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Using the Least Squares Methods for Detecting Short Circuit Faults in Electrical Systems

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Abstract

This paper presents the technique for estimating parameters based on the method of least squares with and without forgetting factor is presented in this work. This technique is applied to power systems with or without faults. An evaluation in numerical simulation of a coil with iron core with or without fault short-circuit of turns, allows discuss the quality of the estimation of physical parameters of the coil.

Keywords: fault, parameters estimation, electrical systems, least square, detection.

INTRODUCTION

Systems identification is a large area which includes different approaches. This difference is due, firstly, to the family of models: model knowledge or behavior, parametric or non-parametric models, deterministic or stochastic models and secondly, to operating contexts: online or offline, open or closed loop, with or without control of the input signals.

The aim of this work is to apply some approaches of parametric identification on line of dynamic processes, in particular, the method of least squares with or without forgetting factor [1] for the electrical systems. The iron core coil is the basic structure of all the electrical machines. Therefore, it is important to test our approach on this system. We show that the identification methods used to build functioning and dysfunction models useful for applications in the field of detection and diagnosis of faults.

This paper is organized as follows:

In Section2, we present a mathematical presentation of the coil. In Section3, we present a least squares method to identify the parameters of the proposed model. In Section4, we present a least squares with factor forget to improve the speed of convergence of the proposed algorithm. In Section5, we present a model with fault, where we take into account of the failure of short circuit turns. In Section6, we conclude the paper by summarizing the main contribution and at the same time we provide some remarks.

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MODEL OF THE COIL

The coil iron core contains two magnetic and electric circuits when the coil is crossed by an electric current, it creates losses in the two circuits: in the magnetic circuit by hysteresis and in the electric circuit by eddy current. When these losses are negligible the coil is represented by two resistors and an inductor, the schemes of the coil can be illustrated in (figure 1) [2].

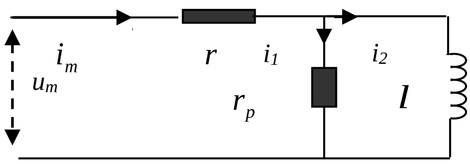

Figure 1: The iron core coil

The use and simplification of mesh and Kirchhoff laws gives the following model:

$$a.\frac{di(t)}{dt}+b.i(t)=c.\frac{du(t)}{dt}+u(t) \quad (1)$$

Such as,

$$a=\frac{(r+r_p)*l}{r_p},\ b=r \text{ and } c=\frac{l}{r_p}$$

LEAST SQUARES METHOD

The method of recursive least squares are used to identify the parameters of the numerical models of physical processes or signals. The idea is to minimize a quadratic criterion corresponding to the square of the error at time k, between the model output and output value of the process or of the signal which will be modeled. The principle of the identification process is shown in the diagram of principle (figure 2) [3]:

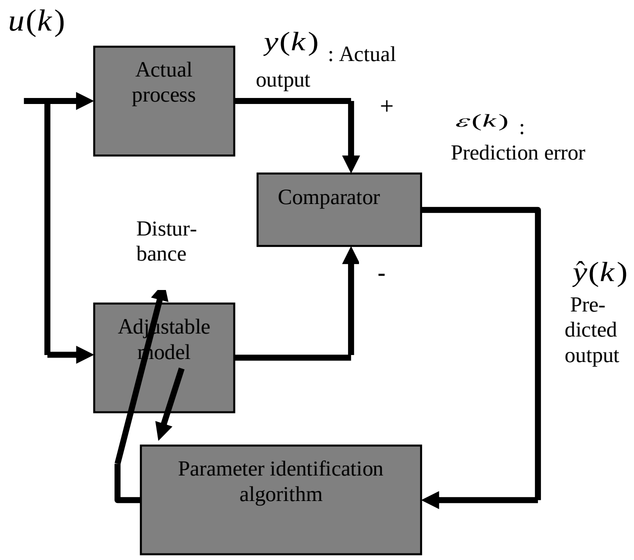

Figure 2: The principle of identification

The quadratic error test is given by:

$$J(N)=\sum_{k=1}^{N}\varepsilon(k)^2 \tag{2}$$

Where $\varepsilon(k)$ is the prediction error at time k, defined as the difference between the output of the process and estimated output by model at time k. This error is estimated from the measurement of the output of the process which can be noisy. In our study, it is assumed that the current *i(k)* is disturbed by a noise measuring *e(k)* defined by the equation (3) [4]:

$$i_m(k)=i(k)+e(k) \tag{3}$$

Where $i_m(k)$ represents the measured current. The prediction error is given by (4):

$$\varepsilon(k)=i(k)-\hat{i}(k)\approx i_m(k)-\hat{i}(k) \tag{4}$$

The recursive least squares algorithm is presented by [5]:

$$\begin{cases} P(k)=P(k-1)-\dfrac{P(k-1).\varphi(k)\varphi^T(k).P(k-1)}{1+\varphi^T(k).P(k-1).\varphi(k)} \\ K(k)=\dfrac{P(k-1).\varphi(k)}{1+\varphi^T(k).P(k-1).\varphi(k)} \\ \hat{\theta}(k)=\hat{\theta}(k-1)+K(k).(y(k)-\varphi^T(k).\hat{\theta}(k-1)) \end{cases} \tag{5}$$

Where P, K and θ is the covariance matrix respectively, the gain and the vector of parameters to be estimated.

To implement the identification algorithm, discretizing equation (1) by using the Euler method *i* is the derivative of approach (6):

$$\frac{di(t)}{dt}=\frac{i(k)-i(k-1)}{dt} \tag{6}$$

Where *dt* is the sampling period. Recurrent equation is obtained (7):

$$i(k)=a_1\cdot i(k-1)+b_1.u(k)+c_1\cdot u(k-1) \tag{7}$$

With the parameter given by equations (8):

$$\begin{cases} a_1=l.(r+r_p)/(l.(r+r_p)+r_p.r.dt) \\ b_1=(l+r_p.dt)/(l.(r_p+r)+r_p.r.dt) \\ c_1=-l/(l.(r_p+r)+r_p.r.dt) \end{cases} \tag{8}$$

Equation (7) is linear with respect to parameters a_1, b_1 and c_1, this condition is necessary to apply the recursive least squares algorithm. Taking into account the measurement error *e(k)* to the current *i(k)* defined by the equation (3), the prediction error follows the recursive relation (9):

$$\varepsilon(k)=a_1.\varepsilon(k-1)+e(k) \tag{9}$$

ESTIMATION OF DIGITAL PARAMETERS

The recursive least squares algorithm allows the estimation of the parameters a_1, b_1 and c_1 of the recurrent equation. This method is applied in a first step on simulated signals on a coil without faults [5].

The excitation signal is a random analog signal type binary sequence pseudo-random, the sampling period is = 0.01 and the noise is Gaussian assumed average value of 0.001 and variance 1. Parameters to estimate have the correct as follow:

$r=3.50\Omega$; $r_p=86.96\Omega$ and $l=40.50mH$

RESULTS

The results of the identification algorithm are show in figures 3 at 7

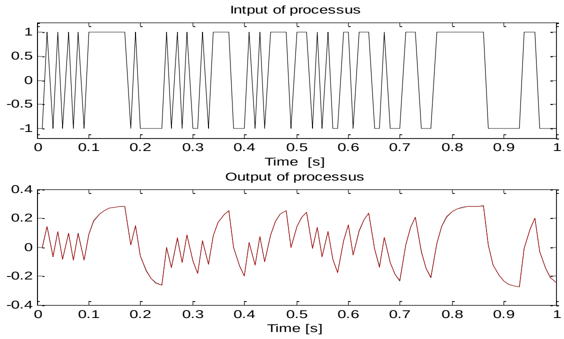

Figure 3: Sequence input-output versus time (s), sequence pseudo-randon binary input (top), actual output (low, solid lines) and measured (bottom dotted lines)

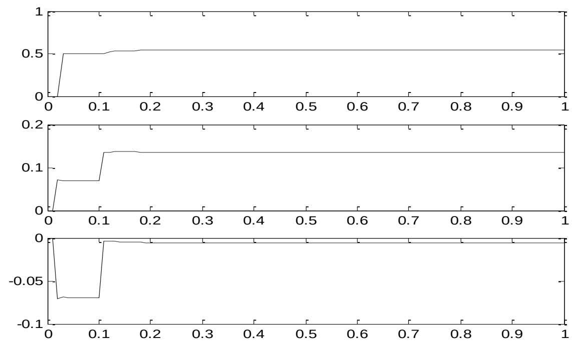

Figure 4: Identification of numerical parameters versus time (s) a_1 (top); b_1 (middle), and c_1 (bottom)

The superposition between the two output signals (solid line) and estimated (dotted line) as well as the identification of residue signal are shown in figure 5.

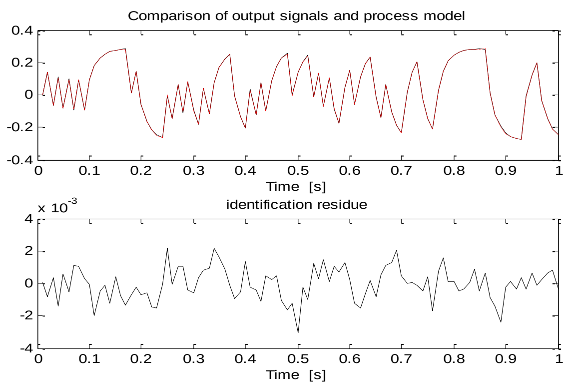

Figure 5: Identification results in function of time (s), actual output (top, solid lines) and measured (top, dotted lines), identification on residues (botton)

ESTIMATION OF PHYSICAL PARAMETERS

From the non-linear system equations (8), and by using the Newton-Raphson method it is possible to estimate the physical parameters of the coil (6).

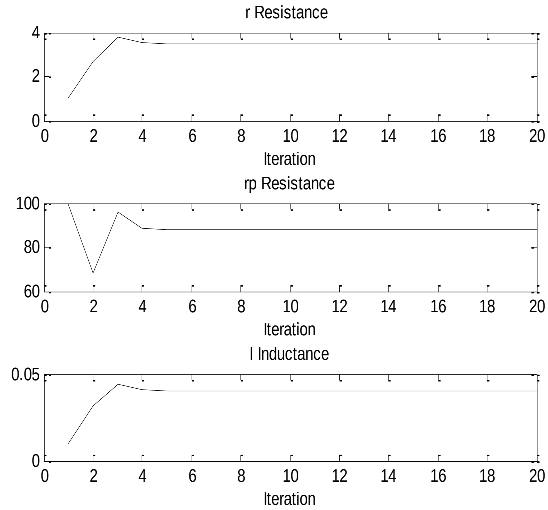

Figure 6: Identification of physical parameters in the number of iteration; r (above); r_p (middle); l (bottom)

The distribution of estimates physical parameters follows quasi-normal distributions whose parameters are detailed in Table 1.

Table 1: Distribution of estimates for series of 1000 acquisitions sequences

Parameters	Average	Variance
r_{est}	3.5028	$< 10^{-4}$
r_{pest}	88.6444	8.24
l_{est} (x 10^{-3})	40.42	$< 10^{-4}$

We note an error of about 3% on the estimated r_p, the estimation error on the other parameters is negligible. Simulation results of the measurement are noise dependent. Indeed when the noise increases, the variance estimates for the parameters a1, b1 and c1 increases. Figure 8 shows the variance of the estimates obtained in accordance with the magnitude of the measurement error for the numerical parameters from a set of 100 acquisition sequences.

Figure 7 shows the histograms of physical parameters obtained for a series of 1000 acquisitions sequences; it can check the appearance of the observed near-normal distributions.

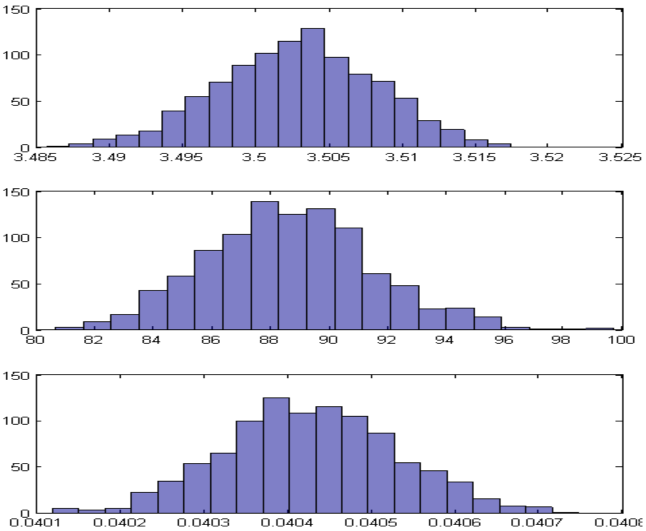

Figure 7 : Histograms of parameters; *r* (above); r_p (middle); *l* (bottom)

Figure 8 shows the variance of the estimates obtained in accordance with the magnitude of the measurement error for the numerical parameters from a set of 100 acquisition sequences.

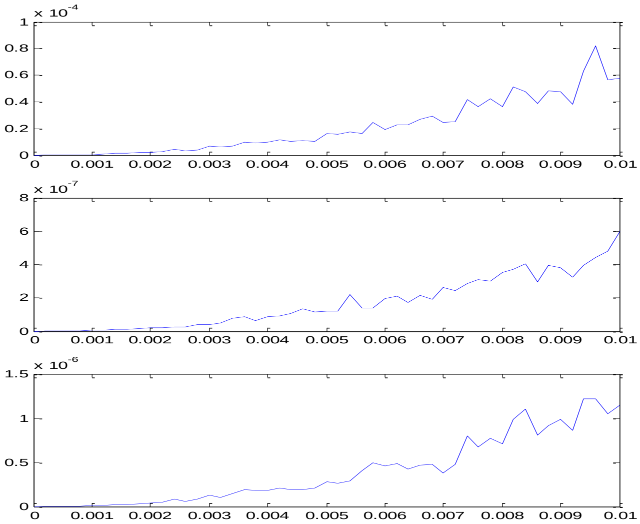

Figure 8: Variance numerical parameters estimated in accordance with the magnitude of the measurement error; a_1 (top); b_1 (middle); c_1 (low)

At the same time the average error of the estimates a_1, b_1 and c_1 remains broadly constant. Figure 9 shows the average estimation error for the numerical parameters from a series of 100 acquisition sequences.

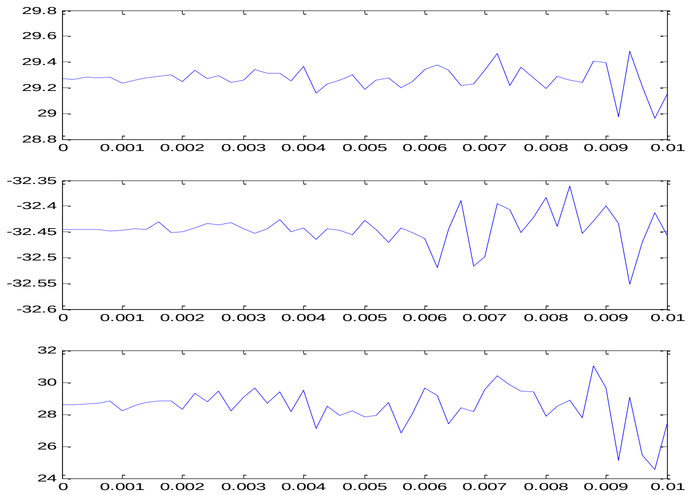

Figure 9 : Estimated average error of digital parameters in accordance with the magnitude of the measurement error; a_1 (top); b_1 (middle); c_1 (low)

The increase of the variance of the estimation of a_1, b_1 and c_1 strongly biased the estimation of the physical parameters with Newton - Raphson (Figure 10). For higher noise values, the algorithm diverges (lack of results in Figure 10).

The results obtained show that the least squares method provides correct results. But convergence is relatively slow and the method is sensitive to measurement noise. It will be difficult to detect the occurrence of faults in the system since them likely to be confused with the noise.

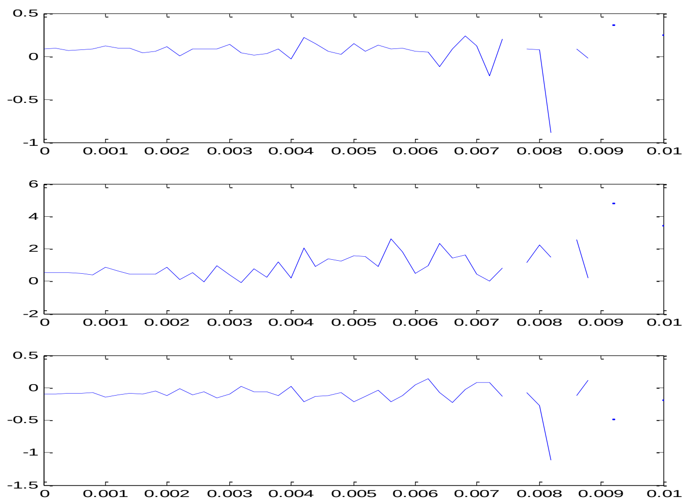

Figure 10 : Mean error estimation for the physical parameters depending on the magnitude of the measurement error; *r* (above); r_p (middle); *l* (bottom)

ESTIMATION OF PHYSICAL PARAMETERS

In this section we improve the speed of convergence using the least square algorithm **with forgetting factor. This** algorithm consists of minimizing the quadratic criterion *J(N)* [6], [7]:

$$J(N)=\sum_{k=1}^{N}(\varepsilon(k))^{2}.\lambda^{N-k} \tag{10}$$

The least squares algorithm with forgetting factor is defined by equations (11) [4]:

$$\begin{cases} P(k)=\lambda^{-1}.\left(P(k-1)-\dfrac{P(k-1).\varphi(k)\varphi^{T}(k).P(k-1)}{\lambda^{-1}+\varphi^{T}(k).P(k-1).\varphi(k)}\right) \\ K(k)=\dfrac{P(k-1).\varphi(k)}{\lambda^{-1}+\varphi^{T}(k).P(k-1).\varphi(k)} \\ \hat{\theta}(k)=\hat{\theta}(k-1)+K(k).(y(k)-\varphi^{T}(k).\hat{\theta}(k-1)) \end{cases} \tag{11}$$

The forgetting factor $0<\lambda<1$ determines the sensitivity and accuracy of the convergence of the algorithm with respect to the system dynamics. In our case we studied the impact of forgetting on the quality of the estimator. The average estimation error on the physical parameters is very sensitive to the forgetting factor (Figure 11) but the variance of the estimate decreases as the forgetting factor approaches 1 (Figure 12), namely when the method tends to least squares without forgetting.

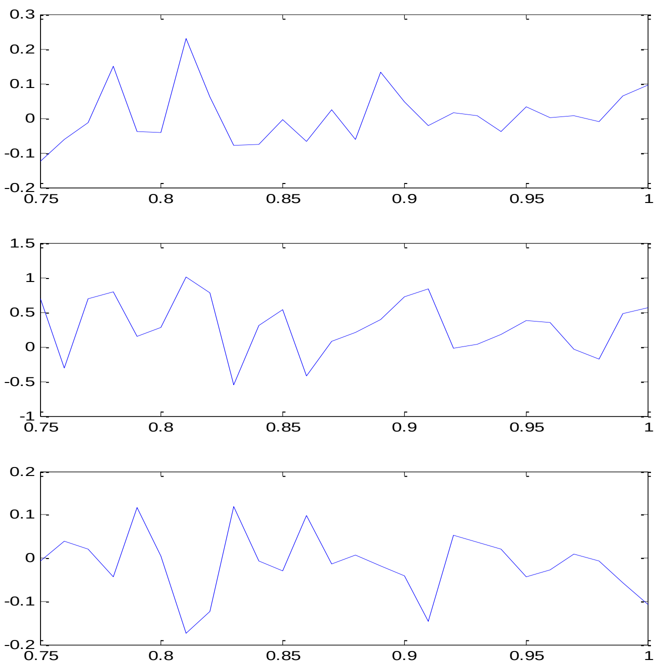

Figure 11 : Mean error estimation for the physical parameters based on forgetting factor; *r* (above); r_p (middle); *l* (bottom)

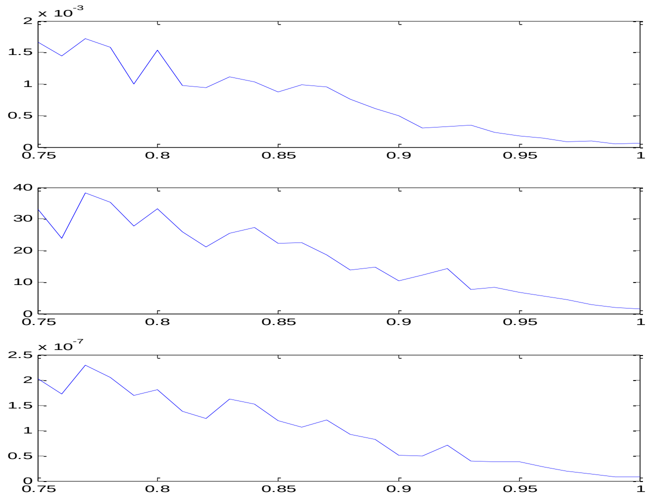

Figure 12: Variance estimates for the physical parameters based on the forgetting factor; *r* (above); r_p (middle);*l* (bottom)

Finally, note that the use of a forgetting factor slightly less than 1 allows increasing the speed of convergence [8]. The study on the calculated sum of the iterations of the least square algorithm and the Newton-Raphson algorithm squared errors illustrates this result (Figure 13). It is found that the sum of calculated iterations of the algorithm of Newton-Raphson square error is minimal for a forgetting of the order of 0.97 factor - 0.98 [9] [10]. At the same time, the sum of squared errors calculated on the iterations of the least squares algorithm increases. In fact, the sum of squared errors calculated for this algorithm reaches a minimum for a forgetting of the order factor of 0.75 - 0.8. The sum of squared errors on the estimate of a1, b1 and c1 is then lower but the final estimate of the parameter is less precise. This justifies the use of a higher forgetting factor. In conclusion it is necessary to jointly study the convergence speed and accuracy of the method.

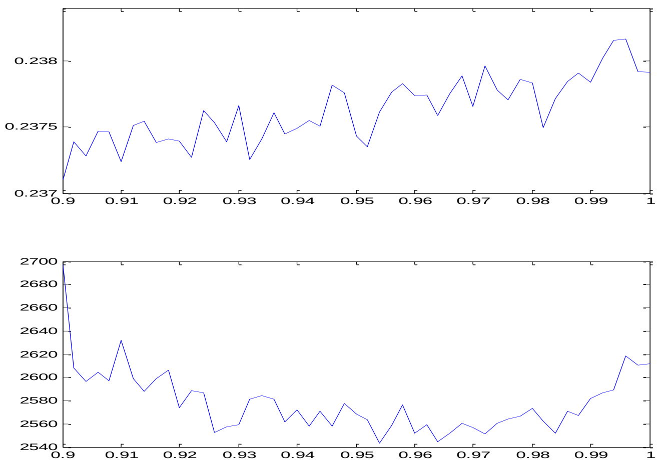

Figure 13 : Sum of squared errors based on the forgetting factor; least square algorithm (top); Newton-Raphson algorithm (bottom)

MODEL WITH FAULT

The most frequent fault in electrical power systems is the failure of short circuit turns. In the short circuit coil is the source of a new winding through which a high current armature. This results in an additional magnetic field having the same direction as the nominal field. By applying the laws of electricity the model is given by equation (7) with modified values (13) for the parameters a_1, b_1 and c_1.

$$\begin{cases} a_1 = l'.(r'+r'_p)/(l'.(r'+r'_p)+r'_p.r'.dt) \\ b_1 = (l'+r'_p.dt)/(l'.(r'_p+r')+r'_p.r'.dt) \\ c_1 = -l'/(l'.(r'_p+r')+r'_p.r'.dt) \end{cases} \quad (12)$$

With,

$$\begin{cases} r'_p = \dfrac{r_p.(1-n_{cc})^2.r}{n_{cc}.r.(r_p+(1-n_{cc})^2/n_{cc})} \\ r' = (1-n_{cc}).r \\ l' = (1-n_{cc})^2.l \end{cases} \quad (13)$$

and n_{cc} is the ratio of short circuit current:

$$n_{cc} = \frac{N_{cc}}{N_s} \quad (14)$$

N_{cc} is where the number of turns in short circuit and N_s is the total number of turns.

In the same manner as previously done on the simulation model with a default short circuit defined by the parameter n_{cc}. The identification is carried out with the least squares method for without forgetting coefficients a_1, b_1 and c_1 and the Newton-Raphson method for the physical parameters [11]:

The sensitivity of the parameters a_1, b_1 and c_1 versus n_{cc} is presented in figure 14. The figure 15 shows the average estimate of numerical parameters depending n_{cc} error. The sensitivity of physical parameters over n_{cc} is shown in figure 16. The figure 17 shows the average estimated physical parameters based on n_{cc} error. All results presented are from sets of 100 acquisition sequences.

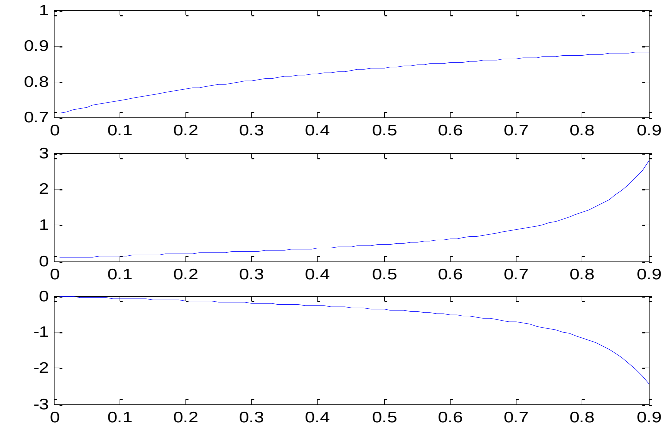

Figure 14 : Average numerical parameters depending n_{cc}; a_1 (top); b_1 (middle); c_1 (low)

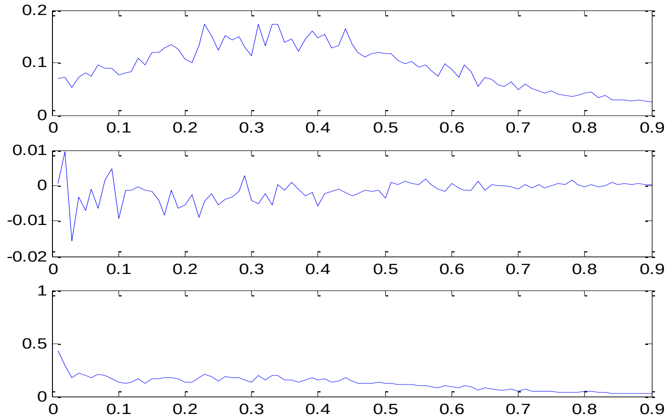

Figure 15 : Mean error estimation for numerical parameters as n_{cc}; a_1 (top); b_1 (middle); and c_1 (low)

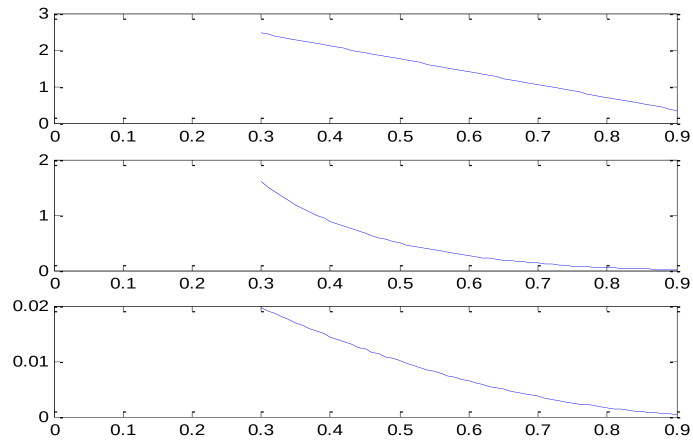

Figure 16 : Average physical parameters according to n_{cc}; r (above); r_p (middle); l (bottom)

DISCUSSION

Simulation results show that the sensitivity of the least squares method to the fault increases with n_{cc}. This method will be used in future work to detect short circuit faults. On the other side, the estimation of physical parameters is difficult for small values of n_{cc}. This part should be improved in our future work on the fault diagnosis.

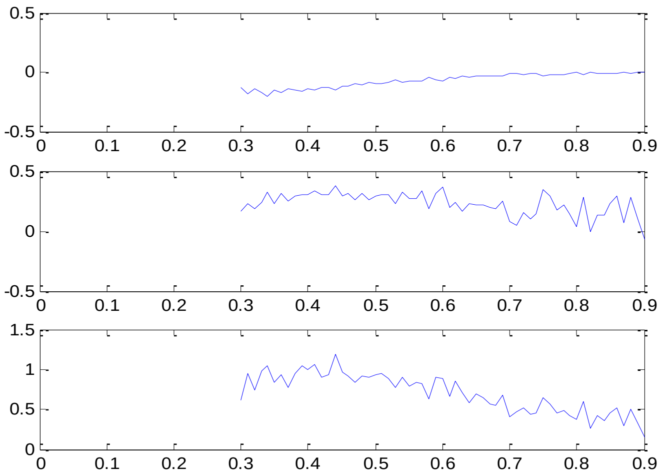

Figure 17 : Mean error estimation for numerical parameters as n_{cc}; r (above); r_p (middle); *l* (bottom)

CONCLUSION

In this paper, the parameter identification methods based on recursive least squares to estimate the physical parameters of the iron-core coil are applied. The results show that the estimated values are correct, but the convergence is slow and sensitive to measurement noise. The application of the MCR method with forgetting factor allows increasing the speed of convergence.

In future work, identification methods will be used for the detection and diagnosis of faults. Indeed, we have demonstrated the sensitivity of the identified parameters to a fault. Furthermore, the proposed methods allow us to construct a set of reference models with and without fault will be used for the detection (compared to the model without fault) and diagnosis (comparison with models dysfunction).

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