ADALINE-BASED MECHANICAL PARAMETERS IDENTIFICATION OF INDUCTION MOTOR

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Abstract - This work presents two novel identification methods of the mechanical parameters in induction motor (IM) field oriented drives. The identified parameters are: the moment of inertia and the viscous damping coefficient. The two used methods are based on the Adaline (ADAptive-LInear-NEurone) strategy which is a type of artificial neural networks (ANNs). The training of the network is made on-line and the resulting weights take values according the motor’s parameters. During the phase of identification, the IM turns without load and according to the field oriented control (FOC) principle. The two methods are simple to implement because they require only the knowledge of the stator current and the mechanical speed of the IM. The effectiveness of the two methods and the accuracy of the found parameters are proved by two direct starting tests.

Keywords – Induction Motor (IM), Field-Oriented Control (FOC), Parameters Identification, Artificial Neural Networks (ANNs), Adaline.

1. INTRODUCTION

The knowledge of the electric parameters of an induction motor (IM) is not enough to study the dynamic states or to obtain good performances in position or speed control. These states are moreover conditioned by the knowledge of the mechanical parameters such as the moment of inertia \(J\), the viscous damping coefficient \(f\) and the disturbance load torque \(T_d\), then, the study of these states is effective only when is well-know the value of these mechanical parameters.

To identify the moment of inertia \(J\), conventional techniques can be used. In this case, one distinguishes the direct methods and the indirect methods. In the direct methods case, the user is brought to extract the rotor and to take some measurements which requires other devices and not always adaptable for all the electric motors [1]. In the indirect method case, one can quote that known as slowdown method. This method requires that the shaft end of the turning system be easily accessible. Measurement is carried out by adding on the motor shaft a known inertia wheel \(J_0\). The slowdown curves with and without the added inertia makes possible to deduce the moment of inertia \(J\) [2]. The viscous damping coefficient \(f\) can be estimated in steady state by measuring the power consumption at a given speed and during a no-load test. Generally, the classic methods used to identify \(J\) and \(f\) are inaccurate, cumbersome, not always possible to adopt in practice and not able to track changes in the system. In recent years, some other new methods were developed for mechanical parameters identification. Among these methods, one can quote those based on the Least Mean Squares (LMS) algorithm or that of Recursive Least Squares Algorithm (RLSA) used in case of on-line identification. These methods, sensitive to measurement noise, were used such in [3] and [4] and they provide partially the parameters of the motor. In many papers, the Extended Kalman Filter (EKF) [5] or mainly on the observers techniques [6], [7] are tried. A Reduced-Order Extended Luenberger Observer (ROELO) is applied by [7] to estimate the motor inertia value. In [6], an algorithm is proposed for identifying the moment of inertia based on observing the position error signal generated by the speed observer that contains error information on the moment of inertia. These methods require that be checked some conditions like the observability or the evaluation of the covariance matrix in case of the EKF method. Certain authors proposed heuristic approaches for the parameters identification although these methods are often used in data classification or in complex systems modelling. An off-line method based on the genetic algorithm (GA) is proposed in [8]. The paper [9] deals with the application of Genetic Algorithm (GA), Particle Swarm Optimisation (PSO) and a modified PSO with a function “Stretching” (SPSO) algorithms to the off-line identification of the electromagnetic and mechanical parameters of an IM model. Some other methods based on the ANNs such as feed-forward and recurrent networks are used by [10], [11] for the on-line identification of IM parameters.

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In this paper, we present two new methods for on-line identification of the mechanical parameters $J$ and $f$. These methods are based on the use of Adaline. Their implementation are simple and do not require any additional hardware. The electromagnetic torque and the measured mechanical speed will be used as identification signals. It is not necessary to use a torque sensor since the IM operates under FOC conditions. Consequently the quadratic stator current $I_{sq}$ will be an image of the developed electromagnetic torque [12]. The two methods provide in real-time the two parameters $J$ and $f$ that represent a major advantage when we want to make an on-line adjustment of the regulators used in speed or position control. This work is organized as follows: section 2 gives the IM model as well as the FOC principle exploited during the identification process. In section 3, we present the Adaline basic concept and their learning process, and then we give the used identification strategies. The obtained experimental results of identification are presented in section 4. Finally, section 5 is devoted to the conclusion.

2. MODELING OF INDUCTION MOTOR IN FIELD-ORIENTED CONTROL

During the identification, the IM operates under FOC conditions without disturbance load ($T_d=0$). The coulomb friction $\Gamma_s$ is assumed to be null. As for DC motors, this control ensures a decoupling between the rotor flux and the produced electromagnetic torque [12]. It should be noted that the quadratic stator current $I_{sq}$ ensures the control of the electromagnetic torque through the quadratic axis stator voltage $V_{sq}$, while the direct rotor magnetizing current $I_{rmd}$ ensures the control of the rotor flux through the direct axis stator voltage $V_{sd}$. The rotor flux orientation according to the d-axis implies the cancelation of the q-axis rotor magnetizing current ($I_{rmq}=0$).

Two PI regulators are used to control the electromagnetic torque $T_{em}$ and the rotor magnetizing current $I_{rmd}$. The decoupling terms $E_d$ and $E_q$ are added at the output of each regulator to reconstitute the voltage vector $V_{sd}$ and $V_{sq}$ to be applied to the IM [12]. The rotation speed of the rotor flux $\omega_r$ is calculated by adding the rotor electric speed ($\rho \Omega$) and the slide pulsation $\omega_r$. The decoupling of the IM leads to linear relations linking the currents $I_{rmd}$ and $I_{sq}$ to the voltages $V_{sd}$ and $V_{sq}$ respectively. The rotor magnetizing current $I_{rms}$, the electromagnetic torque $T_{em}$ and the slip pulsation $\omega_s$ are estimated by the following relations:

\[
\dot{I}_{rmd} = \frac{a_1}{s + a_1} I_{sd}
\]

With: $a_1 = \frac{1}{T_r}$ and $b_1 = \rho (1 - \sigma) L_s$.

The IM control diagram adopted for the parameters identification is shown in fig. 1.

Fig. 1. IM control diagram used in the identification process.

The functional diagram of the mechanical system is shown in fig. 2. This model is described by the following differential equation:

\[
\frac{d\Omega}{dt} = \frac{1}{J}(T_{em} - T_f)
\]

with:

\[
T_{em} = b_2 \left( I_{rmd} I_{sq} - I_{rms} I_{sd} \right)
\]

and

\[
T_f = f \Omega + \text{sign}(\Omega) \Gamma_s + T_d
\]

Fig. 2. Functional diagram of the mechanical system.

Under some assumptions like $T_d=0$ and $\Gamma_s=0$, the mechanical equation linking the rotor speed to the electromagnetic torque is given by the following transfer function:

\[
\frac{\Omega}{T_{em}} = \frac{K}{\tau_m s + 1}
\]
3. ADALINE FOR MECHANICAL PARAMETERS IDENTIFICATION

3.1. THE ADALINE NEURAL NETWORK

The Adalines neural networks are well-known in the ANNs theory. They are mainly used as identification or control method of the electric systems [13], [14]. As this is shown in fig. 3, the Adaline is equivalent to only one neuron which is composed of an input vector \( X(k) \), a weights matrix \( W(k) \), and an activation function \( f(v) \). The weights vector \( W(k) = [w_1(k) \ldots w_n(k)]^T \) corresponds to the whole of neuron synaptic forces. The input vector \( X(k) = [I \ x_1(k) \ldots x_A(k)] \) corresponds to the whole of neuron input stimulus. The activation function \( f(v) \) specifies the neuron behaviour.

![Fig. 3. Representation of the Adaline Neural Network.](image)

Various activation functions can be used in the ANNs case. However, the Adaline use the linear activation function \( f(v)=v \), consequently the output \( y_{est}(k) \) of the Adaline is given by: \( y_{est}(k)=X(k)W(k) \). When the Adaline is excited, it produces the output \( y_{est}(k) \) which depends on the inputs. The weights vector \( W(k) \) is continuously modified during the network learning process. In the ANNs theory the learning processes can be divided in two categories: on-line training and off-line training. The Adaline is a neuron which is able to make on-line training [15]. A learning rule must be employed to update or modify the neuron weights vector. The learning rule of Adalines is based on an error minimization algorithm called Least Mean Square (LMS) learning rule. This simple and effective method can be found in [15] and [16]. The LMS learning rule is given by the following equation:

\[
w(k+1) = w(k) + \eta e(k)X^T(k)\]

(8)

Where \( e(k) \) is the prediction error of the desired output \( y_{est}(k) \).

\( \eta \) is a learning parameter. A high value of \( \eta \) accelerates the weights convergence but it does not ensure a good stability of the network. The choice of a small value for \( \eta \) leads to a better stability of the network but the weights convergence can be very long [17]. Consequently, to accelerate the weights convergence and to refine the results, \( \eta \) must be variable during the training. Its value will be selected relatively high at the beginning, and will decrease appreciably and take a small value at the end. The expression of \( \eta \) is given by the following equation:

\[
\eta = \eta_i \left( \frac{\eta_f}{\eta_i} \right)^{-\frac{\tau_{num}}{\tau_{max}}}
\]

(9)

Where \( \eta_i \) and \( \eta_f \) are respectively the initial and final values of the learning rate and \( \tau_{num} \) is the training time. When the Adaline is used for the parameters identification, in case of a linear model, and after the learning process, the obtained weights will have a physical significance related to the desired parameters.

3.2. FIRST METHOD: USING DISCRETE FORM OF THE MECHANICAL EQUATION

This method can implemented with all forms of the reference torques. It is based on the preliminary identification of the coefficients of the mechanical equation discrete form. However, in practice, to have a valid viscous dumping coefficient in a wide speed range, it is preferable to choose alternate torques which imposes positive and negative speeds reaching or close of the nominal value. Let us consider the mechanical equation (7) given in its discrete form:

\[
\Omega(k) = B_0\Omega(k-1) + A_0T_{em}(k-1)
\]

(10)

The coefficients \( B_0 \) and \( A_0 \) merge with the Adaline weights \( w_1 \) and \( w_2 \) represented in fig. 4. They are given by the following expressions:

\[
\begin{aligned}
B_0 &= w_1 = \exp \left( \frac{T}{\tau_m} \right) \\
A_0 &= w_2 = K \left( 1 - \exp \left( \frac{T}{\tau_m} \right) \right)
\end{aligned}
\]

(11)

Once the Adaline weights values \( w_1 \) and \( w_2 \) are optimized on-line, the values of the parameters \( f \) and \( J \) will be obtained by inversion of the equations (11), thus, their expressions will be as follows:
The general principle diagram for implementation of this method is shown in fig. 4.

Fig. 4. Principle diagram of the mechanical parameters identification (first method).

3.3. SECOND METHOD: USING THE SPEED’S HARMONIC RESPONSE

This method is restrictive since it is used only if the reference electromagnetic torque has a sinusoidal form. Theoretically, by using this form of torque, the motor speed would be also sinusoidal. So the idea is to use as Adaline inputs two sinusoidal terms whose amplitudes (which are also the Adaline weights) will be adjusted in real-time as much as possible to approach the form of the measured motor speed. Once the weights converge towards fixed and optimal values, it is easy to find the required mechanical parameters $f$ and $J$. Now, we will give the mathematical formulation of this method.

If one imposes an electromagnetic torque having the following forms:

$$T_{em\_ref} = T_{em\_max} \sin \omega t$$  \hspace{1cm} (13)

And if the mechanical system model of the IM is sufficiently representative, then, in steady state the obtained speed response will be written as follows:

$$\Omega(t) = \Omega_{\text{max}} \sin(\omega t + \phi)$$  \hspace{1cm} (14)

$$\begin{align*}
\Omega_{\text{max}} &= \sqrt{\frac{K^2 T_{em\_max}^2}{\tau_m \omega^2 + 1}} \\
\phi &= -\arctan \frac{T_{em\_max}}{\omega \tau_m}
\end{align*}$$  \hspace{1cm} (15)

The speed expression which is given by the equation (14) can be broken into two terms in the following way:

$$\Omega(t) = \Omega_{\text{max}} \left[ \cos \phi \sin \omega t + \sin \phi \cos \omega t \right]$$

$$= A_1 \sin \omega t + B_1 \cos \omega t$$

With: $A_1 = \Omega_{\text{max}} \cos \phi$ and $B_1 = \Omega_{\text{max}} \sin \phi$

Thus, the terms $\sin \omega t$ and $\cos \omega t$ will be considered as inputs of the Adaline. After the learning process, the constant terms $A_1$ and $B_1$ will coincide respectively with the required Adaline weights $w_1$ and $w_2$ given in fig. 5.

Once the weights are known, it is easy to go back to the mechanical parameters in the following way:

$$\begin{align*}
\phi &= \frac{B_1}{A_1} = \frac{w_2}{w_1} \\
\Omega_{\text{max}} &= \sqrt{A_1^2 + B_1^2} = \sqrt{w_1^2 + w_2^2}
\end{align*}$$

(17)

To combine the preceding relations (15), (16) and (17) allows obtaining:

$$\begin{align*}
f &= \frac{1}{K} = \frac{w_1 T_{em\_max}}{w_2 \sqrt{w_1^2 + w_2^2}} \\
J &= \tau_m f = -f \frac{w_2}{w_1 \omega}
\end{align*}$$

(18)

Then the principle diagram of the practical implementation of this method is explained in fig. 5.
Width Modulation (PWM) signals generation and the signals acquisition are carried out numerically via a dSPACE card: DS1102. The control and identification algorithms are implemented in Matlab/Simulink. Then, the Real Time Interface (RTI) is used to build real-time code and to download and execute it on the dSPACE hardware. The Mechanical speed is measured by a two lines incremental encoder with 2.107 points of global resolution. The stator currents are measured by Hall Effect transducers. All the sizes can be visualized and recorded on the PC via the visualization software: Control Desk.

I. Induction Motor Characteristics

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rated power ( P_n ) (kW)</td>
<td>3</td>
</tr>
<tr>
<td>Rated supply voltage ( U_{\text{ms}} ) (V)</td>
<td>220/380</td>
</tr>
<tr>
<td>Stator rated current ( I_{\text{ms}} ) (A)</td>
<td>11.6/3.3</td>
</tr>
<tr>
<td>Rated speed ( N_\text{e} ) (rpm)</td>
<td>1415</td>
</tr>
<tr>
<td>Number of pole-pairs ( p )</td>
<td>2</td>
</tr>
<tr>
<td>Stator resistance ( R_s ) (Ω)</td>
<td>1.5</td>
</tr>
<tr>
<td>Stator cyclic inductance ( L_s ) (H)</td>
<td>0.22</td>
</tr>
<tr>
<td>Leakage factor ( \sigma )</td>
<td>0.0872</td>
</tr>
<tr>
<td>Rotor time constant ( T_r ) (s)</td>
<td>0.099</td>
</tr>
</tbody>
</table>

To obtain an accurate identification and a fast convergence of the used methods, we carried out some adjustments. The identification signals must contain less possible noise. Consequently the speed signal delivered by the incremental encoder is filtered by a first order low-pass filter. The estimated electromagnetic torque is replaced by the reference electromagnetic torque regulator. The identification was carried out with a sinusoidal electromagnetic torque reference. Its magnitude is of 2.25N.m. The imposed electromagnetic torque is replaced by the reference electromagnetic torque and the resulted speed waveform is not completely sinusoidal, especially with the zero crossing. That is explained by the fact that the viscous damping coefficient is not a constant but variable according the mechanical speed. Indeed, \( f \) is very high at low speeds and becomes small when the IM functions at high speeds.

Figure 6 shows the waveform of the identification signals: the electromagnetic torque and the measured speed. It should be noted that, although a sinusoidal form of the imposed electromagnetic torque, the resulted speed waveform is not completely sinusoidal, especially with the zero crossing. That is explained by the fact that the viscous damping coefficient is not a constant but variable according the mechanical speed. Indeed, \( f \) is very high at low speeds and becomes small when the IM functions at high speeds.

To have a clear and easy comparison, it was superimposed on the same graph the results obtained by experiment and those obtained by simulation.

4.1 Validation Tests

To check the exactitude of the identified parameters, it was carried out two direct starting tests of the IM. The mechanical speed and the stator phase current are recorded during the transient and steady state. To avoid current peaks in the starting phase, the IM is fed by a PWM voltage-source inverter and put out a reduced three-phase voltage and frequency \( (V_{\text{max}}=100V, f=30\text{Hz}) \). Similar tests are carried out in simulation, under Matlab/Simulink, with the identified parameters and under the same conditions. To have a clear and easy comparison, it was superimposed on the same graph the results obtained by experiment and those obtained by simulation.

Figure 7 shows the identified parameters by using the first method. At the end of training, the identified values are: \( J=0.037\text{kg.m}^2 \), for as for the viscous damping coefficient \( f \), we note that its value oscillates around 0.012 N.m/s/rad. This oscillation is explained by the fact that the viscous damping coefficient is not constant in this considered speed range. The resulted value of \( f \) is an average value in this speed range.

Figure 8 shows the evolution of the parameters \( J \) and \( f \) during the training when using the second method. At the end of the training, the two parameters take constant values: \( J=0.0394\text{kg.m}^2 \) and \( f=0.0123\text{N.m.s/rad} \). We notice according to figure 8(b) that, the viscous damping coefficient \( f \) is better identified by this method. The signals noises and offset are eliminated during the Adaline training. Therefore we obtain a better precision value of \( f \).

Figure 9 and figure 10 give the validation results obtained respectively by the first and the second method. These parameters are summarized in table II. Incontestably, it can be deduced that the identified parameters by using the two methods are exact. The theoretical curves and those obtained by experiment, for speed and current signals, coincide perfectly. In both cases, the transient state duration is 0.2s. The maximum value of the current borders 18A and takes 3A in steady state. Nevertheless, we can notice a light gap between the simulation and the experiment which appears at the beginning and at
the end of the transient state. It is due to the viscous damping coefficient which is only the average value on the considered range speed.

### II. Values of the Identified Parameters

<table>
<thead>
<tr>
<th></th>
<th>( J ) (kg·m(^2))</th>
<th>( f ) (N·m·s/rad)</th>
</tr>
</thead>
<tbody>
<tr>
<td>First Method</td>
<td>0.037</td>
<td>0.012</td>
</tr>
<tr>
<td>Second Method</td>
<td>0.039</td>
<td>0.0123</td>
</tr>
</tbody>
</table>

![Graph](image1.png)

Fig. 7. Identification of \( J \) and \( f \) using the first method.

![Graph](image2.png)

Fig. 8. Identification of \( J \) and \( f \) using the second method.

![Graph](image3.png)

Fig. 9. Validation test (first method).

![Graph](image4.png)

Fig. 10. Validation test (second method).

### 5. Conclusion

In this work, we presented and developed two online identification methods for the moment of inertia \( J \) and the viscous damping coefficient \( f \). The two methods, based on the Adalines strategy, are very simple to implement. They require only the knowledge of the quadratic current, the mechanical speed and a field oriented control operation. The first method, exploits the discretized form of the mechanical equation. While, the second method requires a sinusoidal form of the imposed torque. The feasibility of the suggested methods was checked by experiment. The exactness of the found parameters was tested by comparing the experimental results and those obtained in simulation. Nevertheless, for the viscous dumping coefficient, and because of its disparate value, one admits that the second method is more accurate.

A possible future work, in order to refine the identification, is to introduce a coulomb friction into the global load torque or/and to modelize the viscous damping coefficient by a higher degree polynomial versus the mechanical speed.

### 6. References


