Online Parameters Estimation and Autotuning of a Discrete-Time Model Predictive Speed Controller for Induction Motor Drives

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***Abstract*—This paper proposes a new method that can online and automatically estimate and fine-tune the parameters of a discrete-time model predictive controller for providing high-performance speed control in an induction motor (IM) drive. The suggested control system combines the model reference adaptive method with the fuzzy-logic technique, and its operation can be initiated without requiring any human intervention or the knowledge of the motor drive parameters. Therefore, no extra work by the user is needed to adjust the controller parameters according to the operating conditions, and also high performance is attained because any variations of the system model can be considered through a fine-tuning procedure. The proposed autoadaptive discrete-time model predictive control (ADMPC) system is based on the optimization of an objective function that considers the reference and the real speed as well as the acceleration of the IM drive by using the state-space model. The implementation of the proposed ADMPC scheme is easy, since no additional hardware is required, but only the replacement of the firmware of the IM drive. Selective simulation and experimental results are presented to validate the effectiveness of the proposed ADMPC system and demonstrate the high performance of the motor drive.**

***Index Terms*—Control systems, fuzzy control, induction machines, model predictive control (MPC), model reference adaptive (MRA) control motor drives, variable speed drives.**

I. Introduction

THE high performance in speed-controlled motion applications is mainly characterized by the objectives of fast rising time, low overshoot, high accuracy, and satisfactory rejection of the load variations [1]. The proportional-integral (PI) control is for years the state of the art in electrical motor drive applications due to the advantages of simple structure and easy implementation that ensure low computational requirements by the microcontroller [2]. However, high performance over a wide range of speed and load torque cannot be easily accomplished with a PI controller with constant parameters. On the other hand, although a control scheme with adaptive PI controller

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synchronous motor (PMSM) drives have been proposed, such as a cascade control structure for speed ripple minimization [12], a generalized design for speed and position control [13], a constrained state feedback speed control technique [14], a torque ripple compensation control scheme [15], finite set MPC algorithms [16], [17] and an MPC scheme with short prediction horizons [18]. Also, various MPC designs for induction motor (IM) drives have been proposed, such as a predictive algorithm for speed and rotor flux control [19], a predictive torque control method based on state-space models [20], a cascaded speed and current MPC method [21], and a fuzzy predictive direct torque control scheme [22]. The problem of computational load of the MPC has been investigated and several control strategies have been proposed, such as the finite and trajectory horizon methods [23] and [24], respectively, a cascaded free MPC technique [25] and a mathematical programming method that is based on branch and bound approach [26]. Also, an attempt to increase the sampling rate by properly manipulating the predictive and control horizons has been proposed in [27].

Since the parameters of the electrical machine are of great importance for the design of high-performance controllers, a growing research interest has been observed in the last years, and several efforts have been carried out and reported in the technical literature to address the above problem. Specifically, an observer-based identification method for implementing sensorless control in PMSM and an adaptive parameter identification method for PMSM by means of synchronizing the dynamic response of the drive with the model system have been proposed in [28] and [29], respectively. Several techniques based on Kalman filter [30], [31] and sliding-mode observers [32], [33] have been proposed, and a parameter sensitivity analysis for an open-loop speed-controlled IM drive has been reported in [34]. Also, a method for determining the inertia and friction aided by the estimation of the flux-linkage in a PI-controlled PMSM drive [35], an adaptive speed control scheme based on the load inertial identification [36], and a method for inertia and friction estimation in motor drives by using position measurements [37] have been presented.

The benefits of the adaptive MPC for improving the motor drive performance have been extensively investigated [38], [39], and several efforts have been conducted for the design of flexible structured MPC controllers [40], [41]. Also, attempts to design an adaptive predictive controller by observing the falling and rising slopes of the converter output current have been reported in [42] and [43]. However, none is focused on the autoadaptive of the controller parameters so that a motor drive becomes capable to start its operation without any human intervention. Therefore, there is a need for a method that can online and automatically estimate the MPC controller parameters and also fine-tune them according to the operating conditions and by considering any variations of the motor drive model. Moreover, the new technique should be based on iterative procedures that can initiate without requiring the knowledge of the motor drive parameters, except those that are already needed for the operation of the space vector control. Finally, the new technique should not require any changes in the hardware so that it can be easily applicable in a motor drive.

Thus, the aim of this paper is to fulfil the above gap in the current knowledge and to present an autoadaptive discrete-time model predictive control (ADMPC) system for speed-controlled IM drives that can online determine and fine-tune the predictive controller parameters, without needing any human intervention. Thus, the knowledge of the IM drive model is not required, and also the operation of the drive can be initiated without requiring any extra work by the user so that the drive can be adjusted to the operating conditions. Moreover, improved performance of the IM drive is attained because the MPC parameters are fine-tuned by considering any potential variations of the system model. The above points can be implemented without requiring additional hardware or changes in the drive topology but only the replacement of the firmware of the drive.

The ADMPC can be accomplished through an integrated system that combines the model reference adaptive (MRA) technique [44], [45] with a fuzzy-logic control scheme. The parameters of the IM model that are needed for the implementation of the MPC are online experimentally determined and then fine-tuned in each control step through the MRA technique, whereas a weighting factor that provides a correct balance between the objectives of fast rising time and desired overshoot in the IM drive performance is online regulated by the fuzzy-logic control scheme. In this paper, although the proposed ADMPC strategy with the combined MRA and fuzzy-logic control scheme has been developed for IM drives, it can also be applied in PMSM drives by properly changing the mathematical methodology.

The IM drive with the proposed ADMPC scheme is realized by utilizing a certain number of control and prediction horizons considering the control constraints, the rotor speed, and the acceleration/deceleration response of the motor drive, in order to determine the proper reference q-axis current that can provide high performance in the IM drive. The theoretical considerations and the effectiveness of the suggested ADMPC scheme have been validated with several simulation and experimental results.

II. IM Dynamic Model

The dynamic mechanical model of an IM is expressed as follows [46]:

$$J_m \frac{d\omega_r}{dt} + F_d \omega_r = T_e - T_L \tag{1}$$

where J_m is the inertia, ω_r is the rotor mechanical speed, F_d is the friction coefficient, T_L is the load torque, and T_e is the IM electromechanical torque that is given by

$$T_e = \frac{3}{2} p \frac{L_m}{L_r} (i_{qs}\psi_{dr} - i_{ds}\psi_{qr}). \tag{2}$$

Since for decoupling control it is desirable that $\psi_{qr} = 0$, the torque expression results in the following [56]:

$$T_e = \frac{3}{2} p \frac{L_m}{L_r} \psi_{dr} i_{qs} \tag{3}$$

where p is the number of pole pairs, L_m and L_r are the magnetizing and rotor inductances, respectively, ψ_{dr} is the d-axis rotor flux-linkage, and i_{qs} is the q-axis stator current. Combining (1) and (3) yields

$$\frac{d\omega_r}{dt} = \frac{3}{2}p\frac{L_m}{L_r J_m}\psi_{dr} i_{qs} - \left(\frac{F_d}{J_m}\omega_r + \frac{T_L}{J_m}\right). \quad (4)$$

By using the first-order Taylor expansion series, the product $\psi_{dr} i_{qs}$ can be given with respect to the steady-state operating condition as follows:

$$\psi_{dr}(t)\, i_{qs}(t) \approx \psi_{dr}^0 i_{qs}^0 + \psi_{dr}^0 \left[i_{qs}(t) - i_{qs}^0\right] + i_{qs}^0 \left[\psi_{dr}(t) - \psi_{dr}^0\right] \quad (5)$$

which results in

$$\psi_{dr}(t) i_{qs}(t) \cong \psi_{dr}(t) i_{qs}^0 + \psi_{dr}^0 i_{qs}(t) - \psi_{dr}^0 i_{qs}^0 \quad (6)$$

where ψ_{dr}^0 and i_{qs}^0 are the steady-state *d*-axis rotor flux-linkage and *q*-axis stator current, respectively.

Since the IM magnetic flux is kept constant at the steady-state operation, we have

$$\frac{d(\psi_{dr}^0 i_{qs}^0)}{dt} = 0 \quad (7)$$

and

$$i_{qs}^0 \frac{d\psi_{dr}(t)}{dt} = 0. \quad (8)$$

For a given load torque, the second derivative of the rotor speed can be obtained from (4) and by using (7), (6), and (8) as follows:

$$\frac{d^2\omega_r}{dt^2} = \frac{3}{2}p\frac{L_m \psi_{dr}^0}{L_r J_m}\frac{di_{qs}}{dt} - \frac{F_d}{J_m}\frac{d\omega_r}{dt}. \quad (9)$$

III. Discrete MPC Speed Controller for the IM Drive

The state-space IM model can be represented in the following form:

$$\dot{\boldsymbol{x}}_m = A_s \boldsymbol{x}_m + B_s u_m$$
$$y_m = C_s \boldsymbol{x}_m \quad (10)$$

where x_m is the state-space vector, u_m and y_m are the input and output, respectively, and A_s, B_s, and C_s are matrices of appropriate dimensions. Thus,

$$\begin{bmatrix} \ddot{\omega}_r(t) \\ \dot{\omega}_r(t) \end{bmatrix} = \begin{bmatrix} -\frac{F_d}{J_m} & 0 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} \dot{\omega}_r(t) \\ \omega_r(t) \end{bmatrix} + \begin{bmatrix} \frac{3}{2}p\frac{L_m \psi_{dr}^0}{L_r J_m} \\ 0 \end{bmatrix} \frac{di_{qs}(t)}{dt} \quad (11)$$

and

$$\omega_r(t) = \begin{bmatrix} 0 & 1 \end{bmatrix} \begin{bmatrix} \dot{\omega}_r(t) \\ \omega_r(t) \end{bmatrix}. \quad (12)$$

Considering sampling period T_s and sampling instant *k*, the above state-space model of a speed-controlled IM drive can be discretized as follows:

$$x_m(k+1) = A_d x_m(k) + B_d u_m(k)$$
$$y_m(k+1) = C_d x_m(k+1) \quad (13)$$

where A_d, B_d, and C_d are the discrete forms of the matrices A_s, B_s, and C_s, respectively, which can be determined by using the second-order Taylor expansion series of the exponential matrix [19], [55]

$$A_d = e^{A_s T_s} \approx I + A_s T_s + \frac{A_s^2 T_s^2}{2}$$
$$B_d = \int_0^{T_s} e^{A_s \tau} B_s d\tau \approx B_s T_s + \frac{A_s B_s T_s^2}{2}$$
$$C_d = C_s. \quad (14)$$

The DMPC technique that is adopted in this paper is realized by introducing two mutually coupled elements, the model of the control system of the IM drive and the optimizer that can determine the future control actions through appropriate control and prediction horizons. In particular, for a given set-point signal *r*(*k*) at sample time *k*, the objective of the DMPC is to determine the future behavior of the IM drive based on the system model and following a control law that is defined by the optimization of a cost function. Thus, a correct balance between the computation load and the error between the predictive output and the actual value of the set-point input signal is attained. The optimization of the cost function is sought in every sampling interval by considering the measured control variables and then the control and prediction horizons are properly updated.

Specifically, for a given sampling time *k*, the output of the predictive control procedure is derived from the state-space model and is given by

$$Y = Hx(k) + F\Delta U \quad (15)$$

where

$$Y = \begin{bmatrix} y(k+1) & y(k+2) & y(k+3) & \cdots & y(k+N_p) \end{bmatrix}^T$$
$$H = \begin{bmatrix} C_d A_d & C_d A_d^2 & C_d A_d^3 & \cdots & C_d A_d^{N_p} \end{bmatrix}^T$$
$$F = \begin{bmatrix} C_d B_d & 0 & 0 & \cdots & 0 \\ C_d A_d B_d & C_d B_d & 0 & \cdots & 0 \\ C_d A_d^2 B_d & C_d A_d B_d & C_d B_d & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ C_d A_d^{N_p-1} B_d & C_d A_d^{N_p-2} B_d & C_d A_d^{N_p-3} B_d & \cdots & C_d A_d^{N_p-N_c} B_d \end{bmatrix}$$
$$\Delta U = \begin{bmatrix} u(k) & u(k+1) & u(k+2) & \cdots & u(k+N_p-1) \end{bmatrix}^T \quad (16)$$

N_c is the control horizon, and N_p is the prediction horizon. The first term $H\,x(k)$ of (15) relates to the objective for minimum error between the prediction output and the set-point input signal, whereas the second term $F\,\Delta U$ depends on the size of ΔU and deals with the effectiveness of the objective law.

The control law is defined by minimizing the following cost function [9]

$$G = (R_s - Y)^T (R_s - Y) + \Delta U^T R \Delta U \quad (17)$$

where R_s is the data vector of the set-point signal *r*(*k*) at sample time *k*, and *R* is a diagonal matrix in the form $R = r_w I_{N_c \times N_c}$, where $r_{\rm w}$ is a weighting factor that affects the closed-loop performance of the IM drive and $I_{N_c \times N_c}$ is an identity matrix with

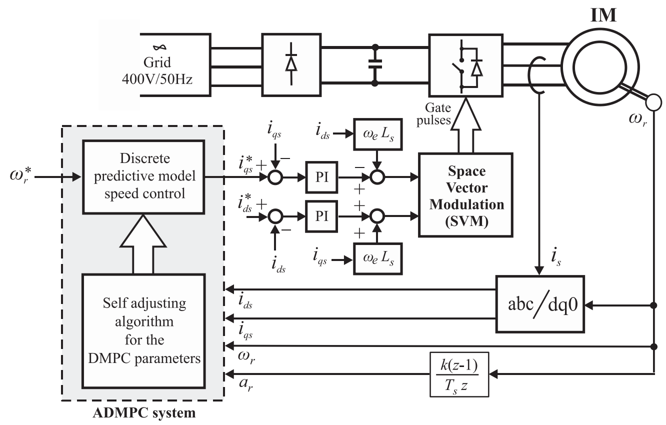


Fig. 1. Layout of the speed-controlled IM drive with the proposed ADMPC system.

dimensions $N_c \times N_c$. The data vector R_s is expressed by the following form:

$$R_s^T = \begin{bmatrix} 1^1 & 1^2 & \dots & 1^{N_p} \end{bmatrix} r(k). \tag{18}$$

Substituting (15) in (17) yields

$$G = [R_s - Hx(k)]^T [R_s - Hx(k)] - 2\Delta U^T F^T [R_s - Hx(k)] + \Delta U^T (F^T F + R)\Delta U. \tag{19}$$

The cost function of (17) can be minimized by

$$\frac{\partial G}{\partial \Delta U} = 0 \tag{20}$$

and the following optimal condition is obtained:

$$\Delta U = [(F^T F + R)^{-1} F^T] [R_s r(k) - Hx(k)]. \tag{21}$$

The above condition governs the control law of the DMPC, and the first term $K_x = (F^T F + R)^{-1} F^T R_s$ refers to the set-point change, whereas the second term $K_y = (F^T F + R)^{-1} F^T H$ corresponds to the feedback signal within the framework of the predictive control.

IV. Implementation of the Proposed ADMPC Strategy

The structure of the IM drive with the proposed discrete-time model predictive controller is illustrated in Fig. 1. The space vector field oriented control technique is applied. The predictive controller is realized by the optimal condition (21) that properly manipulates the control and prediction horizons and considers the actual d- and q-axis stator currents, the rotor speed, and the acceleration of the IM drive for providing the proper reference q-axis current i_{qs}^*.

As can be seen in (21) and considering (11), (16), and (18), for the implementation of DMPC system, the knowledge of the following parameters is required:

$$B_s(1) = \frac{3}{2} p \frac{L_m^2}{L_r J_m} = P_1 \tag{22}$$

$$A_s(1,1) = -\frac{F_d}{J_m} = P_2 \tag{23}$$

the weighting factor r_w, and the control N_c and the prediction N_p horizons.

The obvious choice for the calculation of parameters P_1 and P_2 could be from the IM drive model. However, in most of the cases, inertia J_m and friction coefficient F_d are difficult to be determined, since time-costly experiments are required that, in most of the applications, are not allowed to be conducted. Moreover, J_m and F_d may vary due to the aging of the mechanical parts of the IM drive, which results in the degradation of the DMPC accuracy and performance. In addition, degradation of the IM drive accuracy and performance may be caused by the variation of the inductances L_m and L_r due to the variation of the magnetic saturation.

Therefore, an autoadaptive technique is required that can automatically determine parameters P_1 and P_2 of the DMPC system without needing the knowledge of the model. Moreover, in order to consider any variations that are caused by the aging of the mechanical parts of the IM drive and the magnetic saturation of the motor, the fine-tuning of the above parameters is required. Thus, an IM drive with the proposed ADMPC can start its operation without requiring any presetting process for the adjustment of the parameters, and also high performance of the IM drive can be accomplished for any load and speed conditions and by considering any variations in the model that may be caused by the aging of the drive and changes in the operating conditions.

The weighting factor r_w affects the closed-loop performance of the IM drive with DMPC and specifically the overshoot level and rising time response of the drive. Therefore, an easy experimental procedure is required to determine parameter r_w in order to ensure a correct balance between the objectives of low overshoot and fast rising time. The experimental procedure that determines parameter r_w should be conducted online during the operation of the drive and without needing any intervention by the user and therefore it can consider any variations of the load torque and reference speed, as well as variations of parameters P_1 and P_2, which may be caused by aging and magnetic saturation in the IM drive.

The selection of N_c and N_p is decided by considering the computational capabilities of the predictive controller and the fact that the performance of the MPC can be improved, as N_c and N_p increase. However, the expected performance improvement may be confined at high N_c and N_p values. On the other hand, since the increase of N_c and N_p results in the increase of the computational burden, it may lead to the confinement of the sampling frequency of the speed predictive controller, which would worsen the performance of the motor drive. Therefore, a correct balance between the controller computational capabilities, motor drive performance requirements, and sampling frequency is required. Since the above objectives depend on the hardware capabilities of the system and the specific requirements of an application with respect to the motor drive performance, N_c and N_p values as well as the sampling frequency are manually selected by the user. It should be noted that the proposed technique for the online estimation and autotuning of the MPC parameters can be applied in any IM drive irrespective of the selected N_c, N_p, and sampling frequency values.

In a motor drive, it is desirable that the control signals move smoothly to reach their steady state. This can be accomplished by distributing the control process over the longest period of the predictive time [9]. Therefore, since $N_c \leq N_p$, it is preferable that $N_c = N_p$.

A. MRA Algorithm to Determine and Fine-Tune Parameters P_1 and P_2

Parameters P_1 and P_2 are online estimated and fine-tuned through the MRA technique. The concept of the MRA method is to build an adjustable predictor for the system output by using a sequence of inputs [44]. The parameters of the system are adjusted through an iteration procedure that aims to minimize the error of the prediction output with the measured output of each sampling instant. Thus, an estimated model is obtained that asymptotically gives a correct description of the real system. The MRA control technique has been used in PI-controlled IM drives to estimate the rotor time constant [51] and in developing sensorless speed and predictive torque controllers, [47]–[48] and [49]–[50], respectively.

Considering (22) and (23), (4) can be rewritten as follows:

$$\frac{d\omega_r}{dt} = P_1 i_{ds} i_{qs} + P_2 \omega_r - \frac{T_L}{J_m} \tag{24}$$

and for a given sampling time *k*, the discrete form is

$$\omega_r(k) = T_s \left[P_1 i_{ds} i_{qs}(k-1) + P_2 \omega_r(k-1) - \frac{T_L(k-1)}{J_m} \right] + \omega_r(k-1). \tag{25}$$

In a servo drive application, although the load torque may change in the long run, the difference of the load torque between two successive sample instants is low and thus it can be considered approximately constant within a sampling interval [52]–[54]. However, even if an abrupt load change may occur during a sampling period, the convergence capability of the MRA is not affected, but perhaps the recursive process of the MRA might slightly increase. It has been proved by the simulation and experimental results, which will be presented in the following sections, that a sampling frequency of 0.5 kHz gives satisfactory performance of the MRA in both linear and step changes of the load torque.

Taking into account the above considerations and the rotor speed for the *k*–1 sampling instant

$$\omega_r(k-1) = T_s \left[P_1 i_{ds} i_{qs}(k-2) + P_2 \omega_r(k-2) - \frac{T_L(k-2)}{J_m} \right] + \omega_r(k-2) \tag{26}$$

from the subtraction between (25) and (26) we have

$$\omega_r(k) = T_s \left[P_1 i_{ds} \Delta i_{qs}(k-1) + P_2 \Delta\omega_r(k-1) \right] + 2\omega_r(k-1) - \omega_r(k-2) \tag{27}$$

where

$$\Delta i_{qs}(k-1) = i_{qs}(k-1) - i_{qs}(k-2) \tag{28}$$

$$\Delta \omega_r(k-1) = \omega_r(k-1) - \omega_r(k-2). \tag{29}$$

For a given sampling instant *k*, the estimated rotor speed is given by

$$\hat{\omega}_r(k) = 2\omega_r(k-1) - \omega_r(k-2) + \phi^T(k-1)\hat{h}(k-1) \tag{30}$$

where

$$\phi^T(k-1) = \left[i_{ds} \Delta i_{qs}(k-1) \quad \Delta\omega_r(k-1) \right] \tag{31}$$

$$\hat{h}^T(k-1) = T_s \left[\hat{P}_1 \ \hat{P}_2 \right] \tag{32}$$

and $\hat{P}_1$ and $\hat{P}_2$ are the estimation of parameters P_1 and P_2, respectively.

The recursive parameter identification algorithm is accomplished by the following procedure.

1) The algorithm starts with an initial rough estimation of the *h* matrix, $\hat{h}^T(0) = T_s[P_1 \quad P_2]$. The initial values of parameters P_1 and P_2 are decided by (22) and (23) through a rough empirical estimation of the inertia and friction considering the application conditions, while the magnetizing inductance can be obtained by the space vector control of the IM drive.
2) For any given sampling instant *k*, the error between the measured rotor speed and that estimated by the IM drive model is determined
$$e(k) = \omega_r(k) - \hat{\omega}_r(k). \tag{33}$$
3) From (31) and (33), the adaptive gain matrix Γ(*k*–1) is calculated
$$\Gamma(k-1) = \Gamma(k-2) - \frac{\Gamma(k-2)\phi(k-1)\phi^T(k-1)\Gamma(k-2)}{1 + \phi^T(k-1)\Gamma(k-2)\phi(k-1)} \tag{34}$$
where Γ(*k*) is a 2 × 2 diagonal matrix with the form
$$\Gamma(k) = \begin{bmatrix} \Gamma_1(k) & 0 \\ 0 & \Gamma_2(k) \end{bmatrix}.$$
4) From (31), (33), and (34), the new *h* matrix is obtained that gives the new estimation for parameters P_1 and P_2
$$\hat{h}(k) = \hat{h}(k-1) + \frac{\Gamma(k-1)\phi(k)e(k)}{1 + \phi^T(k)\Gamma(k-1)\phi(k)}. \tag{35}$$

Then, the flow of the process returns to step 2). Steps 2)–4) are continually repeated during the operation of the IM drive.

From the above iterative procedure, parameters P_1 and P_2 can be experimentally determined without requiring any intervention by the user and without needing the knowledge of the IM drive model. Also, they can be continually fine-tuned by considering any changes in the model that may be caused by the aging, magnetic saturation, and variations of the IM drive operating conditions. The block-diagram of the above parameter identification recursive method is illustrated in Fig. 2.

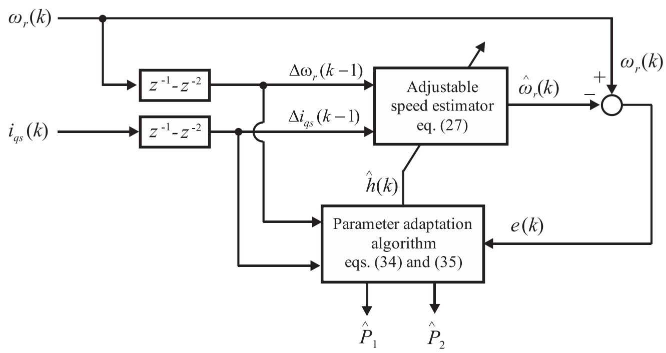


Fig. 2. Block-diagram of the MRA recursive estimation method for parameters P_1 and P_2.

In order to validate the stability of the proposed MPC parameter estimation technique, the methodology of [44] is utilized. Specifically, it should be proved that the estimated parameter vector $\hat{h}$ is always driven toward a value so that the posteriori error converges to zero, $\lim_{k\to\infty} e(k) = 0$ [57]. This is validated, if we prove that

$$\lim_{k_1\to\infty} \sum_{k=0}^{k_1} e^2(k+1) < \infty. \tag{36}$$

From (27) and (30), the posteriori prediction error for the $k+1$ sampling instant (that is defined on the basis of the knowledge of new parameter matrix h at $k+1$), is given by

$$e(k+1) = -\phi^T(k)\tilde{h}(k+1) \tag{37}$$

where $\tilde{h}$ is the error between the estimated and the actual parameter $\tilde{h}(k+1) = \hat{h}(k+1) - h(k+1)$. Also, from (35), we obtain the following:

$$\phi(k)e(k+1) = \left[1+\phi^T(k)\Gamma(k)\phi(k)\right]\Gamma^{-1}(k)\left[\tilde{h}(k+1)-\tilde{h}(k)\right]. \tag{38}$$

From (37) we have

$$\sum_{k=0}^{k_1} e^2(k+1) = \sum_{k=0}^{k_1} -\phi^T(k)\tilde{h}(k+1)e(k+1) \tag{39}$$

and since $\phi^T(k)\tilde{h}(k+1) = \tilde{h}^T(k+1)\phi(k)$, it is rewritten as

$$\sum_{k=0}^{k_1} e^2(k+1) = \sum_{k=0}^{k_1} -\tilde{h}^T(k+1)\phi(k)e(k+1). \tag{40}$$

By substituting (38) in (40), (41) shown at the bottom of this page is obtained. Taking into account that Γ(*k*) is a positive matrix, it is concluded that the following expression is also positive:

$$\left[\tilde{h}(k+1)-\tilde{h}(k)\right]^T \Gamma^{-1}(k)\left[\tilde{h}(k+1)-\tilde{h}(k)\right] \geq 0. \tag{42}$$

Thus, we have

$$\tilde{h}^T(k+1)\Gamma^{-1}(k)\tilde{h}(k+1) + \tilde{h}^T(k)\Gamma^{-1}(k)\tilde{h}(k) - 2\tilde{h}^T(k+1)\Gamma^{-1}(k)\tilde{h}(k) \geq 0 \tag{43}$$

and finally

$$\tilde{h}^T(k+1)\Gamma^{-1}(k)\tilde{h}(k) \leq \frac{1}{2}\tilde{h}^T(k+1)\Gamma^{-1}(k)\tilde{h}(k+1) + \frac{1}{2}\tilde{h}^T(k)\Gamma^{-1}(k)\tilde{h}(k) \tag{44}$$

Then, by substituting (44) in (41), (45) shown at the bottom of this page is obtained.

From (45), it is concluded that $\lim_{k\to\infty} e(k) = 0$ and therefore the proposed parameter estimation technique of an MPC system is stable.

B. Fuzzy-Logic System (FLS) to Determine and Fine-Tune Parameter r_w

As can be observed from (21), the matrix *R* plays the role of a tuning term in both the set-point *r*(*k*) and the feedback signal *x*(*k*). Therefore, parameter r_w is a weighting factor that influences both the rising time r_t and the overshoot OS of the IM drive. In order to adjust parameter r_w, a FLS is adopted, which provides a correct balance between the objectives of fast rising time and desired overshoot.

As can be seen in Fig. 3, the FLS observes the difference in the rising time between two successive changes of the rotor speed $\Delta r_t = r_t(z) - r_t(z^{-1})$ and the difference between the current

$$\sum_{k=0}^{k_1} e^2(k+1) = \sum_{k=0}^{k_1}\left[1+\phi^T(k)\Gamma(k)\phi(k)\right]\left[-\tilde{h}^T(k+1)\Gamma^{-1}(k)\tilde{h}(k+1) + \tilde{h}^T(k+1)\Gamma^{-1}(k)\tilde{h}(k)\right] \tag{41}$$

$$\begin{aligned}\sum_{k=0}^{k_1} e^2(k+1) &\leq \sum_{k=0}^{k_1}\left[1+\phi^T(k)\Gamma(k)\phi(k)\right]\left[-\frac{1}{2}\tilde{h}^T(k+1)\Gamma^{-1}(k)\tilde{h}(k+1) + \frac{1}{2}\tilde{h}^T(k)\Gamma^{-1}(k)\tilde{h}(k)\right]\\ &= \left[1+\phi^T(k_1)\Gamma(k_1)\phi(k)\right]\left[-\frac{1}{2}\tilde{h}^T(k_1+1)\Gamma^{-1}(k_1)\tilde{h}(k_1+1)\right] + \left[1+\phi^T(0)\Gamma(0)\phi(0)\right]\left[\frac{1}{2}\tilde{h}^T(0)\Gamma^{-1}(0)\tilde{h}(0)\right]\\ &\leq \left[1+\phi^T(0)\Gamma(0)\phi(0)\right]\frac{1}{2}\tilde{h}^T(0)\Gamma^{-1}(0)\tilde{h}(0) < \infty.\end{aligned} \tag{45}$$

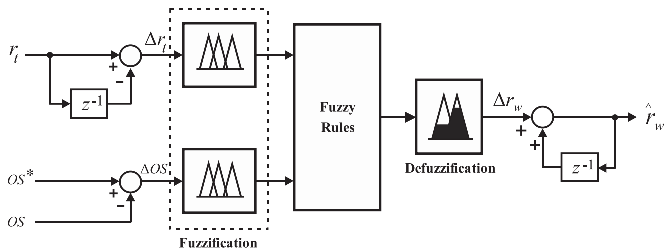


Fig. 3. Block-diagram of the FLS for the r_w parameter estimation.

TABLE I
PARAMETER Δr_w ADAPTER FUZZY RULES

Δr_t \ OS	HD	D	LD	N	LI	I	HI
D	HI	I	LI	LI	S	D	HD
N	HI	I	LI	N	LD	D	HD
I	HI	I	LI	LI	LD	D	HD

and the desired overshoot $\Delta\mathrm{OS}(z) = \mathrm{OS}(z) - \mathrm{OS}^*$. Usually, the desired overshoot OS^* is close to zero. The output of the FLS provides the proper correction factor Δr_w and thus the estimated $\hat{r}_w$ parameter is obtained by $\hat{r}_w(z) = \hat{r}_w(z^{-1}) + \Delta r_w(z)$.

The concept of the fuzzy rules is based on the following considerations. The increase of the overshoot or decrease of the rising time results in the increase of parameter r_w. Also, the increase of r_w due to the overshoot increase is higher compared to the increase of r_w due to the rising time decrease. Thus, the FLS first satisfies the overshoot objective to minimize the ΔOS and then the parameter r_w is fine-tuned by reducing the rising time.

The fuzzy rules and membership functions of the FLS are given in Table I and Fig. 4, respectively. The fuzzy sets are defined as follows: HI is the high increase, I is the increase, LI is the low increase, N is the neutral, LD is the low decrease, D is the decrease, and HD is the high decrease.

C. Proposed ADMPC Algorithm for IM Drives

The flow chart of the proposed IM drive with the ADMPC system is illustrated in Fig. 5. Parameters P_1 and P_2 that are required for the calculation of the matrices A_d, B_d, and C_d are online determined and fine-tuned by the MRA system of Fig. 2, and parameter r_w that is needed for the calculation of the matrix R is obtained by the FLS of Fig. 3.

V. SIMULATION ANALYSIS

The above theoretical considerations have been validated by several simulation and experimental results on the same IM drive of 2.5 kW in order to be easily the comparisons. The parameters of the motor drive and the control system are reported in Table II.

For the examined system, by taking into account the computational burden of the proposed ADMPC system and the desired IM drive performance, the control and the prediction horizons

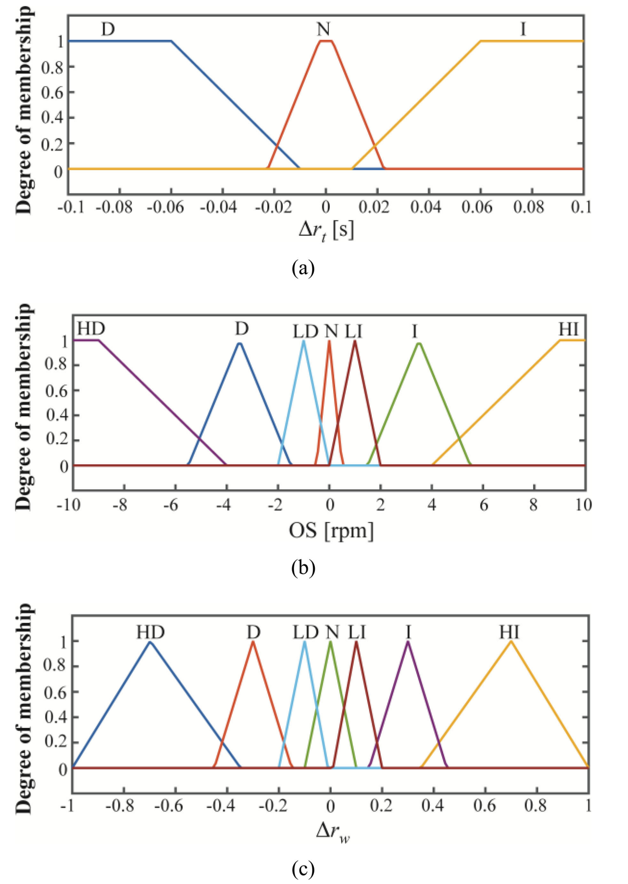


Fig. 4. Membership functions of the FLS. (a) Difference in the rising time $\Delta r_t = r_t(z) - r_t(z^{-1})$. (b) Overshoot, OS. (c) Correcting factor Δr_w of parameter r_w.

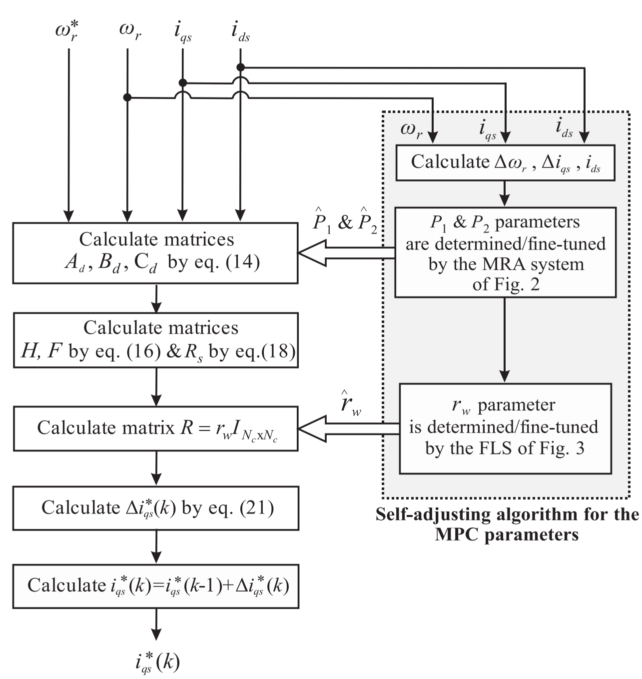


Fig. 5. Flowchart of the proposed ADMPC algorithm for IM drives.

TABLE II
THREE-PHASE, FOUR-POLES IM DRIVE AND CONTROL PARAMETERS

Nominal power	2.5kW	Nominal stat. voltage	400V(rms)
Rated current	5.5 A(rms)	Rated frequency	50Hz
Stator resistance	2.5 Ω	Rotor resistance	2.5 Ω
Magnetizing inductance	0.48 H	Stator leak. inductance	0.03 H
Rotor leak. inductance	0.03 H		
Inertia	0.025 Kgm^2	Friction factor	$7{\cdot}10^{-3}$Nms
SVM sample time	50us	DMPC sampe time	2ms

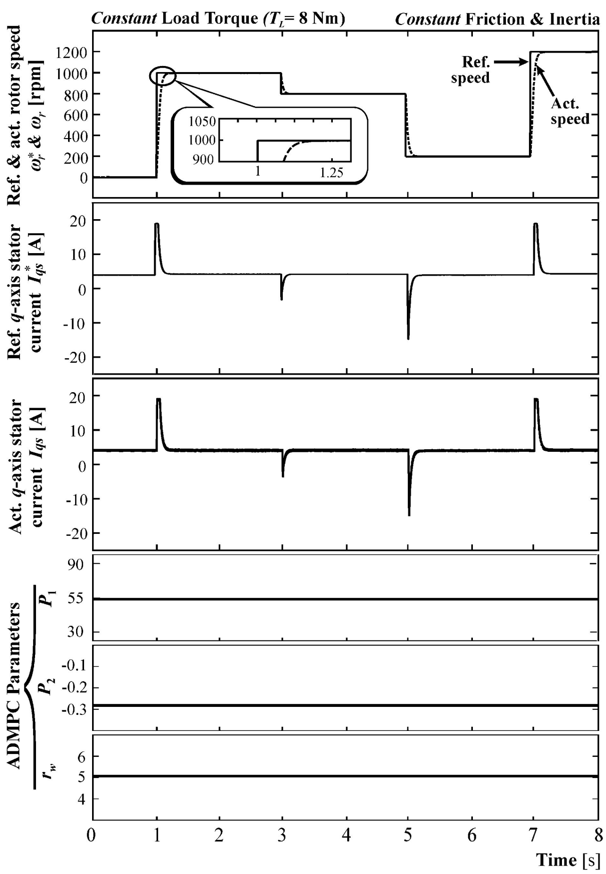


Fig. 6. Simulation results of the IM drive performance with the proposed ADMPC technique, in step changes of the reference speed, for constant load torque 8 N·m, and constant friction and inertia. Parameters P_1 and P_2 are calculated from (22) and (23), respectively, whereas r_w is equal to the optimal value that has been determined by the FLS of Fig. 3.

are selected as $N_c = N_p = 10$. Accordingly, the sampling time of the model predictive speed controller is 2 ms.

Figs. 6–8 illustrate simulation results of the IM drive performance with the proposed ADMPC technique in step changes of the reference speed. For the simulation analysis, the MATLAB/Simulink program has been used.

In Fig. 6, the load torque, friction factor, and inertia are constantly equal to $T_L = 8\,\mathrm{N{\cdot}m}$, $F_d = 0.007\,\mathrm{N{\cdot}m{\cdot}s}$, and $J_m = 0.025\,\mathrm{Kg{\cdot}m^2}$, respectively. Parameters P_1 and P_2 are calculated from (22) and (23), respectively, whereas r_w is equal to the optimal value that has been predetermined by the FLS of Fig. 3. The speed alternates with step pulses. As can be seen, the performance of the IM drive is satisfactory and meets the

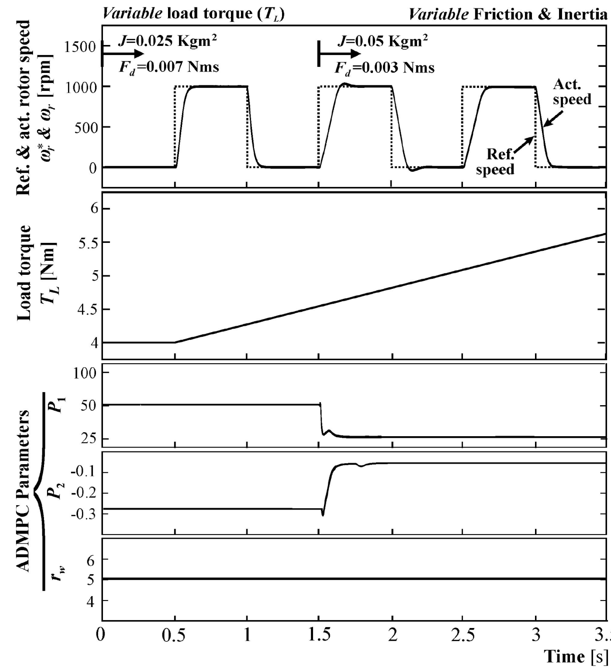
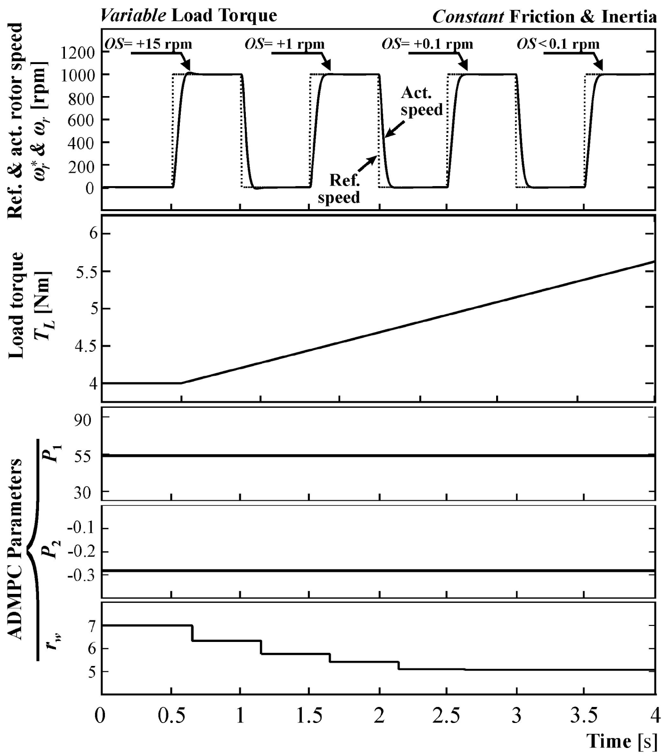


Fig. 7. Simulation results of the MRA system of Fig. 2 in determining parameters P_1 and P_2 for the 2.5-kW IM drive with the proposed ADMPC. The load torque changes linearly, and the friction and inertia change steeply at the beginning of the second speed change. r_w is equal to the optimal value that has been determined by the FLS of Fig. 3.

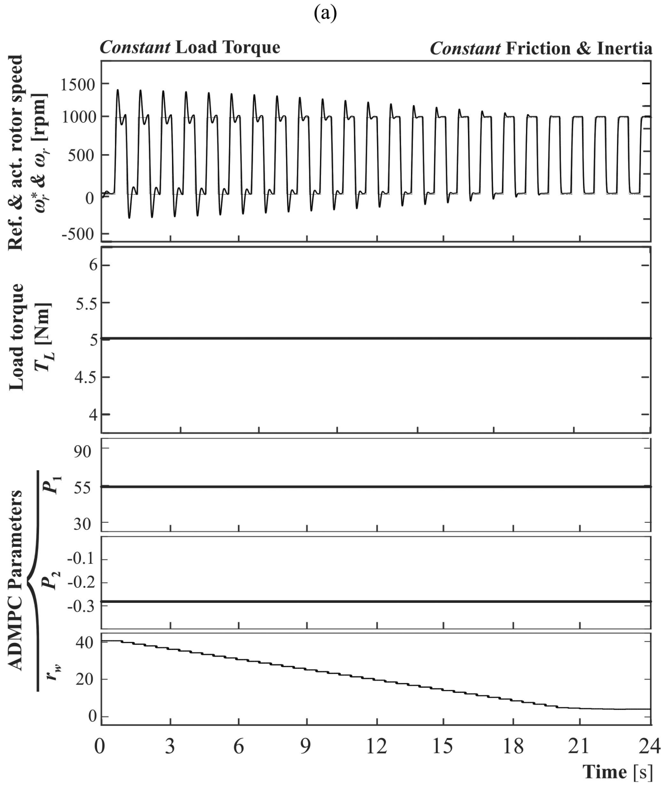
objectives of the ADMPC for almost zero overshoot and fast rising time.

Fig. 7 validates the effectiveness of the MRA system of Fig. 2 to accurately estimate parameters P_1 and P_2 when the load linearly changes during the operation of the drive, and the friction and inertia steeply change at the beginning of the second speed change. r_w is equal to the optimal value that has been predetermined by the FLS of Fig. 3. The speed alternates with step pulses of 1000 rpm. It should be noted that the abrupt change of the friction and inertia during the operation of the drive are not common; however, the worst case is examined through this analysis.

As can be seen in Fig. 7, the ADMPC initially operates with parameters P_1 and P_2 that are equal to 54.2 and –0.28, respectively, which are estimated by the MRA system and correspond to friction factor 0.007 N·m·s and inertia $0.025\,\mathrm{Kg{\cdot}m^2}$. When the friction factor decreases to 0.003 N·m·s and the inertia increases to $0.05\,\mathrm{Kg{\cdot}m^2}$ at the beginning of the second speed change, the MRA estimates the new values of the $P_1 = 27.1$ and $P_2 = -0.06$ within the duration of the pulse of the speed change. Thus, a satisfactory performance of almost zero overshoot and fast rising time is attained in the third step change of speed of the ADMPC-IM drive. The accuracy of the estimated P_1 and P_2 by the MRA system is validated by calculating them from (22) and (23), respectively. It is worth noting that the variation of the load torque does not affect the accuracy of the MRA. This validates the consideration that has been adopted in the development of the MRA system that the load torque has been eliminated for obtaining (27) from the subtraction between (25) and (26).



(a)



(b)

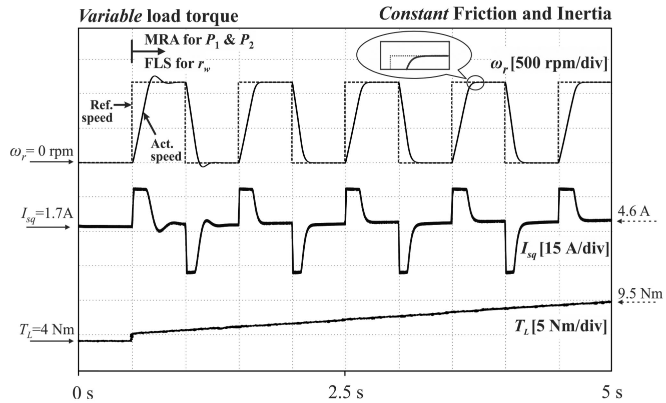
Fig. 8. Simulation results of the FLS performance of Fig. 3 in determining parameter r_w for the 2.5-kW IM drive, with the proposed ADMPC for the cases of (a) small and (b) large discrepancies between the initial and the correct r_w values. Parameters P_1 and P_2 are calculated from (22) and (23), respectively. The load torque changes linearly, whereas the friction and inertia are constant.

Finally, Fig. 8 validates the effectiveness of the FLS of Fig. 3 to determine the weighting factor r_w in order to provide high performance in the IM drive with the proposed ADMPC. The speed alternates with step pulses of 1000 rpm. The load torque changes linearly, whereas the friction factor and the inertia are constantly equal to 0.007 N·m·s and 0.025 Kg·m^2, respectively. Parameters P_1 and P_2 have been calculated from (22) and (23). The fuzzy-logic estimator of r_w can find the optimal value for any initial value in the iteration process. However, as the discrepancy between the initial and the optimal values increases, the convergence time is accordingly increased. It should be noted that r_w should be positive ($r_w \geq 0$) [9], and it usually varies between 1 ÷ 50. In Fig. 8(a), the fuzzy-logic estimator of r_w starts with a random value of 7 (30% higher than the optimal value), and it can converge to the optimal value 5.1 within the next two pulses of the speed change. In Fig. 8(b), the fuzzy-logic estimator of r_w starts with a much higher value of 40.8 (thus, eight times higher than the optimal value) and again finds the optimal value of 5.1, but with larger convergence time (within the next 20 pulses of the speed change). The first case corresponds to the fine-tuning process of r_w during the normal operation of the ADMPC, whereas the latter refers to the first operation of the ADMPC. As can be seen, r_w of 5.1 corresponds to ADMPC-IM drive performance with overshoot less than 0.1 rpm and fast rising time less than 0.13 s.

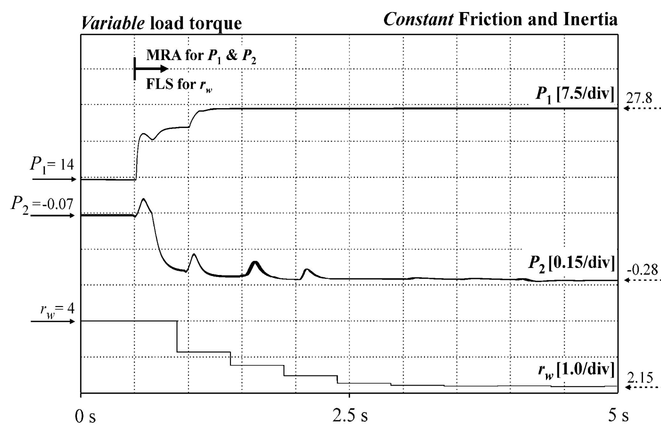
VI. Experimental Results

For the experimental verification, the same 2.5-kW IM drive has been used, as for the simulation analysis, and the experiments have been conducted in a laboratory test bench. The IM drive parameters and the sampling time of the DMPC and space vector modulation (SVM) controllers are reported in Table II. The test IM drive is mechanically coupled with another IM drive that acts as a load and is driven by a commercial power converter. Two LEM LAH25-NP sensors are used for the measurement of the instantaneous stator current of the two phases of the IM drive, a LEM LV25-PN is used for the measurement of the dc-link voltage and an incremental encoder of Heidenhain with a resolution of 4096 ppr is utilized for the measurement of the rotor speed. The proposed ADMPC technique is realized in a DS1104 controller of the company dSPACE.

Fig. 9 illustrates experimental results of the performance of the MRA system of Fig. 2 in estimating parameters P_1 and P_2 and the FLS of Fig. 3 in determining parameter r_w, of the 2.5-kW IM drive with the proposed ADMPC technique. The speed alternates with step pulses of 1200 rpm. The load torque was initially 4 N·m and from 0.5 s starts to increase linearly, whereas the friction factor and the inertia of the system are constant at 0.014 N·m·s and 0.05 Kg·m^2, respectively. The initial values of parameters P_1, P_2, and r_w are randomly selected at 14, –0.07, and 4, respectively. The operation of the MRA and the FLS is initiated at 0.5 s and they can estimate the correct values of parameters P_1, P_2, and r_w of 27.8, -0.28, and 2.15, respectively, in less than 2.5 s (within three speed step pulses). As can be seen, at the first speed step pulse that



(a)



(b)

Fig. 9. Experimental results of the MRA performance of Fig. 2 in estimating parameters P_1 and P_2 and the FLS of Fig. 3 in determining parameter r_w for the 2.5-kW IM drive, with the proposed ADMPC technique. The load changes linearly, whereas the friction and inertia are constant.

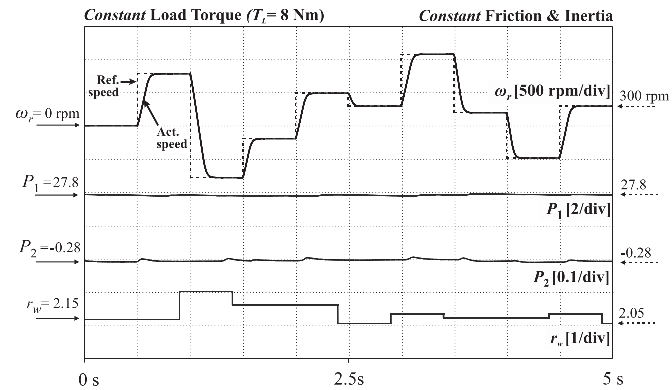


Fig. 10. Experimental results of the MRA system performance in determining parameters P_1 and P_2 and the FLS in determining parameter r_w on the 2.5-kW ADMPC-IM drive for step changes of the speed with variable reference values.

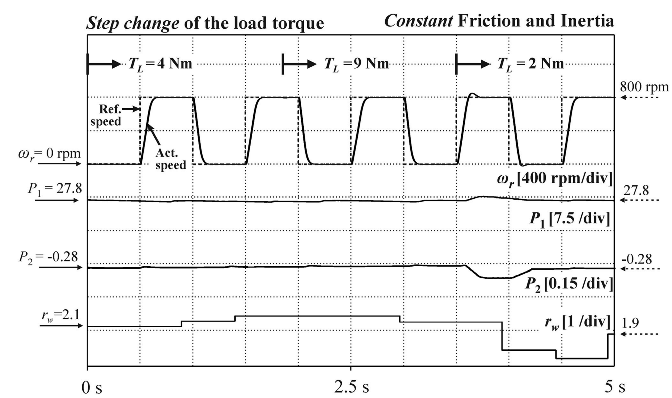


Fig. 11. Experimental results of the MRA system performance in determining parameters P_1 and P_2 and the FLS in determining parameter r_w on the 2.5-kW ADMPC-IM drive for step changes of the load torque.

coincides with the initiation of the MRA and FLS, the overshoot is high (100 rpm or 0.066 p.u., for reference speed 0.66 p.u.) and the settling time is relatively large, i.e., 0.4 s. However, both the speed overshoot and the settling time are considerably reduced at the third speed step pulse to less than 1 rpm and 0.2 s, respectively, when the correct values of parameters P_1, P_2, and r_w are accomplished. The exact settling time and overshoot for the case of the initial values of the above parameters as well as the needed time for the ADMPC to find the optimal values of the parameters depend on the technical characteristics of the IM drive, the discrepancy between the initial and the optimal values of the MPC parameters, and the reference speed value.

Figs. 10 and 11 verify the accuracy of the MRA and FLS parameters estimation techniques of the 2.5-kW IM drive predictive controller against variable reference values in the speed step pulses and variable step changes of the load torque. As can be seen in Fig. 10, the influence of reference speed variations on the MRA performance is low, since parameters P_1 and P_2 depend on the friction and inertia, both of which are constant. The slight oscillation in the parameters estimation is caused by the small variations in the magnetic saturation due to the dynamic operation of the IM drive. The same holds for the load torque variations of Fig. 11. However, the oscillations in the parameters estimation are higher compared to the case of Fig. 10, since the MRA procedure is more influenced by the approximation that has been adopted in the theoretical analysis of the MRA technique that the load torque variation between two successive control steps can be disregarded. It should be noted that the load torque variations are step changes that they are applied in the middle of the speed step pulse (in the second speed pulse, the load changes from 4 to 9 N·m) and at the starting of the forth pulse (the load torque changes from 9 to 2 N·m).

From the experimental results of Figs. 10 and 11, it is concluded that the MRA can successfully estimate and fine-tune the correct values of parameters P_1 and P_2, even if changes of the reference speed and abrupt changes of the load torque occur. Also, the FLS online determines the correct r_w for each case of reference speed and load torque. From the above, it is concluded that the IM drive with the proposed ADMPC technique exhibits satisfactory speed performance for any speed and load torque variations.

Finally, Fig. 12 illustrates experimental results of the 2.5-kW IM drive with the proposed ADMPC technique for constant reference speed of 1250 rpm and step changes of the load torque. As can be seen, in any load torque change, the drive reacts very fast and returns to the steady-state speed in less than 0.1 s.

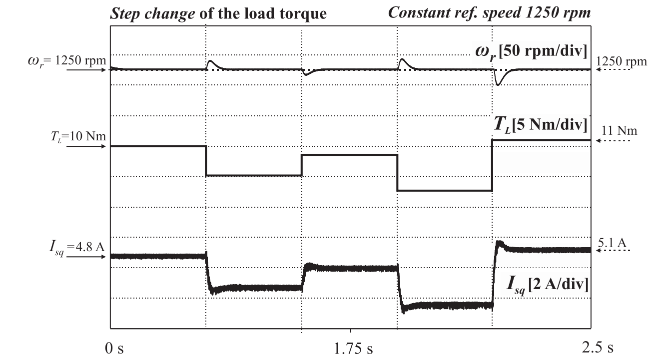


Fig. 12. Experimental results of the 2.5-kW ADMPC-IM drive performance in step changes of the load torque for constant reference speed equal to 1250 rpm. Parameters P_1 and P_2 have been determined by the MRA system of Fig. 2 and r_w by the FLS of Fig. 3.

VII. Conclusion

This paper presents an ADMPC scheme that provides high-performance speed control in IM drives by autoadapting the predictive controller parameters according to the design of the drive and operating conditions. Moreover, the implementation of the proposed ADMPC is easy, since the adaptation of the controller parameters is accomplished online, without any intervention by the user and without requiring the knowledge of the motor drive model. Thus, no additional hardware is required, but only the replacement of the firmware of the motor drive. The adaptive technique for the controller parameters is realized by a system that utilizes the MRA and fuzzy-logic techniques. In this paper, the proposed ADMPC strategy has been developed for IM drives; however, it can also be applied in PMSM drives by properly changing the mathematical methodology. Several simulation and experimental results of various operation conditions, on the same IM drive, have been presented to validate the feasibility and effectiveness of the proposed ADMPC strategy.

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