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Abstract

Two new methods to identify the mechanical parameters in induction motor based field oriented drives are presented in this paper. The identified parameters are: the moment of inertia and the viscous damping coefficient. The proposed methods are based on the adaptive linear neuron (ADALINE) networks. The two parameters are derived and optimised during the online training process. During the identification phase, the motor torque is controlled by the well-known field oriented control strategy. This torque is subjected to variations in order to obtain mechanical speed transients. The two proposed methods are simple to implement compared to the previous techniques. They require only the stator current and mechanical speed measurements. Finally, the effectiveness of the two methods and the accuracy of the derived parameters are proven experimentally by two direct starting tests. The originality of this work is the building of a model representation that it is suitable for implementation with ADALINE networks. This leads to a simple implementation and ease of mechanical parameters identification.

Keywords: Adaptive linear neuron; Artificial neural networks; Field oriented control; Induction motor; Parameters identification

1. Introduction

To achieve high dynamic performance of induction motor (IM) speed control, knowledge of electric parameters is not sufficient. The mechanical parameters such as the moment of inertia and the viscous damping coefficient are needed and very important to design controllers and/or states observers. Therefore, it is essential to develop algorithms for IM mechanical parameters identification.

There are many proposed techniques that identify the motor parameters off-line. However, when these parameters are subject to variations, the motor control performances are deteriorated and the system becomes detuned. It is therefore suitable to track these changes online in order to ensure optimal controller tuning at any time. To identify the moment of inertia J, conventional methods can be used. They are based on direct and indirect techniques. The direct techniques consist of extracting the rotor and performing measurements which require other devices and not always adaptable for all electric motors. For indirect techniques, the slowdown method can be mentioned. This method requires that the turning system "shaft-end" should be accessible. Measurement is carried out by adding a known inertia wheel J_0 to the motor shaft. The slowdown curves both with and without the added inertia permit the deduction of the inertia moment J. The viscous damping coefficient f can be estimated in steady state by measuring the power consumption at a given speed in no-load test. The use of conventional techniques in industrial environments for determining the mechanical parameters can be an arduous and complicated task. Moreover, these techniques are not able to track changes in the system parameters.

In recent years, several estimation strategies have been developed for mechanical parameters identification in field oriented controller drives. The advantage of the field oriented control (FOC) drives is the possibility to obtain the knowledge of the motor torque since the stator currents and the rotor flux are known [14]. In these conditions, many techniques are developed. The methods based on the least mean squares (LMS) algorithms and recursive least squares algorithms used for online identification [15] can be mentioned. The main limitation of these methods is due to its noise sensitivity. In several papers, observer's techniques have been attempted [3, 9]. In [3], an algorithm is proposed for identifying the moment of inertia by observing the position error signal generated by a speed observer which contains error information on the moment of inertia. A reduced-order extended Luenberger observer is also proposed to estimate the motor inertia value [10]. However, these methods require that some conditions such as observability must be checked and need a long computing-time at the implementation.

Recently, heuristic approaches for IM parameters identification are proposed and have provided efficient results. An off-line method based on the genetic algorithm is proposed to estimate mechanical and electrical parameters. Particle swarm optimisation algorithms are also attempted in order to identify the IM parameters. However, the most known and used heuristic method is that based on artificial neural networks (ANNs) [20]. For a few years, these techniques have been proposed and developed as an alternative to conventional methods for modern control challenges [8,11,13]. Latest papers demonstrate the ANN effectiveness in the

state variable estimation and the IM parameters identification [2,5,20]. Among the ANN techniques, the most attractive for linear system identification is that based on single layer called adaptive linear neuron (ADALINE) networks. The main advantages of this technique are its simplicity and the ability to be trained online. In addition, the ADALINE weights can be interpreted physically [2,12]. It is thus very efficient for parameters identification of linear systems. In some areas such as adaptive signal processing [6] or current harmonics identification in power systems [12], the ADALINE has become a powerful tool.

This paper proposes and investigates the use of two new methods for online identification of IM mechanical parameters. These methods are based on the ADALINE and use LMS learning rule to perform the online training. The hardware implementation is very simple and does not require any additional costs other than that commonly used in FOC. The input/output vectors of the ADALINE are the stator current and the mechanical speed, respectively. These input/output vectors can be obtained by using simple sensor devices. The two methods provide the two parameters J and f online. It represents a main advantage when an online tuning controller is required.

The paper is organized as follows. Section 2 gives the IM model and the FOC principle used during the identification process. In section 3, the ADALINE basic concept, the learning process and the identification strategies are given. The obtained experimental results are presented in section 4. Finally, section 5 is devoted to conclusions.

Nomenclature

L_s	Stator cyclic inductance.
R_s	Stator resistance.
T_r	Rotor time constant.
J	Moment of inertia.
f	Viscous damping coefficient.
T_l	Total load torque.
T_d	Disturbance load torque.
Γ_s	Coulomb friction.
T_{em}	Electromagnetic torque.
I_{rmd}, I_{rmq}	Rotor magnetizing currents in (d,q) frame.
$I_{rm}=(I_{rmd}^2+I_{rmq}^2)^{1/2}$	Module of the rotor magnetizing current.
p	Number of pole pairs.
ω_s	Synchronous pulsation.
Ω	Mechanical speed.
σ	Leakage factor.
s , r	Subscripts indicating stator and rotor.
T_e	Sampling period.

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2. Induction motor mechanical model under field-oriented control

The main objective of the FOC is, as in DC motors, to independently control the electromagnetic torque and the rotor flux. This is performed by using a d-q rotating frame synchronously with the rotor flux space vector. As shown in Fig. 1, the d axis is aligned with the rotor magnetizing current space vector, which yields $I_{rmq}=0$ and $I_{rmd}=I_{rm}$. The rotor magnetizing current I_{rm} is generated by the I_{sd} component. Under steady state conditions, I_{sd} is equal to I_{rm}. The rotor flux angular speed ω_s is calculated by adding the rotor electric speed $(p.\Omega)$ to the motor slip pulsation ω_r. The direct and inverse Park transformations require an input angle θ_s obtained by integrating the field pulsation ω_s. The slip pulsation is expressed by the rotor time constant T_r, the quadratic stator current I_{sq} and the rotor magnetizing current I_{rm}.

If suitable orientation of the stator current and the rotor flux is maintained, the rotor flux and the electromagnetic torque can be controlled independently [14]. The I_{sd} current controls the rotor flux through the direct axis stator voltage V_{sd} and the I_{sq} current controls the electromagnetic torque T_{em} through the quadratic axis stator voltage V_{sq}. This is the key of indirect FOC.

With the FOC implementation, I_{rm}, ω_s and T_{em} can be estimated by

$$\hat{I}_{rm} = \frac{a_1}{s + a_1} I_{sd} \tag{1}$$

$$\hat{T}_{em} = b_1 \hat{I}_{rmd} I_{sq} \tag{2}$$

$$\hat{\omega}_s = p\Omega + \hat{\omega}_r = p\Omega + a_1 I_{sq} / \hat{I}_{rm\_ref} \tag{3}$$

with $a_1 = 1/T_r$ and $b_1 = p(1-\sigma)L_s$.

The IM control scheme adopted for the mechanical parameters identification is shown in Fig. 1. Two proportional-integral (PI) regulators are used to control the electromagnetic torque T_{em} and the rotor magnetizing current I_{rmd}. In order to reconstitute the voltage vectors V_{sd} and V_{sq}, to be applied to the IM, the decoupling terms E_d and E_q are added at the output of each regulator.
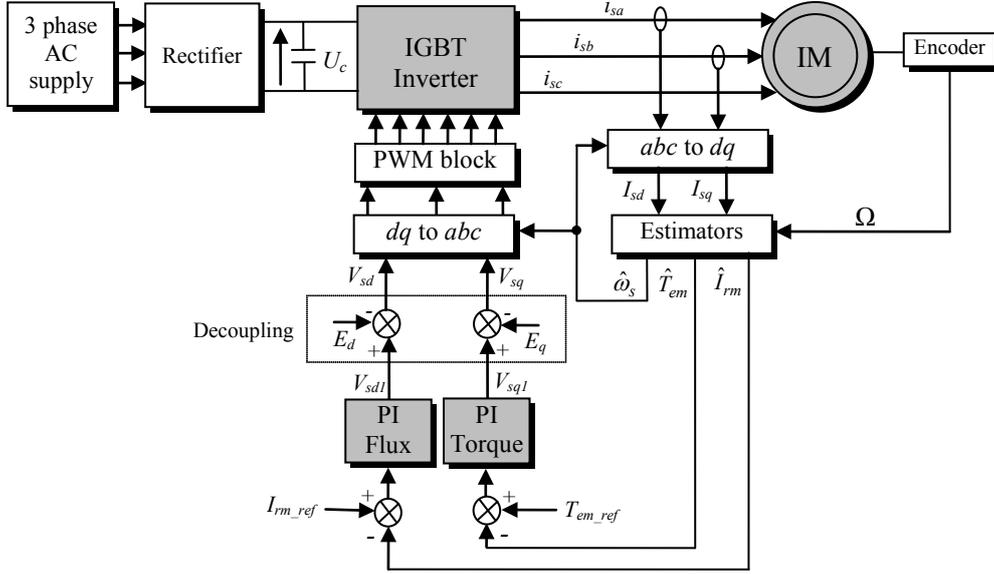
Fig. 1. IM control scheme used in the identification process.

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

$$d\Omega / dt = \left(T_{em} - T_l\right) / J \tag{4}$$

with:

$$T_l = f\Omega + sign(\Omega)\Gamma_s + T_d \tag{5}$$
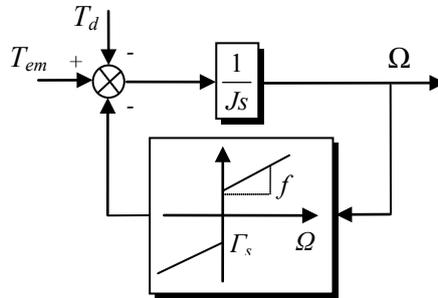
Fig. 2. Functional diagram of the mechanical system.

Under some assumptions like T_d=0 and Γ_s=0, the relationship between the rotor speed and the electromagnetic torque is given by the following transfer function:

$$\frac{\Omega}{T_{em}} = \frac{K}{\tau_m s + 1} \tag{6}$$

Where: $K=1/f$ and $\tau_m=J/f$.

Though the IM dynamic behaviour is the same of the DC motor, the IM control performance is still significantly influenced by the system uncertainties including mechanical parameters. To improve the process control, the constants K and τ_m must be known accurately. Thereafter, the mathematical model given by (6) will be used to determinate the parameters K and τ_m.

3. ADALINE principles

3.1. ADALINE architecture

The ADALINE neural network is well-known in the ANNs architecture. It has been applied successfully in many power applications, including current harmonics estimation [12], voltage and current components extraction of an unbalanced three-phase

system [4], power quality disturbances detection [1], IM electric parameters identification [2,7], and feature of control [16]. As shown in Fig. 3, the ADALINE is equivalent to 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 $W_k=[w_{0k}\ w_{1k}\ \ldots\ w_{nk}]^{\mathrm{T}}$ corresponds to the whole neuron synaptic forces. The input vector $X_k=[1\ x_{1k}\ \ldots\ x_{nk}]$ corresponds to the whole neuron input stimulus. The activation function $f(v)$ specifies the neuron behaviour.
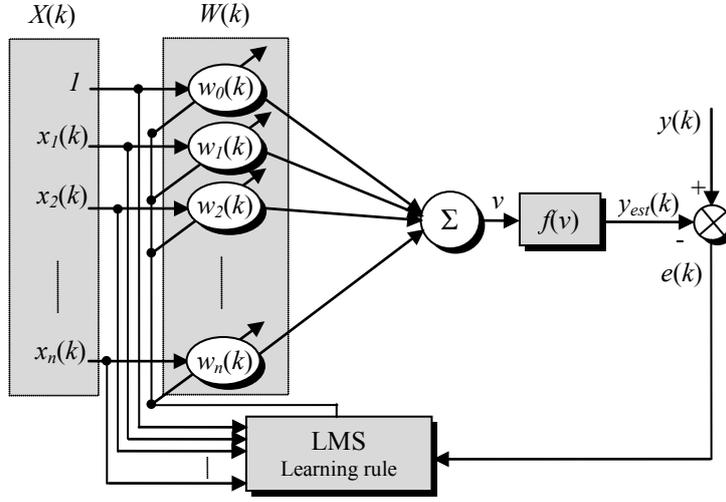
Fig. 3. ADALINE topology.

Various activation functions can be used in the ANN theory. However, the ADALINE uses the linear activation function $f(v)=v$. Consequently, the ADALINE output y_k is given by: $y_k=X_kW_k$. When the ADALINE is excited, it produces the output y_k which depends on the input vector. The weights vector W_k is continuously modified during the network learning process with the purpose of approaching as close as possible the desired output d_k.

3.2. ADALINE training

In the ADALINE theory, the most known training process is that called μ-LMS algorithm [17,18,19]. The weight vector is updated after the presentation of each input sample. The μ-LMS algorithm is performed by using the steepest-descent gradient. It starts with an arbitrary initial value W_0 for the system's weight vector. The instantaneous gradient ∇_k upon the square of the instantaneous linear error is measured and the weight vector is altered in the direction corresponding to the measured negative gradient. The procedure is repeated, causing the mean square error to be successively reduced on average and causing the weight vector to approach a locally optimal value. The method of steepest descent can be described by the following expression:

$$W_{k+1} = W_k + \mu(-\nabla_k) = W_k - \mu\frac{\partial e_k^2}{\partial W_k} \tag{7}$$

where μ is a parameter that controls stability and convergence rate, and ∇_k is the instantaneous gradient value at $W=W_k$.

The ADALINE uses a supervised learning, so a desired output d_k is provided with each input X_k during the training phase. The error information is

$$e_k = d_k - y_k = d_k - X_k^T W_k \tag{8}$$

Performing the differentiation in (7) and replacing the linear error given by (8), we can write

$$W_{k+1} = W_k - \mu\frac{\partial e_k^2}{\partial W_k} = W_k - 2\mu e_k\frac{\partial e_k}{\partial W_k} \tag{9}$$

and

$$W_{k+1} = W_k - 2e_k\mu\frac{\partial(d_k - X_k^T W_k)}{\partial W_k} \tag{10}$$

d_k and X_k are independent of W_k, that leading to

$$W_{k+1} = W_k - 2\mu e_k X_k^T \tag{11}$$

3.3. Learning rate

The learning constant μ determines stability and convergence rate. For time independent input patterns, the weight vector mean and variance convergence is ensured for most practical purposes if

$$0<\mu<1/trace[R] \tag{12}$$

Where $trace[R]=\Sigma$ (diagona1 elements of R) and R is the input correlation matrix defined in ensemble average terms: $R= E(X.X^T)$.

The learning rate μ is an important parameter. The choice of a small value for μ leads to a better network stability but the weights convergence can become very slow. Therefore, to accelerate the weights convergence and to refine the results, μ must be variable during the training process. Its value will be selected relatively high at the beginning, and will decrease significantly and have a small value at the end. The expression of μ can be selected by the following equation:

$$\mu = \mu_i \left(\mu_f / \mu_i \right)^{\frac{t}{t_{max}}} \tag{13}$$

μ_i and μ_f are respectively the initial and the final values of the learning rate. t_{max} is the maximal training time.

4. Identification strategies based on ADALINE

The theoretical basis of this identification strategy is to find and to exploit the linear relationship existing between the weights and the mechanical parameters. If the weights adjustment gives the error between the actual and the estimated rotor speed to the minimum value, then the mechanical parameters are well known.

4.1. Mechanical equation based method

This method can be implemented with any form of torque command T_{em_ref} and the resulted speed Ω. To have a valid viscous damping coefficient in a wide speed range, it is preferable to apply alternate torques which lead to positive and negative speeds close to the nominal value.

Let us consider the mechanical equation (6) written in the recursive form

$$\Omega(k) = B_0\Omega(k-1) + A_0 T_{em}(k-1) \tag{14}$$

The coefficients B_0 and A_0 are equivalent to the ADALINE weights, w_1 and w_2 respectively, as represented in Fig. 4. They are given by the following expressions:

$$\begin{cases} B_0 = w_1 = \exp\left(-T_e / \tau_m\right) \\ A_0 = w_2 = K\left(1 - \exp\left(-T_e / \tau_m\right)\right) \end{cases} \tag{15}$$

Once the optimal weights w_1 and w_2 are correctly known during the training process, they can be used to calculate the parameters f and J by inversion of (15). Their expressions will be as follows:

$$\begin{cases} f = 1/K = \dfrac{1 - w_1}{w_2} \\ J = \tau_m f = -f T_e / \ln\left(w_1\right) \end{cases} \tag{16}$$

The implementation block diagram of this method is shown in Fig. 4.
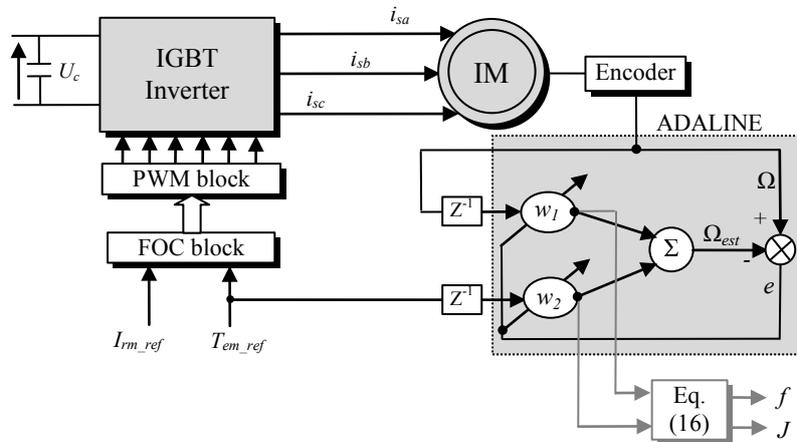
Fig. 4. Overall structure of ADALINE identifier for mechanical equation based method.

4.2. Harmonic speed response based method

This method can be applied only if the imposed torque command T_{em_ref} has a sinusoidal form. Theoretically, with this form of torque, the motor speed response would be also sinusoidal. The use of an ADALINE with two sinusoidal terms ($\sin\omega t$ and $\cos\omega t$) as inputs is suggested (Fig. 5). The ADALINE weights w_1 and w_2 will be adjusted during the training process to approach the measured mechanical speed. Once the weights converge towards fixed and optimal values, it is easy to derive the required mechanical parameters f and J.

Let us give the mathematical formulation of this method. If the reference torque is defined as

$$T_{em\_ref} = T_{em\,max} \sin\omega t \tag{17}$$

and if the IM mechanical model is accurately given by (6), then, in steady state operating conditions the obtained speed response will be written as follows:

$$\Omega(t) = \Omega_{max} \sin(\omega t + \phi) \tag{18}$$

The constants Ω_{max} and ϕ are given by

$$\begin{cases} \Omega_{max} = \sqrt{\dfrac{K^2 T_{em\,max}^2}{\tau_m^2 \omega^2 + 1}} \\ \phi = -\arctan \tau_m \omega \end{cases} \tag{19}$$

The speed response given by (18) can be subdivided into two terms in the following way:

$$\Omega(t) = \Omega_{max} \left[\cos\phi \sin\omega t + \sin\phi \cos\omega t \right]$$
$$= A_1 \sin\omega t + B_1 \cos\omega t \tag{20}$$

Where:
$$\begin{cases} A_1 = \Omega_{max} \cos\phi \\ B_1 = \Omega_{max} \sin\phi \end{cases}$$

The two terms $\sin\omega t$ and $\cos\omega t$ will be considered as ADALINE inputs. As shown in Fig. 5, the constant terms A_1 and B_1 coincide with ADALINE weights w_1 and w_2 respectively. Once the weights are known, it is easy to reconstitute the mechanical parameters in the following way:

$$\begin{cases} \tan\phi = B_1 / A_1 = w_2 / w_1 \\ \Omega_{max} = \sqrt{A_1^2 + B_1^2} = \sqrt{w_1^2 + w_2^2} \end{cases} \tag{21}$$

Combining the relationships (19) with those given by (21) permits to obtain

$$\begin{cases} w_1^2 + w_2^2 = \dfrac{K^2 T_{em\,max}^2}{\tau_m^2 \omega^2 + 1} \\ w_2 / w_1 = -\tau_m \omega \end{cases} \tag{22}$$

Finally, solving the system (22) permits to derive the mechanical parameters

$$\begin{cases} f = \dfrac{1}{K} = \dfrac{w_1 T_{em\,max}}{w_2 \sqrt{w_1^2 + w_2^2}} \\ J = \tau_m f = -f \dfrac{w_2}{w_1 \omega} \end{cases} \tag{23}$$

The implementation principle diagram of this method is explained in Fig. 5.
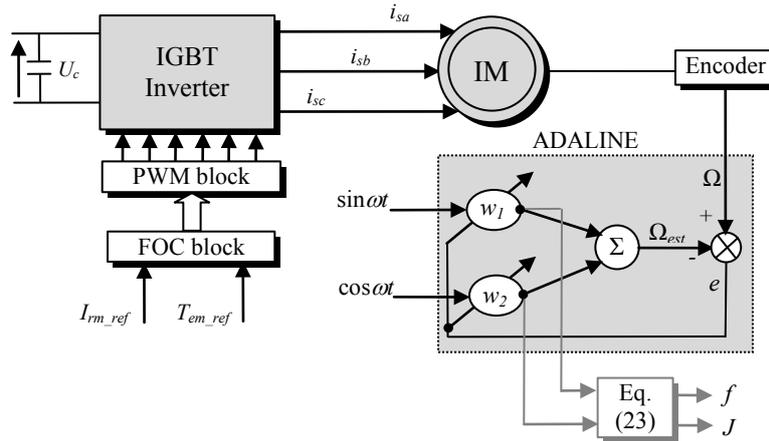
Fig. 5. Overall structure of ADALINE identifier for harmonic speed response based method.

5. Experimental results

The identified system is a squirrel cage IM. The electric parameters R_s, L_s, σ and T_r have been successfully identified by using ADALINE strategies [2]. The IM characteristics are given in Table 1. The IM is supplied by a voltage-source IGBT inverter. The FOC strategy, the Pulse Width Modulation (PWM) signals generation and the signals conditioning are carried out numerically via a dSPACE board based on a TMS320C31 floating point DSP. The control and the identification algorithms are implemented in MATLAB–Simulink using Runge-Kutta resolution method. The real-time interface is used to build real-time code (C language) and execute it on dSPACE hardware. The mechanical speed is measured by an incremental encoder with a global resolution of 2.10^4 point/round. The stator phase currents are measured by Hall Effect transducers. All the signals can be visualized and recorded on a computer via the ControlDesk visualization software. A view of the test bench is given in Fig. 6.

Table 1
Induction motor characteristics

Rated power (kW)	P_n=3
Rated supply voltage Δ/Y (V)	U_{sn}=220/380
Stator rated current Δ/Y (A)	I_{sn}=11/6.3
Rated speed (rpm)	N_n=1415
Number of pole-pairs	p=2
Stator resistance (Ω)	R_s=1.5
Stator cyclic inductance (H)	L_s=0.22
Leakage factor	σ=0.0872
Rotor time constant (s)	T_r=0.099
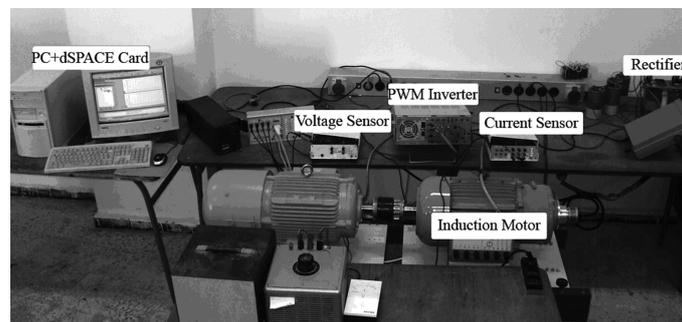
Fig. 6. View of the test bench.

To obtain an accurate identification and a fast convergence of the used methods, some adjustments were carried out. The identification signals must contain the least amount of noise possible. Therefore, the mechanical speed signal, delivered by the incremental encoder, is filtered by a first order low-pass filter. The actual torque is substituted by the torque reference. This approximation is justified since the identification signals are relatively slow compared to the torque regulator response time. The identification was carried out with a sinusoidal torque reference. Its magnitude is 2.25 Nm and the pulsation is set to 0.6rad/s. The

motor rotation speed reaches 90 rad/s. The maximal and minimal values of the learning rates, ensuring an optimal speed convergence, are experimentally adjusted respectively to η_{max}=4.10^{-5} and η_{min}=10^{-7}. The sampling period used in the identification process is T_e=0.5ms.

Fig. 7 shows the identification signals waveform; the torque reference and the measured speed. It can be noted that the resulted speed waveform is not completely sinusoidal, especially with the zero crossing. That is explained by the viscous damping coefficient f which is not constant but depends on the mechanical speed. Indeed, f is very high at low speeds and becomes small when the IM operates at high speeds.
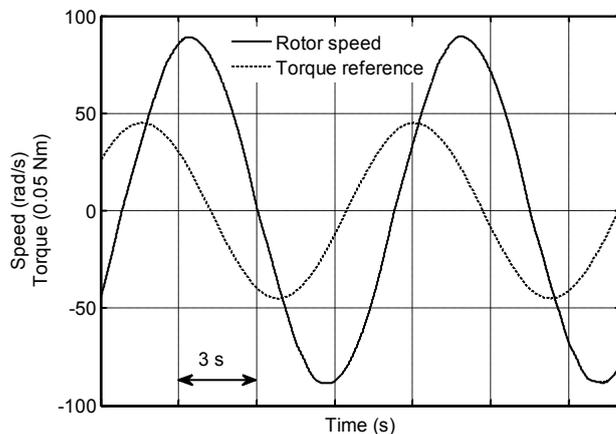
Fig. 7. Identification signals: torque reference and rotor speed.

5.1. Mechanical speed equation based method

Fig. 8(a) shows the ADALINE weights evolution w_1 and w_2. After the transient state, the weights are stabilized at the values: w_1=0.9998 and w_2=0.0133. As shown in Fig. 8(b), the residual error is very low, which is what justifies the good performance of the ADALINE network. Fig. 9 shows the identified parameters. In the steady state, the identified values are: J=0.037 kg.m^2 (Fig. 9(b)) and f=0.012 N.m.s/rad (Fig. 9(a)). The fluctuating value of f is explained by the fact that the viscous dumping coefficient is not constant. The obtained value of f is only an average in this speed range.
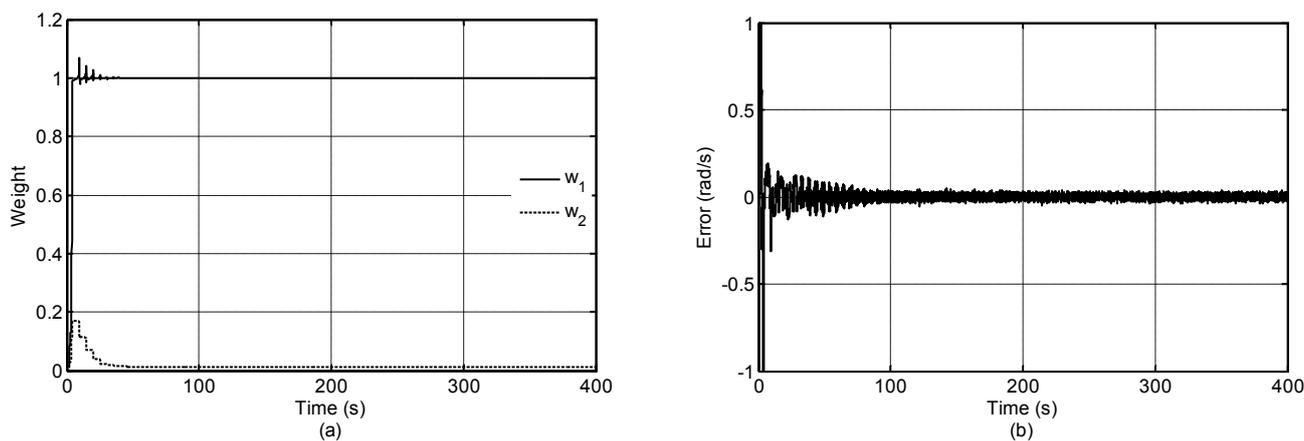
Fig. 8. Evolution of the weights (a) and prediction error (b).
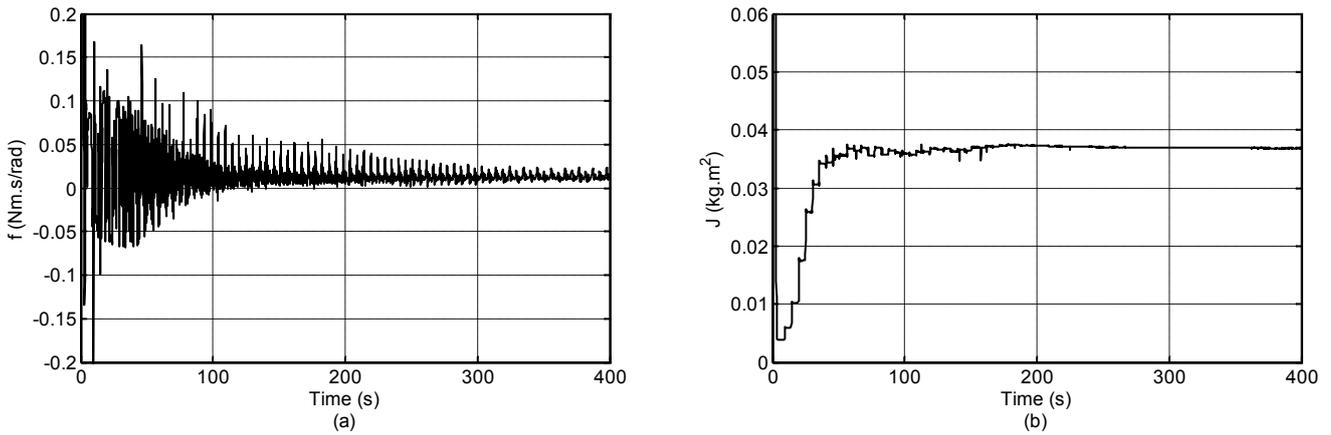
Fig. 9. Identified parameters: viscous damping coefficient (a) and moment of inertia (b).

5.2. Harmonic speed response based method

Fig. 10 shows the ADALINE weights evolution and the error between the actual and the estimated speed. In Fig. 10(a), the weights w_1 and w_2 are stabilized at 37.2 and -78.1 respectively. The error, as shown in Fig. 10(b), still relatively significant compared to that obtained using the first method. This is due to the presence of *arctan* function in (19) which is very sensitive to the weight variations. In Fig. 11, the convergence of the parameters J and f is shown. In the steady state, the two parameters are: J=0.0394 kg.m^2 and f=0.0123 N.m.s/rad. As shown in Fig. 11(a), the viscous damping coefficient f seems better identified than in the first method. A significant improvement in precision is obtained. The application of this method consists to filter the speed signal and to extract the fundamental component. It results in a constant value of J and f.
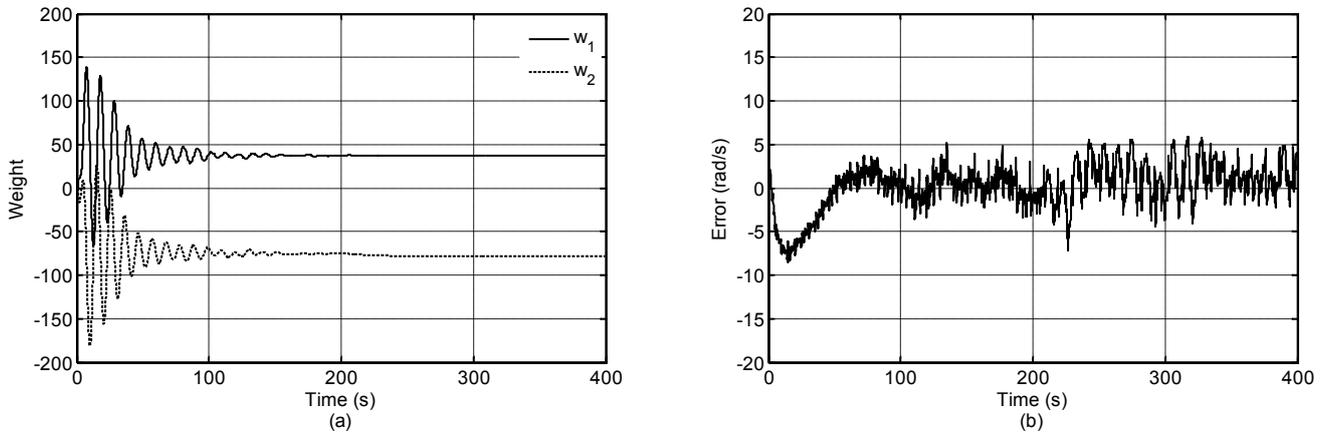
Fig. 10. Evolution of the weights (a) and the prediction error (b).
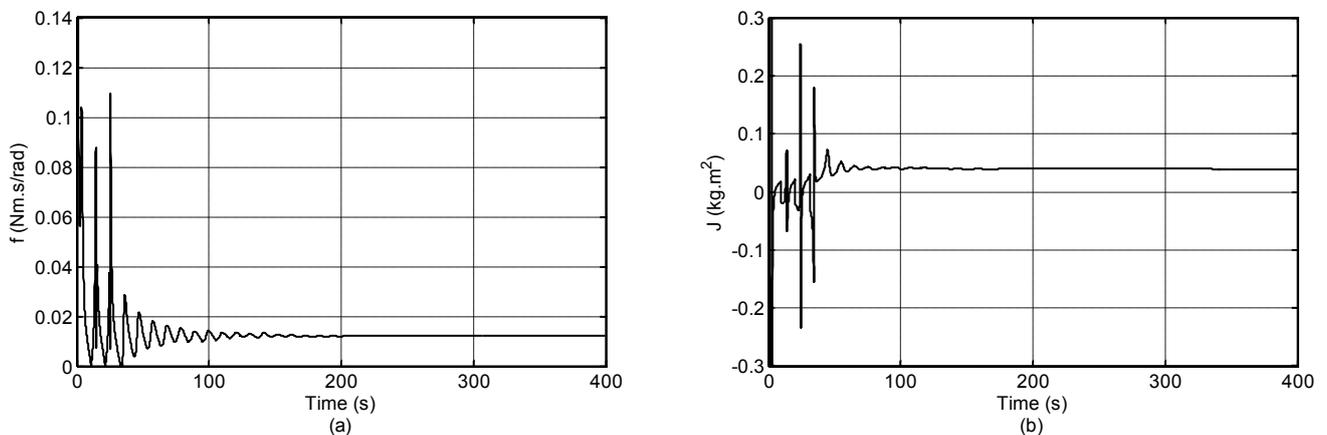
Fig. 11. Identified parameters: viscous damping coefficient (a) and moment of inertia (b).

5.3. Validation tests

   To check the accuracy of the identified parameters related to the two proposed methods; two direct starting tests of the IM are carried out. The mechanical speed and the stator phase current are recorded during the transient and steady state. To avoid current peaks during the starting phase, the IM is fed by a reduced voltage via a voltage-source IGBT inverter. The maximum of the voltage is about 100V and the frequency is set to 30Hz. Two tests are carried out in simulation with the identified parameters and under the same conditions. In order to perform a comparison; the experimental measurements and the computed curves of the identified parameters are superimposed on the same graph. Fig. 12 and Fig. 13 give the validation results of the identified parameters using the two proposed methods. These parameters are summarized in Table 2.

   Incontestably, the identified parameters seem to be identified accurate since the theoretical curves coincide perfectly with those obtained by experiment. In both cases, the transient state duration is 0.2s and the maximal current reaches 20A at the beginning, then, it's equal to 3A in the steady state. Nevertheless, a light shift between the simulation and the experiment curves appears at the transient period. It is due to the viscous damping coefficient which constitutes only an average value on the considered speed range.

Table 2
Values of the Identified Parameters

	J (kg.m^2)	f (N.m.s/rad)
Mechanical speed equation based method	0.037	0.012
Harmonic speed response based method	0.039	0.0123
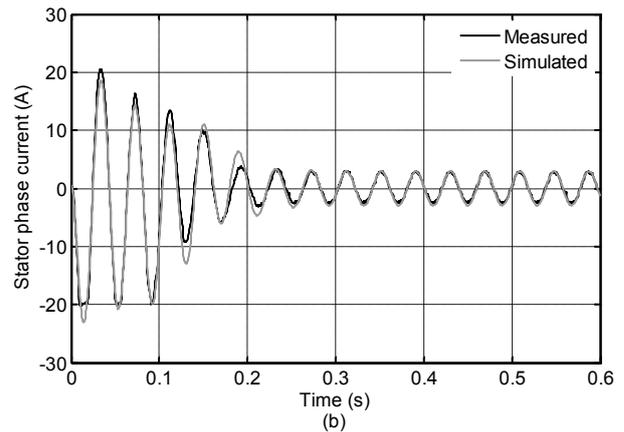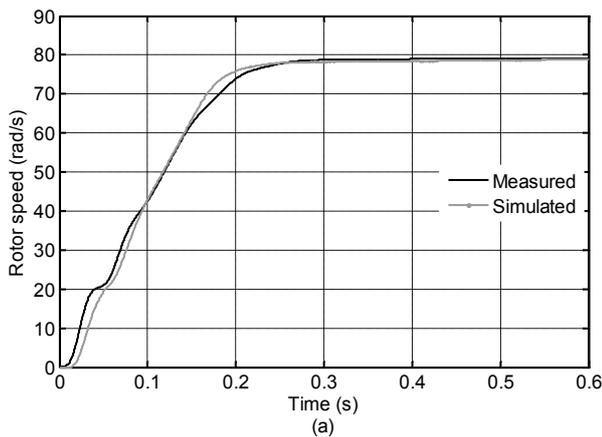
Fig. 12. Validation test (Mechanical speed equation based method).
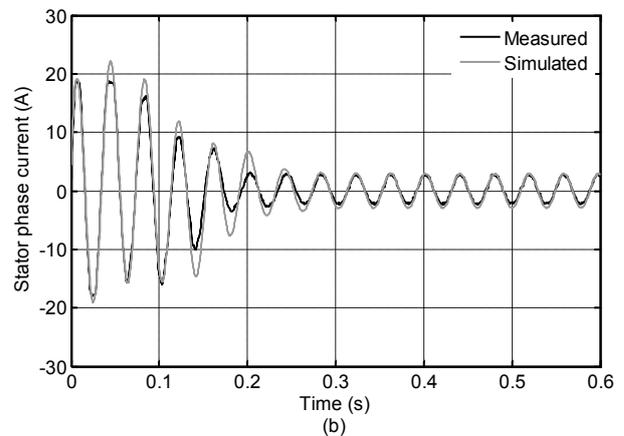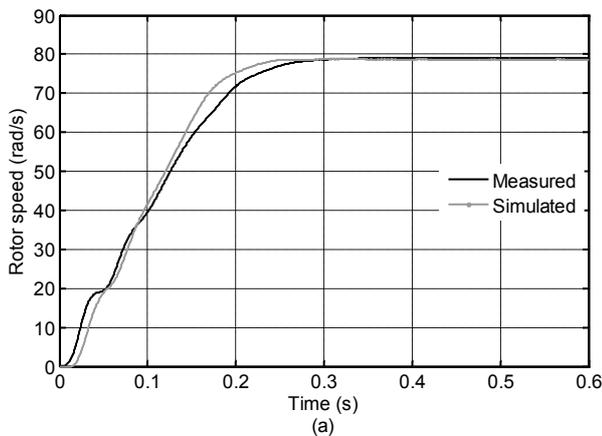
Fig. 13. Validation test (Harmonic speed response based method).

6. Conclusion

This work demonstrates the effectiveness application of the ADALINE for mechanical parameters identification in vector controlled IM drives. Two online techniques are presented to identify the moment of inertia and the viscous damping coefficient. These methods, based on a single neuron, are very simple to implement. They require the knowledge of the phase currents, the mechanical speed, and a FOC. The first method, more general, exploits recursive form of the mechanical equation. The second one is applied in case of a sinusoidal form of the torque reference. The suggested methods feasibility has been checked by experiments and the identified parameters accuracy has been tested by comparing the experimental results, as well as those obtained from simulations. Nevertheless, for the viscous damping coefficient, and regarding its disparate value, the second method is more accurate. A possible direction for future work, for the purpose of refining the identification, could be the introduction of a coulomb friction into the torque loss.

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