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Reduced order model based neural network control of a squirrel cage induction motor drive

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In recent years, much attention has been focused upon neural networks which are generally used to solve highly nonlinear control problems. The implementation of such a control strategy on machine drives has greatly improved their performances. The paper deals with the neural network control of a squirrel cage induction motor drive where the training data base has been obtained using a reduced order model of the controlled system. As a result, the learning rules are found to be easier yielding a reduced structure of the neural net compared to those given by the complete model. Furthermore, a new torque feedback control loop has been introduced in an attempt to improve the dynamic response of the drive. Considering the reduced order model based neural network control and the complete model based neural network control, simulation results show that the training data base given by the reduced order model is sufficient to reach high dynamic responses which are better than those yielded by the complete model training data base. Moreover, it has been found that the robustness of the implemented control system is not affected by measurement perturbations.

1. Introduction

The squirrel cage induction machine drives are regarded as the state of the art of industrial variable speed applications. They represent the best solution for the substitution of the dc machine drives which require expensive systematic maintenance.

Induction machine conventional controls such as direct self control and feedback linearization control have been developed in an attempt to reduce the complex nonlinear dynamic structure of the machine model, which enables the application of linear system control laws (Wishart and Harley 1995).

In recent years, a new area of electrical ac machine drives are being developed thanks to the progress of power electronic switching device technology and to the implementation of numerical control strategies. The most popular numerical control is the field oriented control whose implementation on ac machine drives leads to high performances (Nabae *et al.* 1980, Masmoudi *et al.* 1995). Particularly, the squirrel cage induction motor drive, under rotor flux oriented control, is considered one of the best ac variable speed drives in all applications where a quick dynamic is required. Nevertheless, in field oriented control systems, the simplicity of the implemented controllers is compromised by the machine parameter variations due to heating and saturation, which decreases the control system accuracy. This is why, the implementation of robust non-conventional controls such as fuzzy control and neural control, etc., on machine drives, is presently given increasing attention.

Neural networks have recently been the subject of substantial attention (Thibault and Grandjean 1991). They represent an attempt to model the human brain and have the potential for very complicated behaviour. They provide a novel and a computational attractive mode to investigate a large class of problems involving complexity, nonlinearity and uncertainties of a high order. Neural net models are described by the net topology, the node characteristics and the learning rules. These rules specify an initial set of weights and indicate how these weights should be adapted in order to improve the application performances (Lippmann 1987).

Neural networks have found growing success in diverse industrial control applications (Widrow *et al.* 1994). They appear to offer new and highly promising

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directions for development of innovative control strategies. Their use in the domain of process analysis and control has been treated in the literature (Chtourou 1993, Chtourou *et al.* 1993, Narendra and Parthasarathy 1990, Thibault and Grandjean 1991, Werbos 1989). They were particularly investigated in the field of electric machine control (Godoy and Bimal 1995, Wishart and Harley 1995, Chtourou *et al.* 1996). Godoy and Bimal (1995) proposed an estimator based on neural networks for the electromagnetic torque and the two components of the rotor flux. Wishart and Harley (1995) developed an adaptive controller using a neural network identifier of the induction machine. Chtourou *et al.* (1996) show that an off-line identified neural controller with an integrator yields efficient control of a loaded induction machine. They have found that the implemented control system requires a net topology made up of six input neurons, thirteen hidden neurons and an output neuron. In our opinion, such a net topology remains relatively complex and its reduction would be an interesting task since the rapidity and the cost of the implemented control system are directly related to the number of neurons. Taking into account the fact that the induction machine has been commonly considered as a singularly perturbed system whose model reduction has been the subject of many papers (Krause *et al.* 1979, Gunaratnam and Novotny 1980, Richards and Tan 1986, Derbel *et al.* 1995), we have been interested to use a reduced order model of the induction machine for the computation of a learning data base. It is expected that the learning rules will be easier yielding a reduced structure for the neural net. This paper develops this idea.

In what follows, we first introduce a brief description of the feedforward neural network which is considered in this work. Then the modelling of the induction machine is presented in two ways:

- the complete model whose dimension is equal to five,
- the reduced order model whose dimension is unity.

Taking these models into account, two training data are computed in order to determine the inverse neural model for the machine control. Then, a new control scheme based on a torque feedback loop is introduced in order to compensate the effects of the reduction errors and therefore to improve the dynamic response of the system.

2. Feedforward neural networks

Referring to the published material on neural control, many neural network architectures have been designed and implemented in control schemes. Hecht-Nielsen (1988) reported that at least fifty different types of neural networks have been investigated. The most popular architecture is the feedforward neural network often called a backpropagation network. In the following, we consider this type of neural network architecture.

A feedforward network consists of several layers of processing units (the artificial neurons) where neuron connections occur only between adjacent layers. Input layer neurons introduce each input to the neurons of the hidden layer. Hidden neurons make a weighted sum of all their inputs, and then apply a transfer (or activation or squashing) function to this sum. Such a function can be linear or nonlinear (threshold, sigmoid, sine or hyperbolic tangent function). The most commonly used is the sigmoid (Lippmann 1987, Thibault and Grandjean 1991). A unity constant input is considered, adding a constant to the weighted sum. The output of a neuron is distributed to the neurons of the next layer.

Referring to Cybenko (1989), a three layered neural network is able to approximate all continuous multivariable functions. The quality of the model depends strongly on how well the learning algorithm is able to extract the essence of the data in order to get a representation of the dynamic behaviour of the process. The fitting parameters of the neuron models are the connection weights which are obtained from a learning or training process.

If a training set of input–output vectors is given, the major problem consists on how accurate values of the connection weights (w_{ij}, w_j) can be derived in such a way that the whole network develops an internal representation which captures the underlying relations between input–output pairs. The learning procedure is based on the well known backpropagation algorithm (Rumelhart *et al.* 1986). It consists of a modified version of the gradient descent method used to minimize the sum of squared output error (for more details, see Rumelhart *et al.* 1986). A general layout of the net topology is shown in Fig. 1.

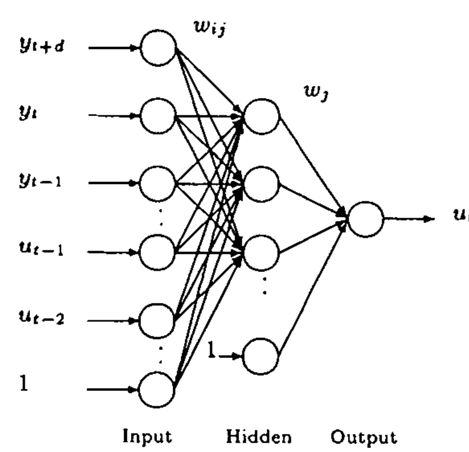

Figure 1. The plant inverse neural model.

3. Problem formulation

3.1. *Induction machine model*

Squirrel cage induction machine drives are regarded as the state of the art of industrial variable speed applications. Such drives represent the best alternative to dc machine drives.

Many representations of induction machines currently exist in the literature. The reference frame of the machine will be chosen in such a way that the quadrature stator voltage is zero. We use the usual notations where subscripts s and r refer to stator and rotor and subscripts d and q refer to the direct and quadrature axis. v, i and ψ stand for voltage, current and flux respectively. ω is the stator angular frequency, ω_m is the rotor speed. J is the moment of inertia and p is the number of the machine pole-pair. Mechanical and iron losses are neglected. Assuming a balanced three phase supply of the stator, the machine equations are (Stern and Novotny 1978, Kovacs 1979, Poloujadoff 1987):

$$\dot{\psi}_s = -(r_s\lambda_s + j\omega)\psi_s + r_s\lambda_m\psi_r + v_s \,, \tag{1}$$

$$\dot{\psi}_r = r_r\lambda_m\psi_s - [r_r\lambda_r + j(\omega - p\omega_m)]\psi_r \,, \tag{2}$$

$$\dot{\omega}_m = \frac{1}{J}[T_e - T_m], \tag{3}$$

where T_m represents the mechanical torque and T_e is the electromagnetic torque:

$$T_e = 3p\lambda_m \Im(\psi_s\psi_r^*) \tag{4}$$

with ψ_r^* is the conjugate of ψ_r and $\Im$ is the imaginary part function, and where λ_s, λ_r and λ_m are derived from the flux–current relationship as follows:

$$\psi = LI \,, \quad I = \Lambda\psi \tag{5}$$

with:

$$L = \begin{pmatrix} l_s & m \\ m & l_r \end{pmatrix}, \quad \Lambda = \begin{pmatrix} \lambda_s & -\lambda_m \\ -\lambda_m & \lambda_r \end{pmatrix} \tag{6}$$

with $\psi = [\psi_s\, \psi_r]^T$ and $I = [I_s\, I_r]^T$.

Results have been found by solving differential equations using a fourth order Runge–Kutta approach. These equations can be expressed in the condensed form as: $\dot{X} = \mathcal{F}(X, U)$, where: $X = [\psi_{ds}\ \psi_{qs}\ \psi_{dr}\ \psi_{qr}\ \omega_m]^T$ represents the state vector of the machine. The input vector of the machine is $U = [v_s\ \omega]^T$ with $v_s = v_{ds} \in \mathbb{R}$ ($v_{qs} = 0$). The output is the mechanical speed ω_m.

We consider the application where the mechanical torque is proportional to the speed:

$$T_m = k\omega_m. \tag{7}$$

The squirrel cage induction machine under study has the following parameters and ratings (Chatelain 1983):

$$\begin{array}{ll} r_s = 0.29\,\Omega & r_r = 0.38\,\Omega \\ l_s = 50 \times 10^{-3}\,\mathrm{H} & l_r = 50 \times 10^{-3}\,\mathrm{H} \\ m = 47.3 \times 10^{-3}\,\mathrm{H} & p = 2 \\ J = 0.5\,\mathrm{kg\,m^2} & k = 1.71\,\mathrm{N\,m\,s\,rad^{-1}} \\ \omega = 100\,\pi\,\mathrm{rad\,s^{-1}} & v_s = 220\,\mathrm{V} \end{array}$$

The training data were obtained by an integration of the state model described above. A noise was added to the input in order to extract the maximum information concerning the machine dynamics.

3.2. *Model reduction*

In this section, electrical variables are considered as rapidly varying quantities and the speed ω_m is considered as slowly varying quantity (Krause *et al.* 1979, Gunaratnam and Novotny 1980, Richards and Tan 1986, Derbel *et al.* 1995). This yields the following equations (Derbel *et al.* 1995):

$$\begin{bmatrix} \bar{\psi}_s \\ \bar{\psi}_r \end{bmatrix} = \begin{bmatrix} r_s\lambda_s + j\omega & -r_s\lambda_m \\ -r_r\lambda_m & r_r\lambda_r + j(\omega - p\bar{\omega}_m) \end{bmatrix}^{-1} \begin{bmatrix} v_s \\ 0 \end{bmatrix} \tag{8}$$

which yields:

$$\begin{bmatrix} \bar{\psi}_s \\ \bar{\psi}_r \end{bmatrix} = \begin{bmatrix} \dfrac{r_r\lambda_r + j(\omega - p\bar{\omega}_m)]v_s}{(r_s\lambda_s + j\omega)[r_r\lambda_r + j(\omega - p\bar{\omega}_m)] - r_r r_s\lambda_m^2} \\ \dfrac{r_r\lambda_m v_s}{(r_s\lambda_s + j\omega)[r_r\lambda_r + j(\omega - p\bar{\omega}_m)] - r_r r_s\lambda_m^2} \end{bmatrix}. \tag{9}$$

Then, the machine-load model is reduced to a first order system such that:

$$\dot{\bar{\omega}}_m = \frac{1}{J}\left[\frac{3pr_r\lambda_m^2|v_s|^2\,(\omega - p\bar{\omega}_m)}{\left|(r_s\lambda_s + j\omega)[r_r\lambda_r + j(\omega - p\bar{\omega}_m)] - r_r r_s\lambda_m^2\right|^2} - k\bar{\omega}_m\right]. \tag{10}$$

The bar over the state variables indicates the approximation yielded by the reduction.

4. Control strategy

Referring to previous works (Chtourou *et al.* 1996, Thibault and Grandjean 1991), the most common control scheme using the plant inverse neural model is shown in Fig. 2. The generalized learning objective of the plant inverse neural model is the minimization of the difference between the estimated action control and the corresponding one in the learning set. An identified plant inverse neural model may not be accurate enough providing a feedforward controller with

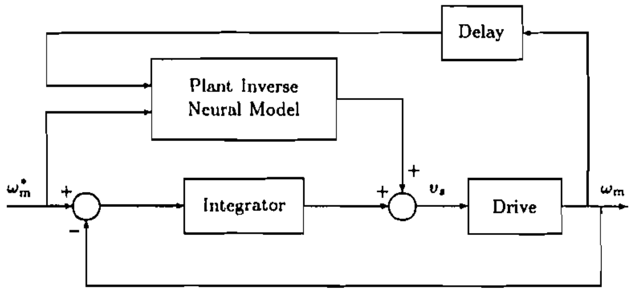

Figure 2. The classical control scheme.

poor performances. In order to ensure offset-free control, an integrator is commonly used as a standard controller.

In Fig. 2, the machine is controlled by the plant inverse neural model whose output provides the stator reference voltage $v_s^*(t)$ and inputs are the desired speed $\omega_m^*(t)$, its delayed outputs $v_s^*(t-i)$ and the delayed measured speed $\omega_m(t-j)$. In the following, we consider an ideal voltage converter feeding the induction machine so that $v_s^* = v_s$. This scheme has been used by Chtourou *et al.* (1996) for the speed control of an induction machine. It has been shown that an accurate response of the control system is reached using six input neurons, thirteen hidden neurons and an output neuron.

The implementation of the reduced order model based plant inverse neural controller on the classical control scheme yielded unstable operation of the drive. In order to overcome this problem, much attention has been focused on the structure of the control scheme which has been rethought in an attempt to improve the dynamic response with the reduction net topology. As a result, a new control scheme has been designed whose structure is shown in Fig. 3.

In Fig. 3, the machine is controlled by the plant inverse neural model whose output provides the stator voltage $v_s(t)$ and inputs are the desired torque $T_e^*(t)$, its delayed outputs $v_s(t-i)$ and the delayed measured torque $T_e(t-j)$. A classical PI controller is inserted in the speed feedback loop providing the desired torque T_e^* in terms of the desired speed ω_m^* and the actual speed ω_m. If the training is sufficiently accurate, it is expected to reach a transfer function $T_e/T_e^* \simeq 1$, which considerably simplifies the design of the PI controller.

5. Simulation results

In this section, two versions of the plant inverse neural model are considered. The first one is obtained using the complete model of the drive. The second one is obtained using the drive reduced model. In both case, the net topology is reduced to six input neurons, six hidden neurons and one output neuron. In order to simplify the study, we have considered an ideal voltage supply converter whose output voltage and frequency are related by the well known constant ratio V/Hz control law. Thus, and taking into account the machine ratings, the angular frequency ω can be expressed in terms of the stator voltage v_s as:

$$\omega = \frac{100\pi}{220} v_s. \tag{11}$$

It is well known that the implementation of such a control law on induction machine drives yields appreciable dynamic responses (Krause 1987, Song *et al.* 1992).

In Fig. 4, the results yielded by the complete model based neural network controller in the torque feedback loop are shown. Figure 4(a) shows the desired speed (interrupted line) and the measured speed (continuous line). Figure 4(b) shows the rms value of the stator voltage. Figure 4(c) shows the electromagnetic torque (continuous line) and the load torque (interrupted line). Figure 4(d) shows the rms values of the stator current (continuous line) and of the rotor current (interrupted line).

Now let us reconsider the variables shown in Fig. 4 in the case of a reduced order model based neural network controller in the torque feedback loop. This leads to the results shown in Fig. 5.

Referring to Fig. 5(a), it is utmostly interesting to notice that we obtain relatively better speed response than the one shown in Fig. 4(a). In other words the reduced order model based neural network controller is more accurate than the one obtained with a complete model training data base. Given the long experience with the singularly perturbed systems, it is quite commonly believed that conventional controls based on reduced order models of such systems decrease the dynamic performances, which is due to the reduction errors. This work is an illustration which proves that

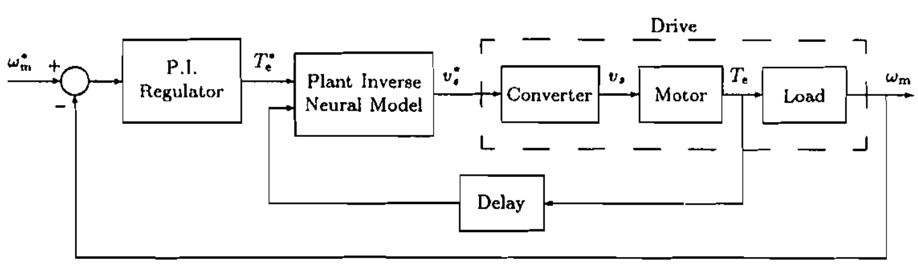

Figure 3. The proposed control scheme.

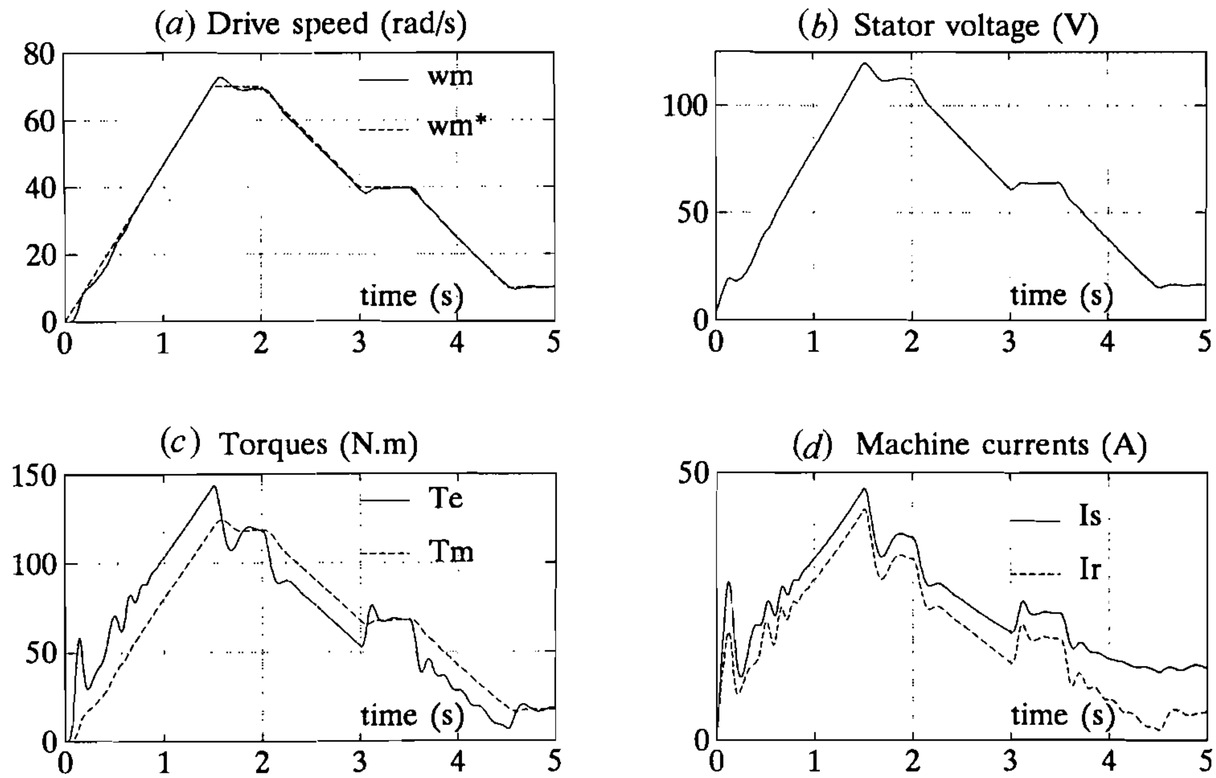

Figure 4. The dynamic response given by the complete model based neural network control system.

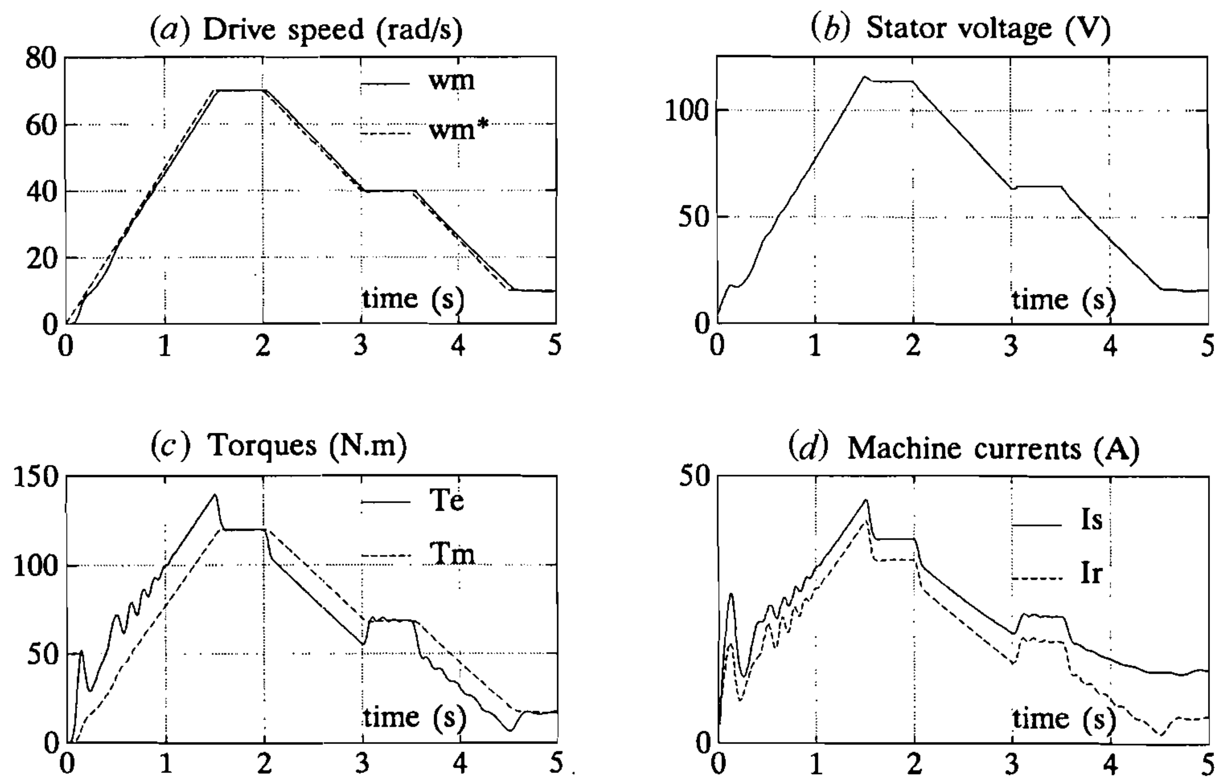

Figure 5. The dynamic response given by the reduced order model based neural network control system.

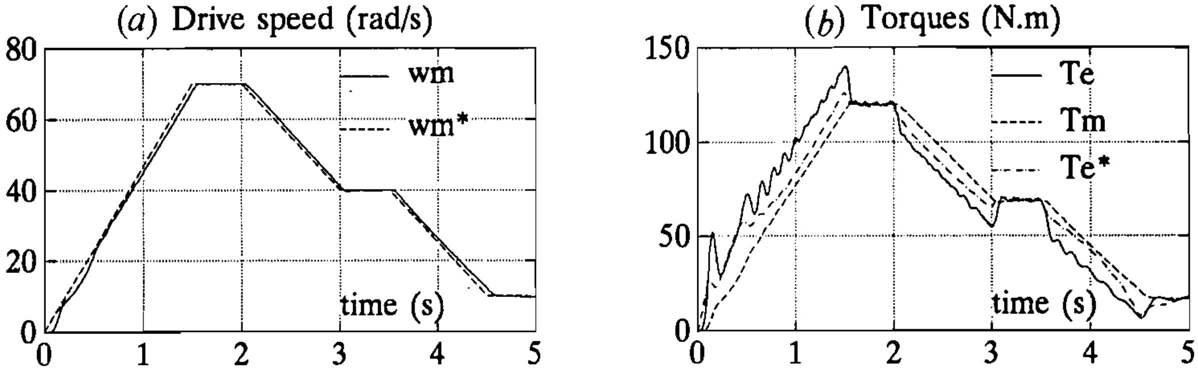

Figure 6. The dynamic response given by the reduced order model based neural network control system with a 5% amplitude noise is added to the measured torque.

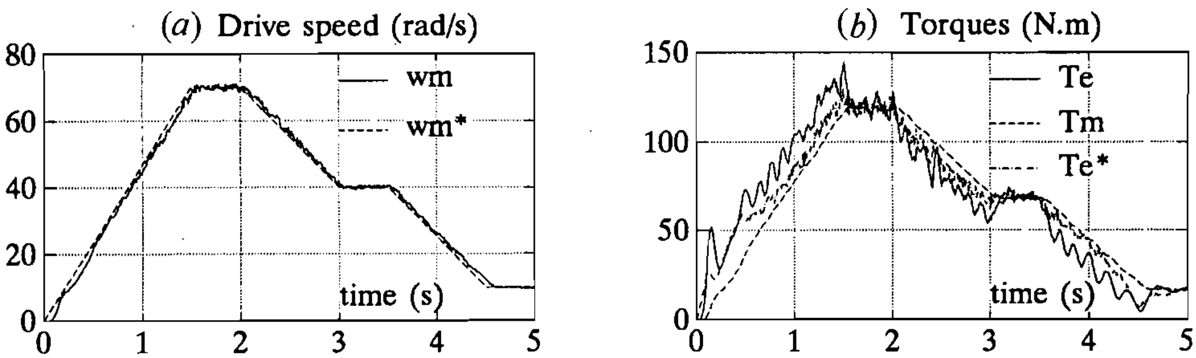

Figure 7. The dynamic response given by the reduced order model based neural network control system with a 2% amplitude noise is added to the measured speed.

this statement is not true in the case of neural network controls.

Referring to Fig. 4 (*c*) and 4 (*d*), and to Fig. 5 (*c*) and 5 (*d*), it is to be noted that the rms value of the rotor current is almost proportional to the electromagnetic torque. This turns out to be very interesting after checking that the machine works at an approximately constant stator flux. In other words the machine behaves like a separately excited dc machine where the stator provides the flux and the rotor gives the required current for the considered load. Thus one can conclude that the implementation of the proposed control scheme leads practically to the same results obtained under a stator flux oriented control of the induction machine.

In order to check the robustness of the control system against measurement perturbations, noises have been added to both torque feedback loop and speed feedback loop. The torque noise amplitude has been limited to 5% of the measured torque, and the speed noise amplitude has been taken equal to 2% of the measured speed. In practice, speed measurement using encoders is generally more accurate than the torque measurement. The obtained results are shown in Figs 6 and 7. Such results confirm the robustness of the implemented control system.

It is to be noted that adding a noise to the torque measurement did not affect the speed response. In fact, the machine is a good filter of these perturbations. This is illustrated in Fig. 6. However, adding a noise to the speed directly affects the torque which can be considered approximately as the differential of the machine speed (Fig. 7).

The analysis of the torque responses given in Figs 6 (*b*) and 7 (*b*) shows that the desired torque T_e^* and the measured torque have almost the same variations. Then, the design of the PI controller turns to be easier taking into account the approximation $T_e/T_e^* \simeq 1$. In this case, the highly nonlinear control problem of the drive is reduced to the control of a first order system by a PI controller.

6. Conclusion

A neural network control of a squirrel cage induction machine drive, where the training data base has been computed using a reduced order model of the drive, has been developed in this paper. As a result, it has been found that the net topology is reduced to six input neurons, six hidden neurons and one output neuron. Whereas in one previous work in which a complete model based neural network controller has been implemented in a classical control scheme, the plant inverse neural model is made up of six input neurons, thirteen hidden neurons and one output neuron.

Thus, the classical control scheme has been rethought in an attempt to reach high dynamic responses with a reduced order model based neural network control. This leads to the introduction of a new control scheme which includes two feedback loops: the torque feedback loop which is inserted in the speed feedback loop. The torque feedback loop is built around the neural controller and the speed feedback loop is controlled with a classical PI controller.

In order to check the performances of the introduced control scheme, two versions of the plant inverse neural network have been treated. The first one is based on the complete model training data base. The second one uses the reduced first order model training data base. Both versions include a net topology made up of six input neurons, six hidden neurons and one output neuron. A comparison between the two neural controllers based on simulation results shows that the dynamic responses of the second one are much more damped than those yielded by the first one. Moreover, it has been shown that the robustness of the implemented control system, with a reduced order model based neural network controller in the torque feedback loop, is not affected by measurement perturbations.

This said, much work is still required before the presented results could become a reality for industrial applications. For instance and as far as in practice the power electronics converter greatly effects the operation of the system, simulation works where the converter model is taken into account is an interesting continuation of this work. Another topic which shall be treated in future consists on the implementation of the introduced control system on an experimental test bench.

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