PRINCIPAL COMPONENTS ANALYSIS METHOD APPLICATION IN ELECTRICAL MACHINES DIAGNOSIS

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Keywords: Diagnosis, Principal components analysis, Residues, Wound rotor induction machine, Modeling.

Abstract: Electrical machines are found in many applications, especially in wind energy conversion chain (WECC). However, these machines still remain the most potential of failures. Many researches and improvements have been carried out but in the aim of optimal operation systems, monitoring and diagnosis techniques are among the interests of existing laboratories and research teams. This paper deals with the principal components analysis (PCA) method application in electrical machines, especially a wound rotor induction machine (WRIM), diagnosis. The used PCA approach is based on residues analysis. To perform the matrix data needed for PCA method data input, an accurate analytical method of the WRIM is proposed. WRIM and PCA models are implemented in Matlab software. The simulation results show the potential necessity of the considered PCA method on the WRIM faults detection compared to some other signal analysis method.

1 INTRODUCTION

Since many years, faults detection in electrical machines has been object of both industrial and teaching laboratories. Previously, DC and synchronous machines were the most used on industry applications, and reliability researches were focused on these types of machines. With technological developments, power electronic progress and the economic issue, the squirrel cage and the wound rotor induction machines have taken their place in several applications domain like transportation, energy production and electrical drives through their robustness, reliability and lower costs. Although researches and improvements have been carried out, these machines still remain the most potential of the stator and the rotor failures.

In fact, this article shows one of several methodology for monitoring and doing diagnostics related to the faults on a wound rotor induction machine (WRIM) based WECC by the residues analysis of its state variables. The approach is based on the principal components analysis (PCA) method.

The first part of this paper deals with the WRIM modeling followed by some reminders of the different types of stator and rotor WRIM faults. The second part is devoted at the PCA principle. The PCA model construction method and the choice criterion of the number of components to be retained is discussed, followed by the PCA residues generation technical for the faults detection and the localization. The third part talks about the method validations using Matlab/Simulink software. The simulation results of several variables (stator and rotor currents, shaft rotational speed, electrical power, electromagnetic torque and other variables issued from mathematical transformations) of healthy and faulted WRIM are analyzed.

F. Ramahaleomiarantsoa J., Heraud N., J. R. Sambatra E. and M. Razafimahenina J..
PRINCIPAL COMPONENTS ANALYSIS METHOD APPLICATION IN ELECTRICAL MACHINES DIAGNOSIS.
DOI: 10.5220/0003542501670175
In *Proceedings of the 8th International Conference on Informatics in Control, Automation and Robotics* (ICINCO-2011), pages 167-175
ISBN: 978-989-8425-74-4

Special attention has been reserved to the PCA residues representations. The last part is reserved to the analyze and discussion of simulation results.

2 WRIM MODELLING

In the process of faults survey and diagnosis, an accurate modeling of the machine is necessary. In this paper, three phases model based on magnetically coupled electrical circuits was chosen.

The aim of the modeling is to highlight the electrical faults influences on the different state variables of the WRIM. For that, some modeling assumptions given in the following section are necessary.

2.1 Modeling Assumptions

In the proposed approach, we assumed that:

- the magnetic circuit is linear, and the relative permeability of iron is very large compared to the vacuum.
- the skin effect is neglected,
- hysteresis and eddy currents are neglected,
- the airgap thickness is uniform,
- magnetomotive force created by the stator and the rotor windings is sinusoidal distribution along the airgap,
- the stator and the rotor have the same number of turns in series per phase,
- the coils have the same properties,
- the WRIM stator and rotor coils are coupled in star configuration and connected to the considered balanced state grid.

2.2 Differential Equation System of the WRIM

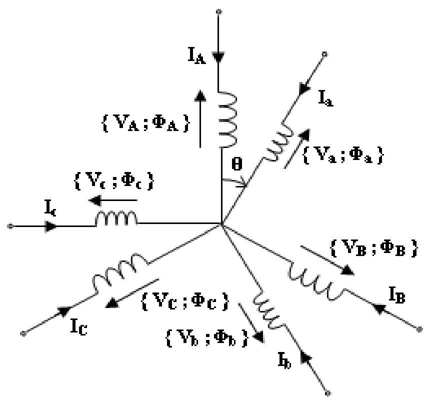

Figure 1: Equivalent electrical circuit of the WRIM.

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 the voltages, the 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.

The figure 1 shows the equivalent electrical circuit of the WRIM. Each coil, for both the stator and the rotor, is modelised with a resistance and an inductance connected in series configuration (Fig. 2).

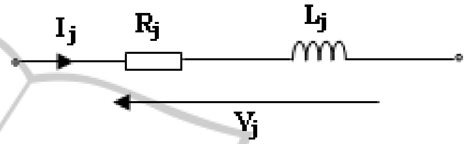

Figure 2: Equivalent electrical circuit of the WRIM coils.

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

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

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

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

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

$$[\phi_S]=[L_S][I_S]+[M_{SR}][I_R] \qquad (3)$$

$$[\phi_R]=[L_R][I_R]+[M_{RS}][I_S] \qquad (4)$$

$[R_S]$ and $[R_R]$ are the resistances matrix, $[L_S]$ and $[L_R]$ the own inductances matrix, and $[M_{SR}]$ and $[M_{RS}]$ the mutual inductances matrix between the stator and the rotor coils.

With (3) and (4), (1) and (2) become:

$$[V_S]=[R_S]\ [I_S]+\frac{d\{[L_S][I_S]\}}{dt}+\frac{d\{[M_{SR}][I_R]\}}{dt} \qquad (5)$$

$$[V_R]=[R_R]\ [I_R]+\frac{d\{[L_R][I_R]\}}{dt}+\frac{d\{[M_{RS}][I_S]\}}{dt} \qquad (6)$$

By applying the fundamental principle of dynamics to the rotor, the mechanical motion equation is (Wieczorek and Rosołowski, 2010):

$$J_t \frac{d\Omega}{dt} + f_v \Omega = C_{em} - C_r \tag{7}$$

$$\Omega = \frac{d\theta}{dt} \tag{8}$$

with:

$$C_{em} = \frac{1}{2}[I]^t * \frac{d([L])}{d\theta} * [I] \tag{9}$$

J_t is the total inertia brought to the rotor shaft, Ω the shaft rotational speed, $[I]=[I_A\ I_B\ I_C\ I_a\ I_b\ I_c]^t$ the currents vector, f_v the viscous friction torque, C_{em} the electromagnetic torque, C_r the load torque, θ the angular position of the rotor relative to the stator and $[L]$ the inductances matrix of the machine.

Introducing the cyclic inductances of the stator and the rotor $L_{SC} = \frac{3}{2} L_S$ and $L_{RC} = \frac{3}{2} L_R$ (L_S is the own inductance of the each phase of the stator and L_R is the own inductance of the each phase of the rotor), the mutual inductances between the stator and the rotor coils M_{SR} and pole pair number p, the inductance matrix of the WRIM car be written as follow:

$$[L] = \begin{bmatrix} L_{SC} & 0 & 0 & M_{SR} f_1 & M_{SR} f_2 & M_{SR} f_3 \\ 0 & L_{SC} & 0 & M_{SR} f_3 & M_{SR} f_1 & M_{SR} f_2 \\ 0 & 0 & L_{SC} & M_{SR} f_2 & M_{SR} f_3 & M_{SR} f_1 \\ M_{SR} f_1 & M_{SR} f_3 & M_{SR} f_2 & L_{RC} & 0 & 0 \\ M_{SR} f_2 & M_{SR} f_1 & M_{SR} f_3 & 0 & L_{RC} & 0 \\ M_{SR} f_3 & M_{SR} f_2 & M_{SR} f_1 & 0 & 0 & L_{RC} \end{bmatrix} \tag{10}$$

$$f_1 = \cos(p\theta) \tag{11}$$

$$f_2 = \cos(p\theta + \frac{2\pi}{3}) \tag{12}$$

$$f_3 = \cos(p\theta - \frac{2\pi}{3}) \tag{13}$$

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

$$[\dot{X}] = [A]^{-1}([U] - [B][X]) \tag{14}$$

with:

$$[X] = [I_A\ I_B\ I_C\ I_a\ I_b\ I_c\ \Omega\ \theta]^t$$

$$[A] = \begin{bmatrix} [L] & 0 & 0 \\ 0 & J_t & 0 \\ 0 & 0 & 1 \end{bmatrix};\ [U] = \begin{bmatrix} [V] \\ -C_r \\ 0 \end{bmatrix};$$

$$[V] = [V_A\ V_B\ V_C\ V_a\ V_b\ V_c]^t;$$

$$[B] = \begin{bmatrix} [R] + \Omega \frac{d[L]}{d\theta} & 0 & 0 \\ -\frac{1}{2}[I]^t \frac{d[L]}{d\theta} & f_v & 0 \\ 0 & -1 & 0 \end{bmatrix}$$

This model of the WRIM will be used to simulate both the healthy and the faulted operation case of the stator and the rotor.

2.3 WRIM Faults

The necessity for having reliable electric machines is more important than ever and the trend continues to increase. Lighter machine having a considerable lifetime is now possible due to advances in engineering and materials sciences domain. Although the constant improvements on design technical of reliable machine, different type of faults still exist. The faults can be resulted by normal wear, poor design, poor assembly (misalignment), improper use or combination of these different causes.

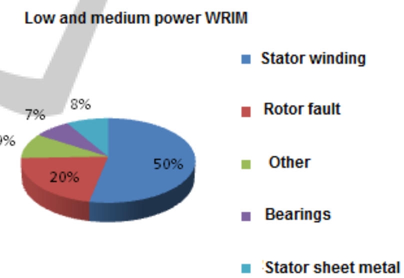

Figure 3: Low and medium power induction machines faults (Razik, 2002; Chia-Chou et al., 2008).

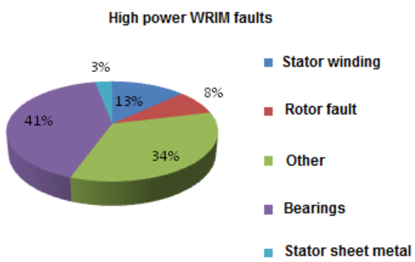

Figure 4: High power induction machines faults (Razik, 2002; Chia-Chou et al, 2008).

Figure 3 and figure 4 present the faults distribution carried out by a German company on industrial system. The figure 3 show the faults of the low and medium power machines (50 KW à 200 KW), and the figure 2 those of the high power machines (from 200 KW) (Razik, 2002; Chia-Chou et al., 2008).

Figure 3 shows that the most encountered faults of the low and medium power on the induction machines are the stator faults and the figure 4 shows that the faults due to mechanical defects give the highest percentages. The induction machines faults can be classified into four categories (Chia-Chou et al., 2008):

The stator faults can be found on the coils or the breech. In most cases, the winding failure is caused by the inter-turns faults. These last grow and cause different faults between coils, between several phases or between phase and earth point before the deterioration of the machine (Sin et al., 2003). The breech of electrical machines is built with insulated thin steel sheets in order to minimize the eddy currents for a greater operational efficiency. In the case of the medium and great power machines, the core is compressed before the steel sheets emplacement to minimize the rolling sheets vibrations and to maximize the thermal conduction. The core problems are very little, only 1% compared to winding problems (Negrea, 2006).

The rotor faults can be bar breaks, coils faults or rotor eccentricities.

The bearings faults can be caused by a poor choice of materials during the manufacturing steps, the problems of rotation within the breech caused by damaged, chipped or cracked bearing and can create disturbance within the machines.

The other faults can be caused by the flange or the shaft faults. The faults created by the machine flange are generally caused during the manufacturing step.

Although the induction machines are robust, they can be seats of different types of faults that can be classified into two categories (Kliman et al., 1996):

- The hard and brutal faults modelised by an abrupt inputs change or system parameters.
- The soft and arising faults due to gradual changes of system parameters compared to their normal values.

As previously mentioned, for the state survey of the electrical machines, the PCA method was adopted.

3 PCA METHOD APPROACH

The PCA principle is based on simple linear algebra. It can be used as exploring tool, analyzing data and models design. The PCA method is based on a transformation of the space representation of the simulation data. The new space dimension is smaller than that the original space dimension. It is classified as without models method categories (Liu, 2006). It can be considered as a full identification method of physical systems (Marx et al., 2007; Ku et al., 1995; Huang, 2001). The PCA allow to provide directly the redundancy relations between the variables without identifying the state representation matrix of the system. This task is often difficult to achieve.

3.1 PCA Method Formulation

We note by $x_i(j) = [x_1\ x_2\ x_3 \ldots x_m]$ the measurements vector « *i* » represents the measurement variables that must be monitored and ranging from *1 to* m and « *j* » the number of the performed measurements for each variable « *m* », ranging from *1 to N*.

The measurements data matrix ($X_d \in R^{N*m}$) can be written:

$$X_d = \begin{pmatrix} x_1(1) & \ldots & x_m(1) \\ \ldots & \ldots & \ldots \\ x_1(N) & \ldots & x_m(N) \end{pmatrix} \tag{15}$$

This data matrix can be described with a possible smallest set of new synthetic matrix, that is a orthogonal linear projection of a subspace of *m* dimension in a less dimension subspace *l (l<m).* The method consists in identifying the PCA model and is based on two steps (Li and Qin, 2001):

- Determination on the eigenvalues and the eigenvectors of the covariance matrix R.
- Determination of the structure of the model, which consists to calculate the components number « *l* » to be retained in the PCA model.

3.2 Eigenvalues and Eigenvectors Determination

Variables must be centered and reduced to make data matrix independent of variables physical units.

Then, the new obtained normalized measures matrix is:

$$X = [X_1 \ldots X_m] \tag{16}$$

And the covariance matrix R is given by:

$$R = \frac{1}{N-1} XX^T \tag{17}$$

In decomposing R, (16) can be expressed as:

$$R = P\Lambda P^T \tag{18}$$

With

$$PP^T = P^T P = I_m \tag{19}$$

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

The eigenvectors matrix P is expressed as:

$$P = [p_1, p_2, ..., p_m] \tag{20}$$

p_i is the orthogonal eigenvectors corresponding to λ_i . Then, the principal components matrix is:

$$T = XP \tag{21}$$

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

3.3 PCA Model Construction

To obtain PCA model, the components number "l" to be retained must be determined. This step is very important for PCA construction. For that, many rules have been proposed by (Li and Qin, 2001). Most are from sometimes subjective heuristics method or criteria used in system identification in privileging the data matrix approximation of the data matrix. In this paper, "average eigenvalues" criterion is used. The principle is based on the determination of the variances of each component with the centered and reduced variables. The number of variables l to be retained to construct the PCA model is equal to the number of components whose variance is greater than unity.

By taking into account the number of components to be retained and by partitioning the principal components matrix T, the eigenvectors matrix P and the eigenvalues matrix Λ (Valle et al., 1999; Benaicha et al., 2010), the constructed PCA model is given by:

$$T = \left[T_p^{N*l} T_r^{N*(m-l)} \right] \tag{22}$$

$$P = \left[P_p^{N*l} P_r^{N*(m-l)} \right] \tag{23}$$

$$\Lambda = \begin{bmatrix} \Lambda^{l*l} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \Lambda^{(m-l)(m-l)} \end{bmatrix} \tag{24}$$

T_p and T_r is respectively the principal and residual parts of T, P_p and P_r is respectively the principal and residual parts of P.

With this PCA model, the centered and reduced matrix X can be written as:

$$X = P_p T_p^T + P_r T_r^T \tag{25}$$

In considering:

$$X_p = P_p T_p^T = \sum_{i=1}^{l} P_i T_i^T \tag{26}$$

$$E = P_r T_r^T = \sum_{i=l+1}^{m} P_i T_i^T \tag{27}$$

The centered and reduced matrix data is given by:

$$X = X_p + E \tag{28}$$

X_p is the principal estimated matrix and E the residues matrix which represent information losses due to the 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 $\lambda_{l+1}, ..., \lambda_m$. Therefore, in this case, data compression preserves all the best the information that it conveys. Under the application of PCA at diagnosis, the number of components has a significant impact on each step of faults detection and localization procedure.

Nine state variables (m=9) have been chosen to be monitored and 10000 measures (N=10000) during 4s are considered. The WRIM faults are introduced from the initial time (t=0s) to the final time (t=4s) of the different simulations. The machine is coupled to a mechanical load torque (10Nm) at t=2s. The considered faults are respectively, increases from 10% to 40% of the resistance value of both the stator and rotor coils.

The following figures (Fig. 5 and Fig. 6) represent the residues variation of the WRIM stator current versus time and show the number l impact in the diagnosis approach:

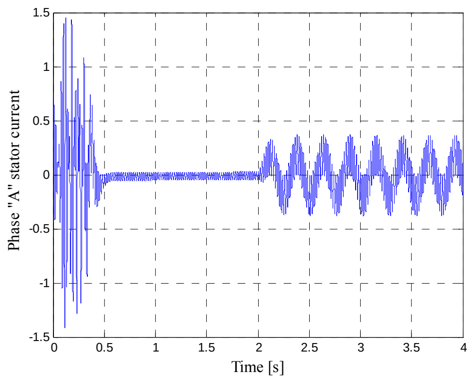

Figure 5: Stator current residue for l = 5.

Figure 6 show that the chosen number of components is too high then the residual space dimension is reduced. Some faults are projected in the principal space and the stator current residues can not be detectable.

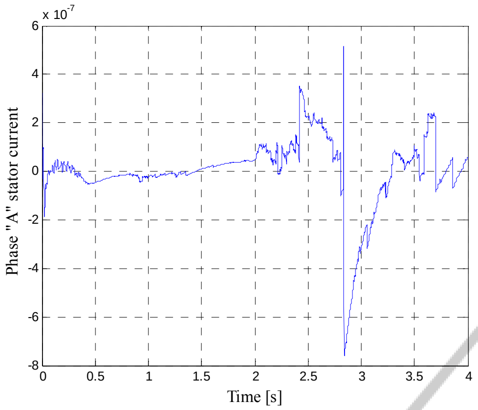

Figure 6: Stator current residue for $l = 6$.

However, with the figure 5, the number of components is well chosen. Faults can be detected and localized and the PCA model is well reconstructed.

Generally, the detection approach in the case of diagnosis based on analytical model is linked with the residues generation step. From these residues analysis, the decision making step must indicate if faults exist are not. The residues generation approach can be the state estimation approach or the parameter estimation approach.

The residue indicates the information losses given by the matrix dimension reduction of the state variables matrix data to be monitored. Indeed, a small residue means that the estimated value tends to the exact value in healthy operation case.

In our case, the eigenvalues corresponding to the number of the retained principal components represent 93% of the total sum of eigenvalues. 0nly 7% of the total represent the residues subspace. One can conclude that the PCA model has been well constructed.

4 PCA METHOD APPLICATION ON WRIM

The WRIM data simulation approaches with the PCA method are given by the following figure:

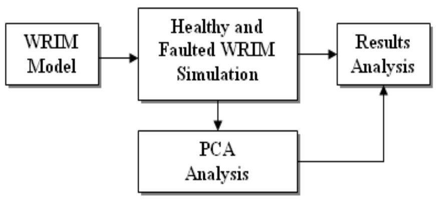

Figure 7: Synoptic diagram of the different steps of the data treatment.

The simulation approach is divided in four blocs:

- WRIM modeling: mathematical equations calculation and simulation.
- Simulations results: graph showing the output states of the system (healthy and faulted operation)
- Simulations data: simulation results acquisition as matrix form.
- PCA: data treatment and system diagnosis.

4.1 Considered Faults

In normal operation, a resistance value variation compared to its nominal value (in ambient temperature, 25°C) is considered as faulted machine due to machine overload or coils fault (Razik, 2002).

The resistance versus the temperature is expressed as:

$$R = R_0(1 + \alpha \Delta T) \tag{29}$$

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

4.2 Simulation Results

The different simulation results have been performed with respect to the simulation conditions mentioned earlier.

Figure 8 to figure 17 represent the real variations without PCA method (Fig. 8 to Fig. 14) and the residue variations with PCA application (Fig. 15 to Fig. 17) of the faulted WRIM state variables in considering stator faults.

With the WRIM state variables, other quantities issued to their transformations have been calculated:

- quadrature axis and direct axis currents with Park transformation,
- α axis and β axis currents with Concordia transformation.

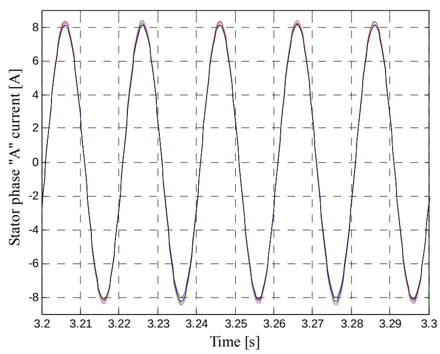

Figure 8: Real variations versus time of the stator current of the healthy and faulted WRIM.

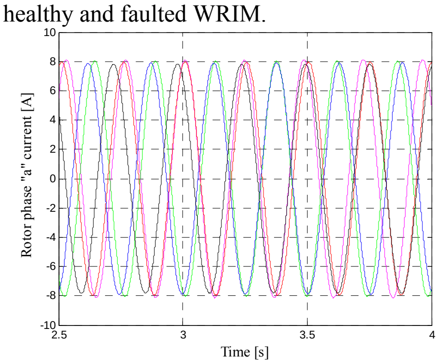

Figure 9: Real variations versus time of the rotor current of the healthy and faulted WRIM.

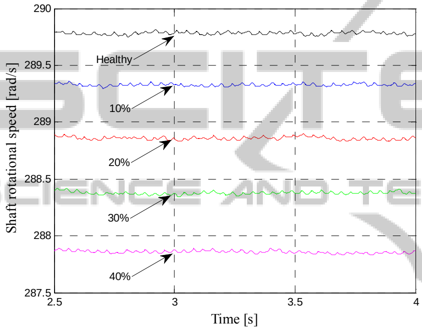

Figure 10: Real variations versus time of the shaft rotational speed of the healthy and faulted WRIM.

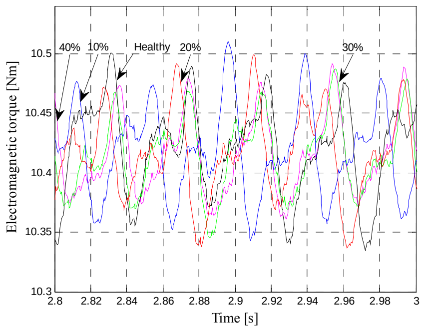

Figure 11: Real variations versus time of the electromagnetic torque of the healthy and faulted WRIM.

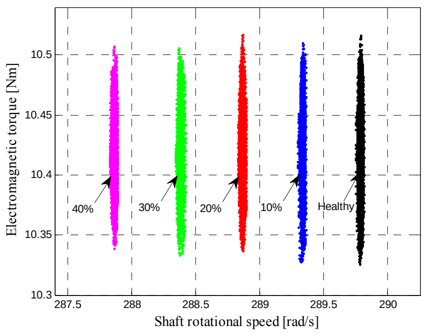

Figure 12: Real variations of electromagnetic torque versus the shaft rotational speed of the WRIM.

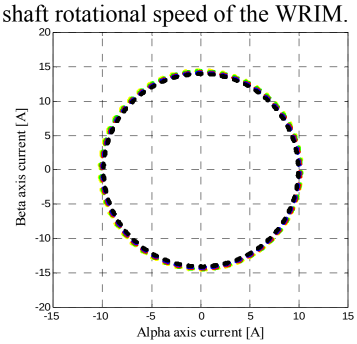

Figure 13: Real variations of β axis current versus the phase α axis current of the stator phase.

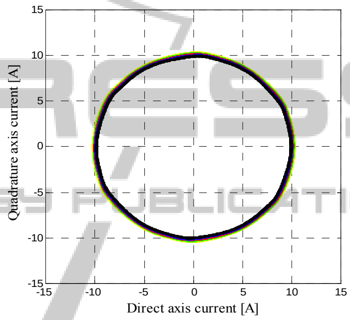

Figure 14: Real variations of the quadrature axis current versus the phase direct axis current of the stator phase.

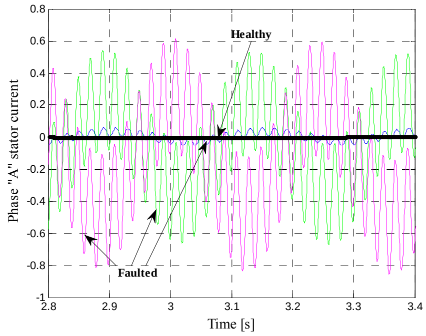

Figure 15: Variations of the stator phase “A” current residues versus time of the healthy and faulted WRIM.

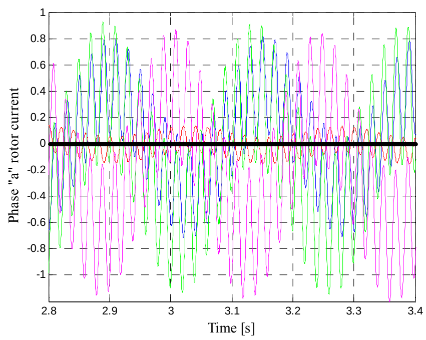

Figure 16: Variations of the rotor phase “a” current residues versus time of the healthy and faulted WRIM.

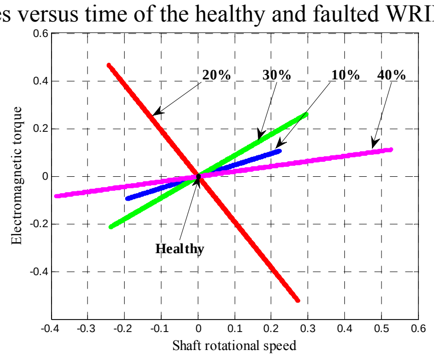

Figure 17: Variations of electromagnetic torque residues versus the shaft rotational speed residues of the WRIM.

4.3 Discussion

Several types of representations are used in the signals processing domain, in particular for electrical machines diagnosis. We can mention the temporal representation (Fig. 8 to Fig.11, Fig. 15 and Fig. 17) and the signal frequency analysis. Although they have demonstrated their effectiveness, the state variables representations between them also show their advantages. They can be performed without mathematical transformation (Fig. 12) and with mathematical transformation (Fig. 13 and Fig. 14).

The latter representation type and the temporal representation are confronted with the PCA method application results (Fig. 15 to Fig. 17). Only the simulation results with stator faults are presented because the global behavior of the state variables in both rotor and stator faults are almost similar.

For the temporal variations case, the rotor currents (Fig. 9) and the shaft rotational speed (Fig. 10) are the variables which produce the most information in presence of faults. The faults occur on the rotor current frequency and the shaft rotational speed magnitude.

Also, the electromagnetic torque variations versus the shaft rotational speed clearly show the WRIM operation zone in the presence of faults (Fig. 12). Contrary to this, the representations with mathematical transformations (Fig. 13 and Fig. 14) do not provide significant information due to the fact that the stator currents remain almost unchanged in the presence of faults (Fig. 8).

With PCA method application, all representation types well show the differences between healthy and faulted WRIM (Fig. 15 to Fig. 17). In the healthy case, residues are zero. When faults appear, the residue representations have an effective value with an absolute value greater than zero.

In the figure 17, the healthy case is represented by a point placed on the coordinate origins. Also, one can show several right lines corresponding to the faulted cases. This behavior is due to the proportional characteristic of the considered faults.

PCA method proved so effective in electrical machines faults detection. This requires a good choice of the number of the principal components to be retained so that information contained in residues is relevant.

5 CONCLUSIONS

PCA method based on residues analysis has been established and applied on WRIM diagnosis.

An accurate analytical model of the machine has been proposed and simulated to performed the healthy and faulted data for PCA approach need.

Several representations of nine state variables of the machine have been analyzed. In the case of temporal variation and without PCA, the rotor current and the shaft rotational speed are the more affected by the considered fault type. The representations of the electromagnetic torque versus the shaft rotational speed in both with and without PCA approach show clearly the presence of faults. Indeed, PCA method is interesting for all type of representation compared to some other signal processing types.

ACKNOWLEDGEMENTS

This research was supported by MADES/SCAC Madagascar project. We are grateful for technical and financial support.

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