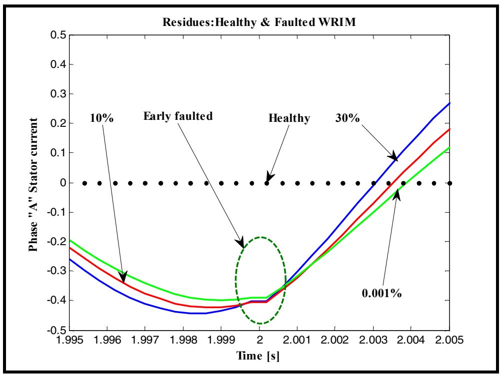

Figure 4. Early faulted in variations of the phase *"A"* current residues versus of the healthy and faulted OWTG

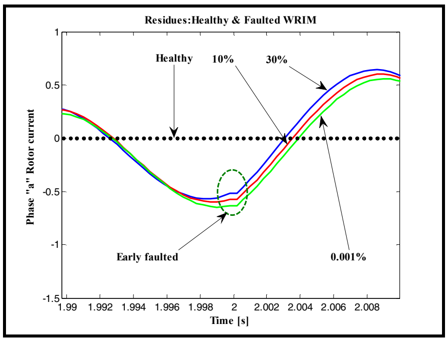

Figure 5. Early faulted in variations of the rotor current residues versus of the healthy and faulted OWTGRIM

C. Discussion

For the electrical machines diagnosis, many methods are used to detect the presence of faults and to identify their times of occurrence on the machine windings. Figure 2 represents the stator current of phase "A" versus time. Faults appear at time t = 2 s. Three types of faults levels are considered in the system. This figure clearly shows that it is difficult to visualize changes in signals and the fault appearance time. However, by the analysis of residues of the stator current by PCA (Fig. 4), changes towards the faults levels (0.001%, 10%, 30%) are obviously shown and the fault appearance time is located on the three signals. The case of a healthy machine that has a zero residue is almost coincident with the x-axis. These observations are found in the case of the rotor current (Fig. 3 and Fig. 5). In figure 3, the presence of faults with the conventional temporal representation is no more evident than that using PCA method (Fig. 5). This one shows the residue analysis interest on PCA method. The difference between healthy and faulted operation are clearer. It is almost not found in the real variation representations (Fig. 3). Figures 4 and 5 highlight the major potential benefits of state variables treatment by PCA method which easily shows faults detection and their times occurrence.

V. CONCLUSION

In this paper, a diagnosis procedure, based on the Principal Component Analysis (PCA) has been presented. An accurate analytical model of the OWTG has been proposed and simulated to perform the healthy and faulted data for PCA approach need.

The fault time occurrence is known from the PCA approach. Indeed, with residues analysis by PCA method, faults are detected even with low variation of the resistance value (increase 0.001%).

Simulation results show the detection efficiency but require a good choice of the principal components number. The fault scenario studied is functional defects of the OWTG. However, a wind turbine is a complex system requiring a fault scenario more complete.

Future work will be based on the use of this technique to establish fault-tolerant control laws of the wind turbine and its accommodation schemes.

REFERENCES

[1] O. Bennouna, N. Héraud, H. Camblong, M. Rodriguez, and M. A. Kahyah, "Diagnosis and fault signature analysis of a wind turbine at a variable speed," *Proceedings of the Institution of Mechanical Engineers, Journal of Risk and Reliability, 2009,* vol. 223, n° 1, pp. 41-50.

[2] R.G. Halligan, and S. Jagannathan, "PCA Based Fault isolation and prognosis with application to Water Pump," *paper1, thesis, Fault detection and prediction with application to rotating machinery*, Missouri University of Science and Technology, 2009.

[3] R. Steve, « Real-time fault monitoring of industrial processes: by A. D. POULIEZOS and G. S. STAVRAKAKIS; Series on Microprocessor-Based and Intelligent Systems Engineering, Vol. 12; Kluwer Academic Publishers; Boston, MA, USA; 1994; 576 pp.; $225; ISBN: 0-7923-2737-3 », *Control Engineering Practice*, vol. 4, n°. 4, p. 584-585, avr. 1996.

[4] O. Bennouna, and N. Héraud,, "Diagnosis & fault detection in wind energy conversion system," *IEEE International Conference on Environment and Electrical Engineering EEEIC*, May 2011.

[5] B. Lu, Y. Li, X. Wu, et Z. Yang, « A review of recent advances in wind turbine condition monitoring and fault diagnosis », in *Power Electronics and Machines in Wind Applications, 2009. PEMWA 2009. IEEE*, 2009, p. 1–7.

[6] Y. Amirat, M. Benbouzid, B. Bensaker, et R. Wamkeue, « Condition Monitoring and ault Diagnosis in Wind Energy Conversion Systems: A Review », in *Electric Machines & Drives Conference, 2007. IEMDC'07. IEEE International*, 2007, vol. 2, p. 1434–1439.

[7] E. D. Khodja, and A. Kheldoun, "Three-phases Model of the Induction Machine Taking Account the Stator Faults," *World Academy of Science, Engineering and Technology 52*, page 157-150, 2009.

[8] M. Wieczorek, and E. Rosołowski, "Modelling of induction motor for simulation of internal faults," *Modern Electric Power Systems, MEPS'10*, paper P29, Wroclaw, Poland, 2010.

[9] F.J. Ramahaleomiarantsoa, N. Heraud, E.J.R. Sambatra, and J.M. Razafimahenina, "Principal components analysis method application in electrical machines diagnosis," *8th Int. Conf. on Informatics in Control, Automation and Robotics, ICINCO*, Noorduijkerhout, The Netherlands, 2011.

[10] E. Kiliç, O. Özgönenel, Ö. Usta, and D. Thomas, "PCA based protection algorithm for transformer internal faults," *Turk J Eng & Comp Sci*, vol. 17, page 125-142, 2009.

[11] L. Liu,"Robust fault detection and diagnosis for permanent magnet synchronous motors," *PhD dissertation, College of Engineering,* The Florida State University, USA, 2006.

[12] S. Borquet, and O. Léonard," Coupling principal component analysis and Kalman filtering algorithms for on-line aircraft engine diagnostics," *Control Engineering Practice*, volume (17), page 494-502, 2009.

[13] S. Klenk, and G. Heidemann," A new method for Principal Component analysis of high- dimensional data using Compressive Sensing," *Intelligent Systems Department*, Stuttgart University, Germany, 2010.

[14] A. Benaicha, M. Guerfel, N. Bouguila, and K. Benothman," New PCA-based methodology for sensor fault detection and localization," *International Conference of Modeling Simulation, MOSIM'10*, Hammamel, Tunisia, 2010.

[15] O. Bennouna, N. Héraud, M. Rodriguez, and H. Camblong, "Data reconciliation and gross error detection applied to wind power," *Proceedings of the Institution of Mechanical Engineers, Journal of Systems and Control Engineering, 2007,* vol. 221, n° 3, pp. 497-506.