On-Line Stator Winding Inter-Turn Short-Circuits Detection in Induction Motors Using Recursive Levenberg-Marquardt Algorithm

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Abstract: Within the framework of the diagnosis of the stator windings faults, the authors propose in this paper a recursive diagnosis method for on-line detection and location of an inter-turn short-circuit by parameters identification. This approach based on the Recursive Levenberg-Marquardt (RLM) algorithm is used for the minimization of the objective function represented by the quadratic criterion obtained by the difference between the real outputs and their estimations. Tests and validations of failure detection by parameter identification require a model suited for fault modelling. For this purpose, a faulty induction motor model is proposed. Electric parameters of this model as well as fault parameters are estimated by RLM adaptive algorithm through an output-error technique. Because the parameters values of this model present magnitude order very different, the normalization of these parameters is proposed in order to obtain the sensitivity functions with the same magnitude order. The estimation results, which used simulated data, are presented to show the effectiveness and the advantage of the proposed approach for use in real-time stator faults diagnosis.

Keywords: Faults detection, on-line parameters identification, induction motor, stator winding inter-turn short-circuits, recursive Levenberg-Marquardt

1. Introduction

Induction Motors (IMs) are widely used and play a crucial role in modern industry systems. One of the most common faults is stator winding shorted turns, which covers approximately 30%-40% of the overall fault conditions in IMs [1]. Therefore, fast detection techniques able to detect these kinds of faults at an early stage of evolution are particularly welcome, in order to avoid the catastrophic failure in industrial process [2].

During the last two decades, several techniques have been studied, related to the analysis of the presence of internal faults in the stator windings of induction motors. Reviews about some of these techniques are reported in [1], [3], [4].

In order to detect shorted turns in stator windings, three main solution techniques are commonly used in the literature. The first technique is based on signal analysis, which often uses spectral tools to underline specific frequency components related to the fault [5], [6]. The second technique is related to knowledge-based approach [5], [7], [8]. The third class is based on state or parameters estimation and implies the use of mathematical models of the studied system [9], [10], [11], [12].

Recently, the trend is oriented towards techniques that are insensitive to the voltage unbalance and machine load variation. Thus, continuous identification has been used to perform the diagnosis procedure [10], [11], [12], [13], [14]. These techniques study the deviation of motor parameters to detect and localize faults in IMs.

Tests and validations of failure detection by parameter estimation require a model suited for fault modelling. For these purposes, a model of squirrel-cage IM dedicated to shorted turns windings is used. The parameters of this model have been identified by off-line and on-line identification algorithms using output-error technique [15].

For a fault early detection, it is necessary to follow-up in real-time the electric parameters of the machine as well as the parameters of defects. Kalman Filter (KF) algorithm is one of the most popular adaptive filtering techniques used in non-stationary environments and real-time

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estimation [16]. However, the KF has some inherent limitations mainly due to calculation of complicated analytical derivatives for linearizing the nonlinear model. Moreover, the KF needs statistical knowledge of the noises acting on the states and on the output, which can be difficult to obtain in non-linear cases [14]. In order to overcome such a drawback, a method based on the description of a Recursive Levenberg-Marquardt (RLM) algorithm is proposed in this paper. This method which has less training complexity than KF algorithm as there are fewer parameters to configure, can estimate time-varying system without much increase in computation complexity.

The RLM method was proposed and successfully applied to various fields [17], [18], [19]. In [17], RLM algorithm has been presented for on-line training of neural nets for nonlinear adaptive filtering. Leading to improve performance, the adaptive RLM algorithm has been proposed in [18] for per-tone equalisation in discrete multitone systems.

Sensitivity functions computation, which it is used to compute the gradient and the Hessian, is an important point in the identification procedure. The parameters we wish to estimate have magnitude order very different. This can lead to convergence difficulties of the proposed RLM approach. In order to obtain the sensitivity functions with the same magnitude order, we propose, in this paper, to normalize the parameters values which mean the normalization of the sensitivity functions [20].

In the present work, the RLM approach performed by the normalization of the sensitivity functions is investigated to monitor in real-time a minor stator shorted turns faults in the IM.
This paper is organized as follows: a description of the identification RLM method used to get the on-line faults estimation is presented in the second section. In the third section, we present the model including the stator inter-turn faults. In section four, the RLM algorithm under consideration is implemented and applied to an IM through simulated data that verify the benefits of the method. This paper will be closed by the main concluding remarks.

2. Proposed identification method

The recursive algorithms of identification, also known as on-line estimator, consist in recursively estimating in time the parameters of the IM model [21], [22], [23]. From this point of view, and contrary to the non-recursive techniques, this type of algorithm is adapted to applications where the fast detection of variations of the parameters during the time is necessary. In this section, the proposed recursive algorithm based on RLM method, performed by the normalization of sensitivity functions, will be introduced.

Recursive Levenberg-Marquardt method

Let u_k be the input of system and $\underline{\hat{\theta}}_k$ an estimation of true parameter vector $\underline{\theta}_k$ at k^{th} sample. An estimation output $\hat{y}$ is obtained by simulation of the IM model described in section 3, thus one gets:

$$\hat{y}_k = f_k\left(u_k, \underline{\hat{\theta}}_k\right) \tag{1}$$

Assume that we have K samples of real output y_k, such as u_k and y_k are the k^{th} samples of the system input and output, respectively. Let b_k is a zero mean white noise. The data set is composed of K data pairs $\{u_k, y_k^*\}$ with $t = k \times T_e$ (where T_e : sampling period):

$$y_k^* = y_k\left(u_k, \underline{\theta}_k\right) + b_k \tag{2}$$

Then, we define output estimation error (or residuals) as follows:

$$\varepsilon_k = y_k^* - \hat{y}_k(u_k, \underline{\hat{\theta}}_k) \tag{3}$$

Because $\hat{y}$ is nonlinear in $\underline{\hat{\theta}}$, a Non Linear Programming technique is needed to estimate recursively $\underline{\hat{\theta}}$.

Therefore, we introduce the proposed RLM algorithm that optimizes the following least square cost function F_k, using the forgetting-factor mechanism [17], [18] as:

$$F_k = \frac{1}{2} \times \sum_{k=1}^{K} \lambda^{K-k} \times \{\varepsilon_k\}^2 \tag{4}$$

where $0.95 \leq \lambda \leq 1$ is the forgetting-factor that decides how fast the influence of past data should decrease and this is important to track time-varying systems.

The minimization of the cost function can, therefore, be performed using recursive Gauss-Newton algorithm results in the following updating rule expressed as:

$$\underline{\hat{\theta}}_k = \underline{\hat{\theta}}_{k-1} + (H_k)^{-1} \times G_k \tag{5}$$

where the gradient G_k is defined by differentiating the objective function in Equation (4) with respect to $\underline{\hat{\theta}}_k$ as

$$G_k = F_k' = -\sum_{k=1}^{K} \lambda^{K-k} \times \{\psi_k^T \times \varepsilon_k\} \tag{6}$$

The subscript T denotes the matrix/vector transpose.

The second derivative of the cost function in Equation (4) with respect to $\underline{\hat{\theta}}_k$, known as the Hessian matrix H_k, can be approximated classically [17], [18] by

$$H_k = F_k'' \cong \sum_{k=1}^{K} \lambda^{K-k} \times \{\psi_k \times \psi_k^T\} \tag{7}$$

ψ_k represents the output sensitivity function defined by partial derivative of the predicted output $\hat{y}_k$ with respect to the parameters vector $\underline{\hat{\theta}}_k$ as:

$$\psi_k = \frac{\partial \hat{y}_k}{\underline{\hat{\theta}}_k} \tag{8}$$

Referring to [17], [19], H_k can be rewritten with the recursive algorithm as:

$$H_k = \lambda \times H_{k-1} + (\psi_k \times \psi_k^T) \tag{9}$$

Now a general recursive algorithm to update the parameter vector $\underline{\hat{\theta}}_k$, by comparing the off-line algorithm described in [12], [17], [24] with the recursive version in Equations (5) and (9), can be defined by

$$\underline{\hat{\theta}}_k = \underline{\hat{\theta}}_{k-1} + (1-\lambda) \times \mathcal{R}_k^{-1} \times \psi_k^T \times \varepsilon_k \tag{10}$$

where the matrix $\mathcal{R}_k$ modifies the local search direction defined with the method of the gradient G_k.

Often, Hessian may not be invertible or the inverse may not be definite positive, then the parameter update is not possible. To avoid these difficulties, the diagonal of approximation of Hessian matrix H_k is used for Levenberg-Marquardt update method as:

$$\mathcal{R}_k = (1-\lambda) \times H_k + \delta_k \times diag\{H_k\} \tag{11}$$

where $diag\{\cdot\}$ denotes the diagonal matrix operator.

Substituting Equation (11) in Equation (10), the estimated vector $\underline{\hat{\theta}}_k$ is given by the following recurrence formula:

$$\underline{\hat{\theta}}_k = \underline{\hat{\theta}}_{k-1} + (1-\lambda) \times \mathcal{R}_k^{-1} \times \psi_k^T \times \varepsilon_k \tag{12}$$

$$\mathcal{R}_k = \lambda \times \mathcal{R}_{k-1} + (1-\lambda) \times (\psi_k \times \psi_k^T + \delta_k \times diag\{\psi_k \times \psi_k^T\}) \tag{13}$$

where $\mathcal{R}_k$ is the regularised approximation Hessian matrix and δ_k is the regularisation parameter.

The value of δ_k, affects both the convergence rate and stability of algorithm. Hence, the regularization parameter δ_k is also adaptively adjusted with the following criterion [18]:

$$\delta_k = \begin{cases} \alpha_1 \times \delta_{k-1} \,, & if\, |\varepsilon_k| > |\varepsilon_{k-1}| \\ 1/\alpha_2 \times \delta_{k-1} \,, & if\, |\varepsilon_k| < |\varepsilon_{k-1}| \\ \delta_{k-1} \,, & otherwise. \end{cases} \tag{14}$$

where the numbers α_1 and α_2 are chosen so that the δ-values cannot oscillate [24].

Sensitivity functions normalization

Because the parameters values to be recursively estimating in time have magnitude order very different, the normalization of these parameters is necessary in order to avoid convergence

difficulties of the proposed RLM estimator. So, we propose in this subsection to normalize these parameters which mean the normalization of the sensitivity functions [20].
Consider the parameters vector $\hat{\underline{\theta}}_k$. This vector can be defined as a variation around an initial point $\hat{\underline{\theta}}_0$. For a parameters vector $\hat{\underline{\theta}}_k$, the absolute change can be write:

$$\Delta\hat{\underline{\theta}} = \hat{\underline{\theta}}_k - \hat{\underline{\theta}}_0 \tag{15}$$

Then the relative variation of the parameter $\hat{\underline{\theta}}_k$ around $\hat{\underline{\theta}}_0$ is defined as:

$$\hat{\underline{\vartheta}}_k = \frac{\hat{\underline{\theta}}_k - \hat{\underline{\theta}}_0}{\hat{\underline{\theta}}_0} = \frac{\Delta\hat{\underline{\theta}}}{\hat{\underline{\theta}}_0} \tag{16}$$

So the relative variation $\hat{\underline{\vartheta}}_k$ has the same magnitude order. We can consider the parameters vector $\hat{\underline{\vartheta}}_k$ as the new normalized vector to estimate.

To estimate this new parameters vector by the output-error method, we need sensitivity functions. The sensitivity function with respect to $\hat{\underline{\theta}}_k$ is written:

$$\psi_k = \frac{\partial \hat{y}_k}{\hat{\underline{\theta}}_k} = \frac{\partial \hat{y}_k}{\partial(\hat{\underline{\theta}}_0 + \Delta\hat{\underline{\theta}})} = \frac{1}{\hat{\underline{\theta}}_0} \times \frac{\partial \hat{y}_k}{\partial \hat{\underline{\vartheta}}_k} = \frac{1}{\hat{\underline{\theta}}_0} \times \delta_k \tag{17}$$

where δ_k is the sensitivity function with respect to $\hat{\underline{\vartheta}}_k$. So, δ_k have the same magnitude order. The vector of the actual parameters is then calculated using the formula:

$$\hat{\underline{\theta}}_k = \hat{\underline{\theta}}_0 \times \left(I + \hat{\underline{\vartheta}}_k\right), \; I \text{ represents the identity matrix} \tag{18}$$

Implementation of this method is quite simple because it doesn't change the structure of the proposed RLM algorithm, but only the computation of the sensitivity functions changes.
Induction motor model

Tests and validations of failure detection by parameter estimation require a model suited for fault modelling. For this purpose we describe, in this section, a model of squirrel-cage IM dedicated to inter-turn short-circuits windings.

A. Stator faulty model

In order to take into account the presence of inter-turns short-circuits windings in the stator of an IM, an original model was proposed in reference [11]. Figure 1 shows the stator faulty model in Park's dq-axes with global leakage referred to the stator. The short-circuit current $\underline{i}_{dq_{cc}}$ is represented by the equivalent fault impedance $[Z_{cc}]$ which deflects a part of the stator current. Extending this model to each phase, three short-circuit impedances ($[Z_{cc_1}]$, $[Z_{cc_2}]$ and $[Z_{cc_3}]$ for phase a_s, b_s and c_s, respectively) are added to the healthy part of IM model.

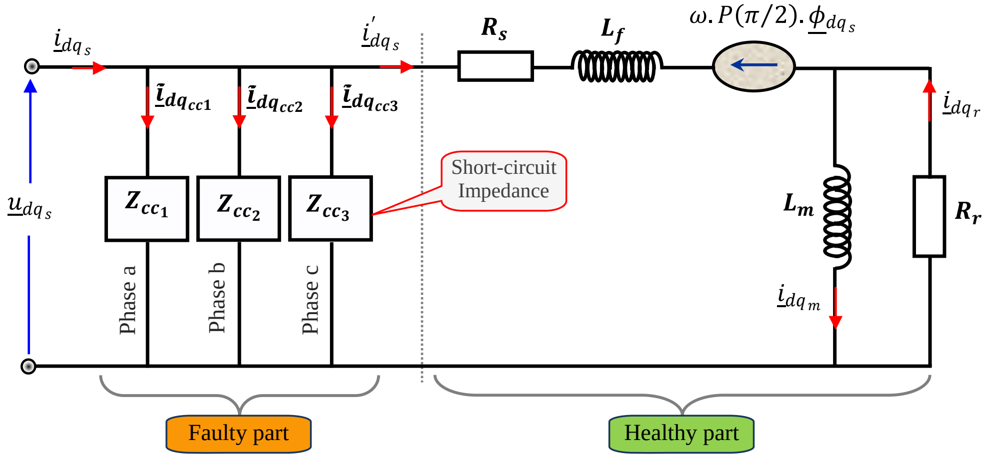


Figure 1. Stator faulty model of induction machine

To localize and detect stator faults in IM, two parameters $(\theta_{cc_k}, \mu_{cc_k})$ are introduced:

1. The localization parameter θ_{cc_k}: this parameter can take only the three values: 0, $2\pi/3$ and $4\pi/3$, corresponding to the short-circuit on the phase a_s, b_s, or c_s, respectively,
2. The detection parameter μ_{cc_k}: is equal to the ratio between the number of inter-turn short-circuits windings (n_{cc_k}) and the whole number of turns in the healthy phase (n_s). This parameter , which allows us to quantify the unbalance, is given by:

$$\mu_{cc_k}(\%) = \frac{n_{cc_k}}{n_s} \times 100 \tag{19}$$

B. State-space modeling of the faulty machine

For simulation, it is necessary to write the faulty model in state-space representation. So, the fourth-order state-space representation of the IM with a winding fault is given by:

$$\begin{cases} \dot{\underline{x}}(t) = A(\omega_m) \times \underline{x}(t) + B \times \underline{u}(t) \\ \underline{y}(t) = C \times \underline{x}(t) + D \times \underline{u}(t) \end{cases} \tag{20}$$

where:

$\underline{x} = [i'_{d_s} \quad i'_{q_s} \quad \phi_{d_r} \quad \phi_{q_r}]^T$: State-space vector

$\underline{u} = \begin{bmatrix} u_{d_s} \\ u_{q_s} \end{bmatrix}$, $\underline{y} = \begin{bmatrix} i_{d_s} \\ i_{q_s} \end{bmatrix}$: System's inputs-outputs

$A(\omega_m) = \begin{bmatrix} -a & \omega_m & b \times \rho_r & b \times \omega_m \\ -\omega_m & -a & -b \times \omega_m & b \times \rho_r \\ R_r & 0 & -\rho_r & 0 \\ 0 & R_r & 0 & -\rho_r \end{bmatrix}$: State matrix

$B = \begin{bmatrix} b & 0 & 0 & 0 \\ 0 & b & 0 & 0 \end{bmatrix}^T$, $C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$: The input B and output C matrices

$$D(\mu_{cc_k}, \theta_{cc_k}) = \left[\frac{2}{3 \times R_s} \times \sum_{k=1}^{3} \mu_{cc_k} \times P(-\theta_r) \times Q(\theta_{cc_k}) \times P(\theta_r)\right]$$

with:

$a = \frac{R_s + R_r}{L_f}$, $b = \frac{1}{L_f}$ and $\rho_r = \frac{R_r}{L_m}$

$P(\theta_r) = \begin{bmatrix} cos(\theta_r) & -sin(\theta_r) \\ sin(\theta_r) & cos(\theta_r) \end{bmatrix}$: Park's transformation matrix

$Q(\theta_{cc_k}) = \begin{bmatrix} cos(\theta_{cc_k})^2 & cos(\theta_{cc_k}) \times sin(\theta_{cc_k}) \\ cos(\theta_{cc_k}) \times sin(\theta_{cc_k}) & sin(\theta_{cc_k})^2 \end{bmatrix}$: Fault localization matrix

i_{d_s}, i_{q_s} dq stator currents components;
ϕ_{d_r}, ϕ_{q_r} dq rotor fluxes linkage;
u_{d_s}, u_{q_s} dq stator voltages;
θ_r rotor position;

R_s, L_f, R_r and L_r are stator resistance, global leakage inductance referred to the stator, rotor resistance and rotor inductance, respectively.

The parameters expression vector to estimate on-line by RLM method is given by:

$$\underline{\theta} = [R_s \quad R_r \quad L_m \quad L_f \quad \mu_{cc_1} \quad \mu_{cc_2} \quad \mu_{cc_3}]^T \tag{21}$$

Because the model of the IM is in continuous time representation, it is better to use an output-error technique in order to estimate its parameters [15], [25].

C. Output-error technique

Figure 2 illustrates a general scheme of principle parameters estimation using output-error technique applied to the IM. As it can be seen, the model of the IM is represented as a multivariable system, with two inputs $\{u_{d_s}, u_{q_s}\}$ and two outputs $\{i_{d_s}, i_{q_s}\}$.

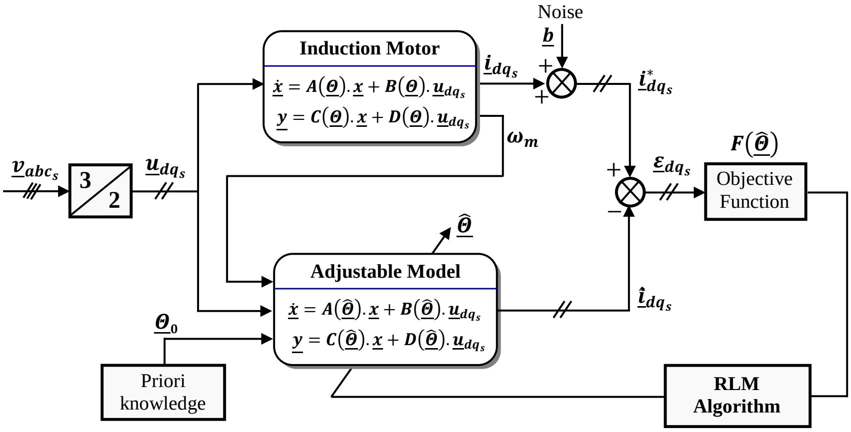


Figure 2. Output-error method applied to the induction motor

Referring to Figure 2, the estimation error (or identification residuals) written $\underline{\varepsilon}_{dq_s}$ between the real currents $\underline{i}^*_{dq_s}$ and its estimation $\underline{\hat{i}}_{dq_s}$ is defined by:

$$\begin{cases} \varepsilon_{d_{s_k}} = i^*_{d_{s_k}} - \hat{i}_{d_{s_k}} \\ \varepsilon_{q_{s_k}} = i^*_{q_{s_k}} - \hat{i}_{q_{s_k}} \end{cases} \tag{22}$$

where $i^*_{d_s}$ and $i^*_{q_s}$ are the real outputs of the system and the estimated currents $\hat{i}_{d_s}$ and $\hat{i}_{q_s}$ represent the model simulation based on an estimation of the parameters vector $\underline{\hat{\theta}}$.

The objective of identification RLM method is to obtain recursively the optimal estimates noted $\underline{\hat{\theta}}_{opt}$ of the real vector $\underline{\theta}$ which minimizes the objective function according to:

$$F(\underline{\hat{\theta}}) = F_{prior} + F_{obse} \tag{23}$$

$$F_{prior} = (\underline{\hat{\theta}} - \underline{\theta}_0) \times P_0^{-1} \times (\underline{\hat{\theta}} - \underline{\theta}_0)^T \tag{24}$$

$$F_{obse} = \frac{1}{\sigma_b^2} \times \sum_{k=1}^{K} \left(\varepsilon^2_{d_{s_k}} + \varepsilon^2_{q_{s_k}} \right) \tag{25}$$

where F_{prior} is the part of objective function that represents the differences between updated parameters and the priori-knowledge related to healthy machine. F_{obse} represents the differences between the real current ($\underline{i}^*_{dq_s}$) and the predicted one ($\underline{\hat{i}}_{dq_s}$). $\underline{\hat{\theta}}$, $\underline{\theta}_0$, P_0 and σ_b^2 are vectors of updated model parameters, priori model parameters, covariance matrix and variance of output-noise, respectively.

4. Simulation results and discussion

A. Simulation setup

Efficiency of the proposed RLM identification algorithm with forgetting-factor has been verified by simulation in Matlab/Simulink environment. A 1.1 kW, 220/380V, 50Hz, 4-poles three-phase squirrel-cage induction motor, with 464 turns per phase in the stator winding, is simulated, whose nominal parameters are: $R_s = 9.8\Omega$, $R_r = 5.3\Omega$, $L_m = 0.5H$, $L_f = 0.04H$.

The simulation is performed during 7sec with a sampling period of 0.7ms and with a load torque of 5N.m applied at 0.5s. While the loaded motor steady state operation is achieved, a short-circuited turns is introduced at the instant 4sec.

The motor is operated under the following stator fault conditions imposed at 4sec:

1. Healthy stator: $\mu_{cc_1} = \mu_{cc_2} = \mu_{cc_2} = 0$,
2. Faulty stator: 3 out of 464 turns ($\mu_{cc_1} = 0.65\%$) in phase a_s stator winding shorted,
3. Faulty stator: 9 out of 464 turns ($\mu_{cc_1} = 1.94\%$) in phase a_s stator winding shorted,
4. Faulty stator: 18 out of 464 turns ($\mu_{cc_1} = 3.88\%$) in phase a_s stator winding shorted.

The stator winding configuration of the IM with shorted turns fault is shown in Figure 3.

In order to test our methodology in stochastic situations, two generating processes of noise for speed and currents are used. Under conditions of a zero-mean white noise such as the Signal to Noise Ratio SNR=30dB and 20dB are added to the currents $\{i_{d_s}, i_{q_s}\}$ and SNR=30dB to the speed ω_m.

The initial parameters of proposed RLM approach are as follows: the adaptation parameters $\alpha_1 = 2$ and $\alpha_2 = 3$, the regularization parameter is initialised with $\delta_0 = 10^{-5}$ and the forgetting-factors are varied by the values: $\lambda = 0.955$ and $\lambda = 0.985$.

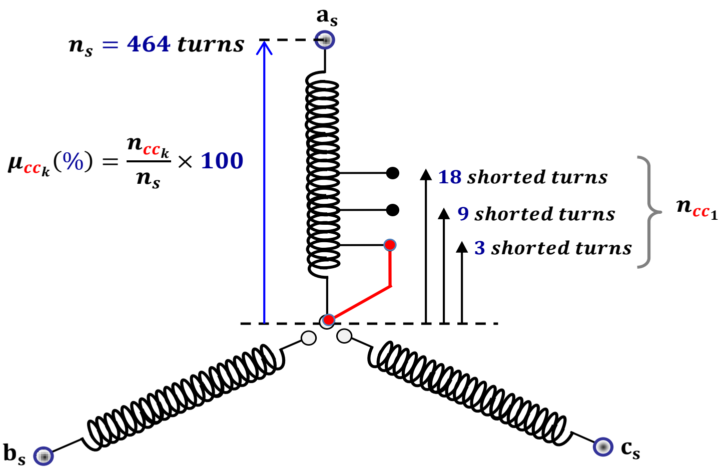


Figure 3. Stator winding configuration with shorted turns faults

B. On-line estimation results

Taking the data length $K = 10000$ points and using the Park's reference frame linked to the rotor, we obtain data set composed of K data pairs $\{\underline{u}_{dq_s}, \underline{i}_{dq_s}\}$.

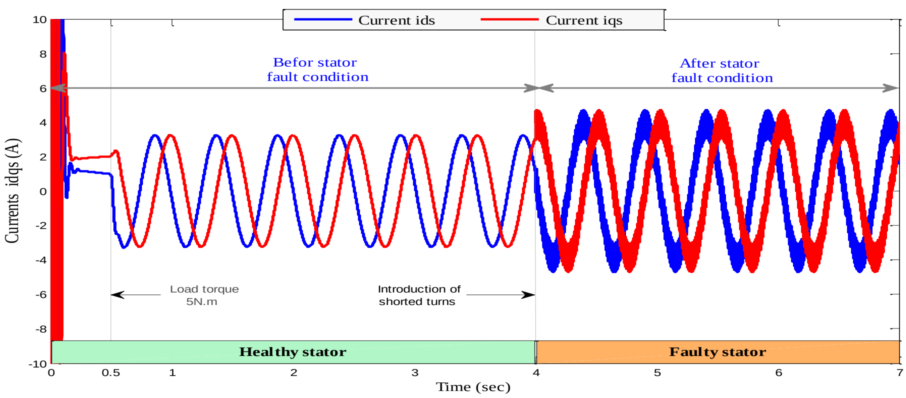


Figure 4. Simulated currents before and after stator fault condition

Figure 4 shows, before and after the shorted turns fault introduced at t=4sec, the simulated stator currents on Park's dq-axes. As observed in Figure 4, for t > 4sec, the effect of the shorted turns is very clear on the stator currents. Therefore, for time interval of t = 0.5:7sec, the signal of the stator currents is non-stationary.

Because the on-line algorithm treats the inputs-outputs $\{\underline{u}_{dq_s}, \underline{i}_{dq_s}\}$ of the system in a recursive manner, a time interval, which varies from 1 to 7sec, is considered.

The identification in real-time consists in carrying out the acquisition of the data from 1 to 7sec, and then to apply the RLM algorithm which treats the samples in a recursive manner. The goal of these tests is to evaluate the robustness of the proposed recursive identification method facing various values of SNR and non-stationary of different stator fault conditions.

For 20 and 30dB of SNR values, Figure 5 shows the estimated parameters as well as the true ones. Furthermore, the estimates have been plotted for various shorted turns values. It can be seen that the estimates are, on average, close to the exact value, whatever of the noise level. Regarding the accuracy of the estimation, let us note that once the value of SNR is decreasing, the uncertainty range increases for each stator fault conditions. Overall, the parameters estimation, even in the presence of high noise level, gives satisfactory results.

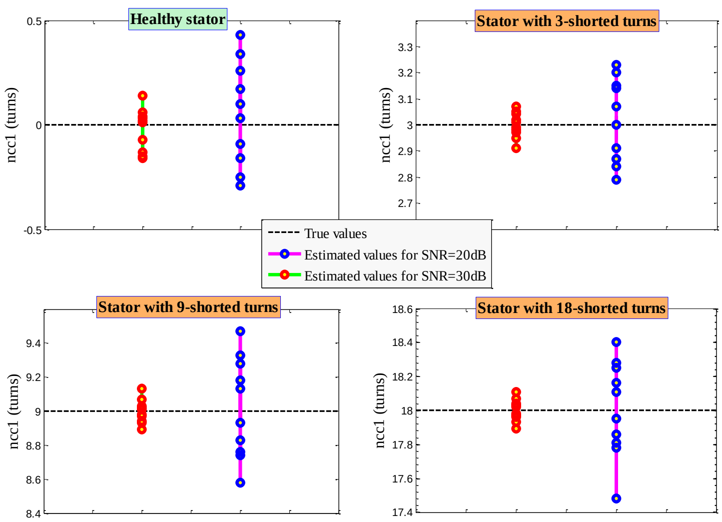


Figure 5. Dispersion of estimated values for ten simulations with different SNR

For 30dB of SNR and for forgetting-factor $\lambda = 0.985$, Table I summarizes the results from the parametric estimation in case of healthy and faulty stator with 3, 9 and 18-shorted turns on phase a_s, respectively. To evaluate the performance of the proposed RLM estimator, the estimation relative error $\{Erv\}$ has been computed and reported in Table I for each case, where $Erv := \|\hat{\underline{\theta}} - \underline{\theta}\| / \|\underline{\theta}\|$.

As illustrated in Table I, for the shorted turn's number $\hat{n}_{cc_k}$ on the stator, the obtained average results show, in general, the good similarity between the estimated parameters and the true ones for the healthy and faulty stator. Thus, under healthy operation, one notes $\hat{n}_{cc_k}$ remain close to zero with reduced estimation error. This error is due to the noises introduced. On the other hand, under operating fault it is clearly shown that the short-circuit parameters are in close agreement with the true ones. Estimation error of estimated parameters in all cases is negligible and doesn't reach two percent in each case. These indicate that the proposed parameter estimation algorithm is effective.

As can be seen in Table I, when the fault occurs, the variations of faulty parameters, contrary to the electrical parameters, are very important. This comparison is important because it is evident that only the faulty parameters ($\hat{n}_{cc_k}$) varies according to the cause of the imbalance. Electrical parameters (R_s, L_f, R_r and L_r) are function of the temperature and of the magnetic state of the machine and their evolutions are independent from the faults.

Table 1. Average results from on-line parametric estimation

Parameters $\hat{\theta}$	Estimated values for SNR=30dB Mean of ten simulation tests			
	Healthy stator	3-shorted turns	9-shorted turns	18-shorted turns
R_s (Ω)	9.8191	9.8201	9.8227	9.8245
R_r (Ω)	5.2975	5.2945	5.2921	5.2907
L_m (H)	0.5008	0.5003	0.4995	0. 4989
L_f (H)	0.0399	0.0397	0.0395	0.0393
$\hat{n}_{cc_1}(turns)$	-0.0146	2.9364	8.9289	17.8709
$\hat{n}_{cc_2}(turns)$	0.1032	0.0967	-0.1066	0.1489
$\hat{n}_{cc_3}(turns)$	0.0498	-0.0580	0.0125	0.0494
$\boldsymbol{Erv}(\%)$	1.0501	1.1354	0.9139	0.9675

For 30dB of SNR, Figures 6a, 6b and 6c show the evolution of estimated parameters during identification procedure versus time t for stator with 3, 9 and 18-shorted turns on phase a_s, respectively. Furthermore, the estimates have been plotted for various forgetting-factor values.

As it can be seen from these figures, the variations of faulty parameters when the fault occurs at the time $4sec$ on the phase a_s, are very clear. At this time, each short-circuit parameter varies to indicate the fault level at the corresponding phase. As observed in Figure 6a, n_{cc_1} varies from zero to approach gradually 3-shorted turns (0.65%) on phase a_s, indicating also that this phase is faulty. On the other hand, n_{cc_2} and n_{cc_3} varies to approach zero showing that the phases b_s and c_s are healthy. These allow an accurate localization and identification of the minor shorted turns fault, even in the presence of noises.

Indeed, when the fault occurs, the RLM algorithm instantaneously reacts in order to provide the shorted-turns information contained in recent data set. As the data length t increases, the parameter estimates given by the RLM algorithm can track the trues parameters of the system and by consequence the estimation accuracies become higher. After less than $0.35sec$ for $\lambda = 0.955$ and $0.95sec$ for $\lambda = 0.985$, the proposed algorithm, performed by the normalization of the sensitivity functions, provides a good estimation of the fault occurring during identification operation with a reduced error. The obtained results demonstrate the high efficiency of RLM algorithm particularly the response times, precision and stability and consequently confirm it validation.

On the other hand, looking at the influence of the forgetting-factor λ, we can draw the following conclusions:

For $\lambda = 0.955$, the parameter estimates converge quickly to their respective exact values but the algorithm becomes more sensitive to noise level,

For $\lambda = 0.985$, the proposed estimator requires more time to track the trues parameters of the system but gives small variances of the estimates.

Furthermore, a good compromise accuracy-response time is obtained for $\lambda = 0.985$.

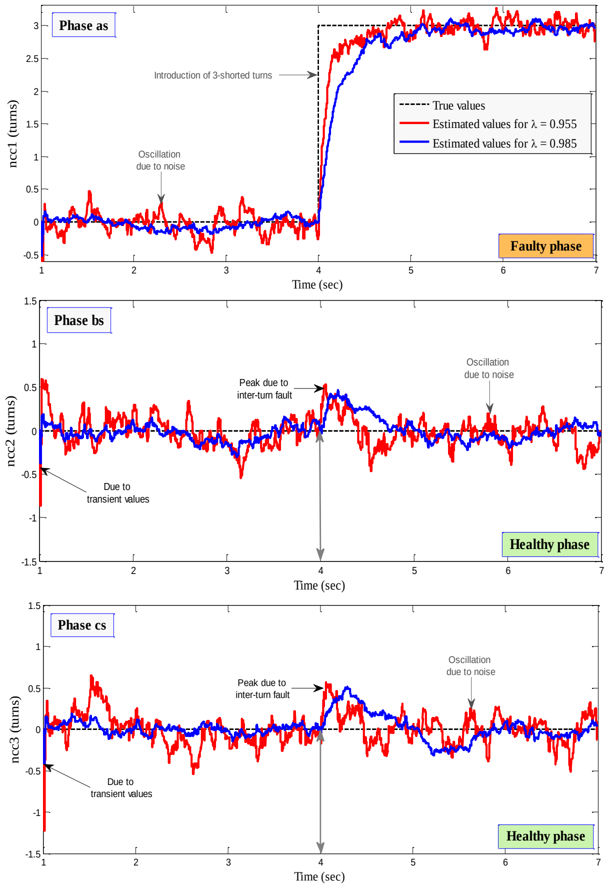
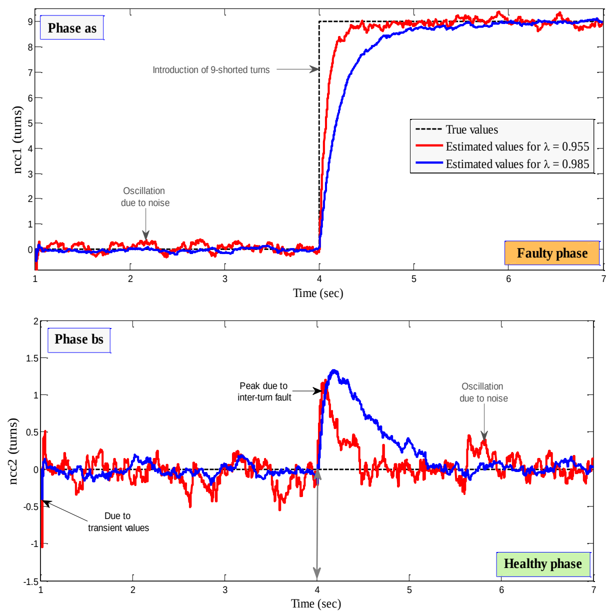


Figure 6a. Short-circuit of 3 turns on phase a_s



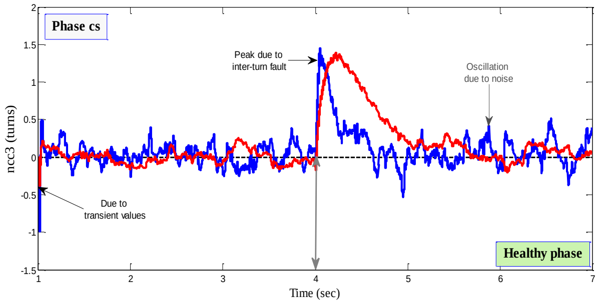


Figure 6b. Short-circuit of 9 turns on phase a_s

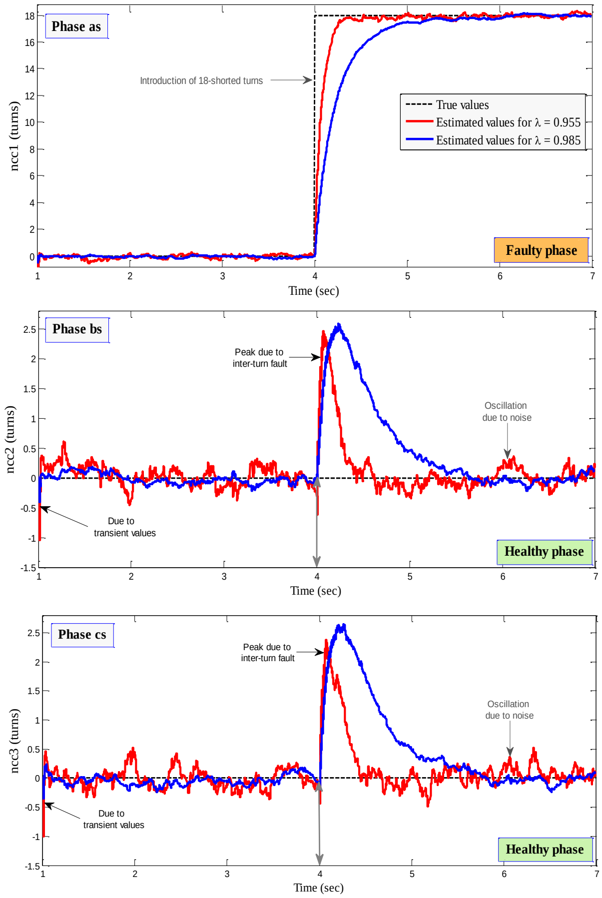


Figure 6c. Short-circuit of 18 turns on phase a_s
Figure 6. On-line estimation of faulty stator parameters

Still in the same conditions, Figures 7a, 7b and 7c compare the simulated currents and their estimations on Park's d-axis with 3, 9 and 18-shorted turns on phase a_s, respectively. It may be seen that the estimated output follows, with different speed, the simulated one. Indeed, for $\lambda = 0.955$, the RLM estimator follows rapidly the desired output, as compared by the estimator for $\lambda = 0.985$, which need more time to adapt.

The comparison between the real currents and their estimations reveals, in general, a negligible error of continuation on the whole horizon of the estimation, except when the shorted turns fault occurs at the time 4sec. Indeed, the RLM algorithm reacts, at this instant, in order to minimize the estimation error.

The estimation error versus times graph is shown in the bottom of Figures 7a, 7b and 7c. As the data length t increases, the identification residuals given by the proposed approach gradually become smaller. In all fault situations, the estimation errors are negligible and don't exceed 0.4A. Notice that identification residuals on the currents explain the types of noises introduced during the simulation of the IM. Then, we can draw a conclusion with respect to the efficiency and the advantage of the adaptive RLM approach to track, in real-time, the change occurring in stator winding of the IM, even in the presence of noises.

Moreover, the peaks observed at the times of the abrupt variations in the shorted turns; their amplitudes depend on its values. It may be seen that once the value of shorted turns is increased, the amplitudes of the peaks values, appear at 4sec, increases for each stator fault conditions. The amplitudes of the peaks values indicate also the severity of stator fault.

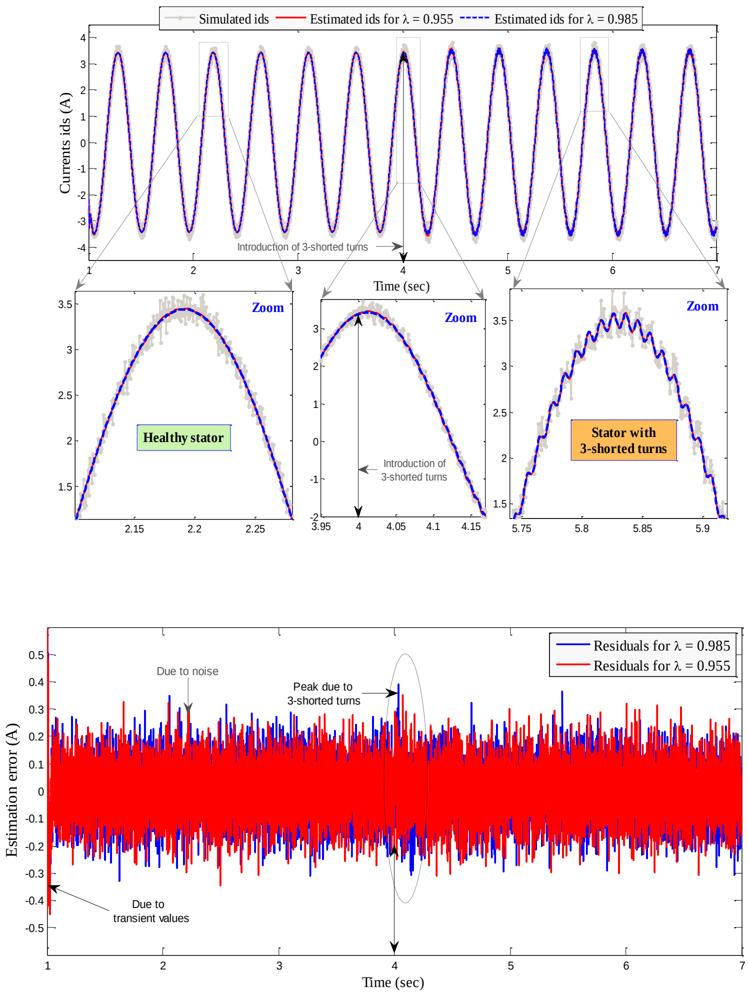


Figure 7a. Short-circuit of 3 turns on phase a_s

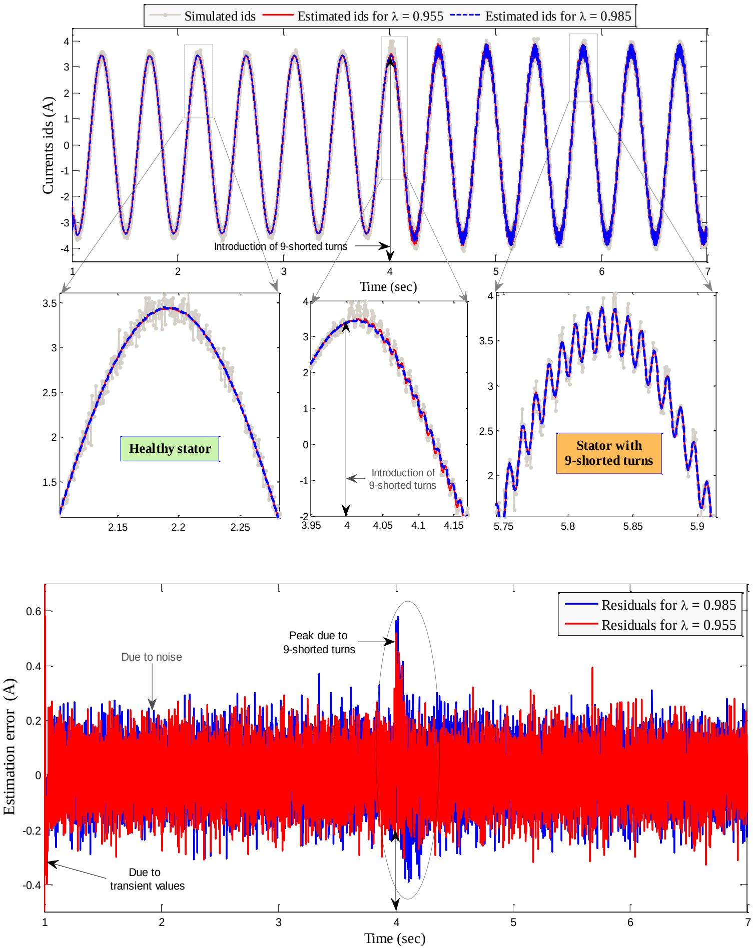
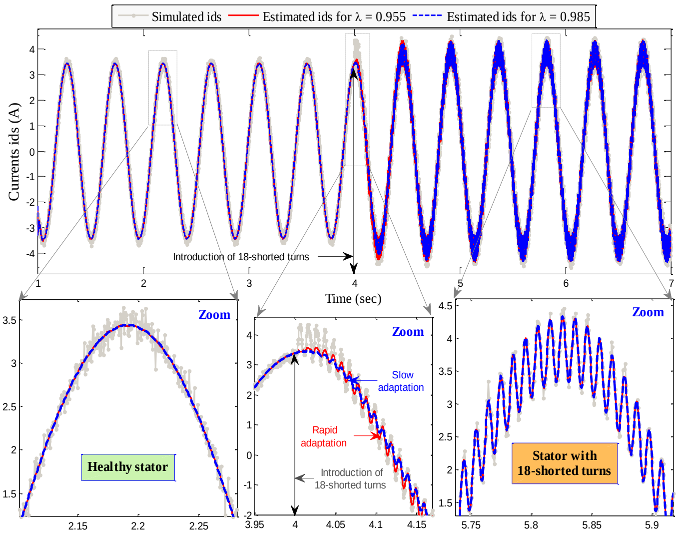


Figure 7b. Short-circuit of 9 turns on phase a_s



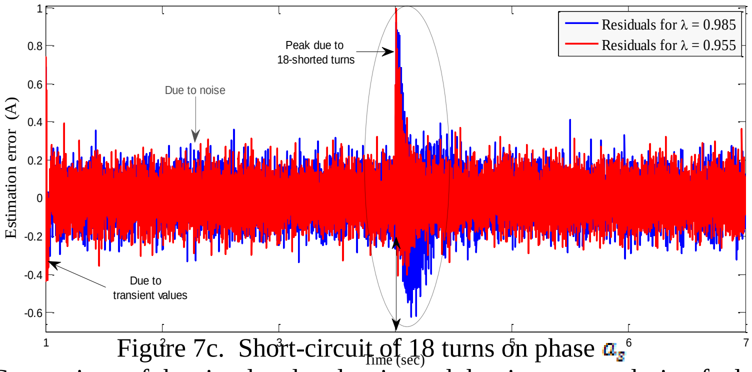


Figure 7c. Short-circuit of 18 turns on phase a_s

Figure 7. Comparison of the simulated and estimated d-axis currents during fault condition

5. Conclusion

This paper proposes recursive parameters estimation method for diagnosing, on-line, stator winding inter-turn short-circuits fault of an induction motor, based on RLM algorithm. The problem of induction motor parameters estimation is converted to a problem of parameter optimization which could be solved via RLM estimator.

Sufficient rules on abrupt parameter variations and noise levels to ensure the robustness of the proposed method are presented. The effect of the forgetting-factor has been also studied. A minor stator fault, 3-shorted turns, is localized and detected, on-line, with a good accuracy.

The RLM method, performed by the normalization of the sensitivity functions, offers very satisfactory results essentially characterized by a reduced tracking error and a much reduced convergence time, despite the very important variation of the faulty parameters, considered in time and in amplitude. The obtained on-line estimation results demonstrate the high performance of the proposed approach particularly the response times, precision and stability.
Finally, the obtained performances permit to conclude about the efficiency and the advantage of the RLM approach for early detection and monitoring in real-time stator winding shorted turns fault of the induction motors, without much increase in computation complexity.

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