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Research Article

States and Parameters Estimation for Induction Motors Based on a New Adaptive Moving Horizon Estimation

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This paper investigates the joint states and parameters estimation problem for induction machine. In order to develop new states and parameters estimation methods that greatly improve the estimation bandwidth, this paper proposes an adaptive moving horizon estimation of the crucial states and parameters of the induction machine. The model of the machine under study is the one taking into consideration the magnetic saturation and the iron losses simultaneously. The estimator used is based on a least squares algorithm but includes a dead zone that ensures robustness and a variable forgetting factor that is based on the constant information principle. The simulation results show that the adaptive estimator can efficiently estimate the states and parameters of the induction machine with a fast convergence rate despite the initial parametric errors.

1. Introduction

In feedback control, system monitoring, and system optimization, state estimation plays a fundamental role because the only information available from the system is noisy measurements. For accomplishing such a task, several methods have been developed [1–6], among many others. Upon the assumption of knowledge of the model of the system and noises, all these techniques have been developed. Assumptions are not easily satisfied in practice, and researchers have been absolutely focused on approaches that do not rely on these requirements [7–11] and have introduced an approach that solves least squares estimation problems. Instead of leaning on statistical assumptions about noise, the method is based on an effective selection of an uncertain model. In this approach, the authors have formulated uncertainty models by relying on the available information about the system. Robust estimation algorithms based on the min-max robust filtering and guaranteed cost paradigm, in the same way, have mobilized the interest of the research community [7, 12]. The moving horizon estimation (MHE) has long attracted the attention of researchers since the work of the pioneers [3, 4, 13, 14], building on the fabulous success of controlling the moving horizon. The interest of these estimation methods comes from the possibility of processing a limited amount of data instead of using all the information available from the start and from the ability to integrate constraints. Over the past two decades, the theoretical properties of various MHE schemes have been investigated, as well as efficient computational methods for real-time implementation (see [15–19]). Many results have been obtained for some algorithms, going from ideal hypotheses (no disturbances and observability) to realistic conditions (bounded perturbations).

In this paper, we study the adaptive moving horizon estimation for the estimation of states and parameters without the speed sensor of an induction machine, aiming to improve the convergence rate of the estimations of the different variables. In [20], the authors introduced the moving horizon estimator, inspired by the double receding horizon control (RHC) problem, which has gained increasing interest over the last decade due to advances in the capabilities of computer calculation and numerical optimization [3, 4] have highlighted extensive studies of the MHE for nonlinear and general linear systems, respectively [21], explored the induction motor state estimation by the moving horizon estimator to achieve better bandwidth and estimation accuracy compared to the model reference adaptive system and extended Kalman filter estimators. However, the authors have assumed that the motor speed is constant over the estimation horizon, so the estimation of the speed of the convergence rate is limited. Moreover, the authors also assumed perfect knowledge of the model parameters, which in practice are not always available.

In [22], the authors propose parameter estimation algorithms for Hammerstein nonlinear ARX systems by making full use of the current and previous input–output data of the system. A weighted multi-innovation stochastic gradient algorithm is presented to improve the convergence rate of identification. The simulation results indicate that the algorithm can improve the accuracy of parameter estimation. Nevertheless, [23], the authors propose a paper that is concerned with the design of a state filter for a time-delay state-space system with unknown parameters based on noisy observation information. The key is to investigate new identification algorithms for the interactive state and parameter estimation of the considered system. Firstly, a direct state filter is formulated by minimizing the state estimation error covariance matrix on the basis of the Kalman filtering principle. Secondly, once the unknown states are estimated, a state filter-based recursive least squares algorithm is proposed for parameter estimation using the least squares principle. Then, a state filter-based hierarchical least squares algorithm is derived by decomposing the original system into several subsystems for improving the computational efficiency. The authors in [24] study the identification of state-space models of bilinear systems; the parameters to be identified of the considered system are coupled with the unknown states, which makes the identification problem more difficult than that of the linear state-space model. For the coupled variables, they introduce the interaction estimation theory to study an online algorithm for joint state-parameter estimation. To be more specific, a state observer in bilinear form is established by minimizing the state estimation error covariance matrix in the same way as a Kalman filter on the condition that the parameters are known. Then, a bilinear state observer based recursive least squares algorithm is developed using the least squares method. Moreover, for the purpose of improving the computational efficiency, a bilinear state observer based two-stage recursive least squares algorithm and a bilinear state observer based multistage recursive least squares algorithm are proposed by decomposing the system into several subsystems based on the hierarchical identification.

In this article, a moving horizon estimator based on adaptive arrival cost is proposed in [25], considering all the dynamics of the induction motor, where the states and parameters are jointly estimated. The formulation of the adaptive moving horizon estimator for the induction motor is introduced and eventually discussed. The simulations show that the design of the adaptive estimator can achieve an accurate estimation despite the initial parameter errors.

The paper is organized as follows: In Section 2, we present the induction motor model taking into consideration the magnetic saturation and the iron losses simultaneously, followed by the adaptive moving horizon estimation formulation in Section 3. The results are discussed in Section 4. The conclusion is drawn in Section 5.

2. Induction Machine Model

The induction machine model in the d-q reference frame can be written as follows:

$$\begin{aligned}
U_{sd} &= R_s i_{sd} + \frac{\mathrm{d}\psi_{sd}}{\mathrm{d}t} - w_s \psi_{sq},\\
U_{sq} &= R_s i_{sq} + \frac{\mathrm{d}\psi_{sq}}{\mathrm{d}t} + w_s \psi_{sd},\\
U_{rd} &= 0,\\
U_{rq} &= 0,\\
\psi_{sd} &= L_{ls} i_{sd} + \psi_{md},\\
\psi_{sq} &= L_{ls} i_{sq} + \psi_{mq},\\
\psi_{rd} &= L_{lr} i_{rd} + \psi_{md},\\
\psi_{rq} &= L_{lr} i_{rq} + \psi_{mq},\\
\psi_{md} &= L_m i_{md},\\
\psi_{mq} &= L_m i_{mq},\\
i_{md} + i_{dFe} &= i_{sd} + i_{rd},\\
i_{mq} + i_{qFe} &= i_{sq} + i_{rq},\\
R_{Fe} i_{dFe} &= L_m \frac{\mathrm{d}i_{md}}{\mathrm{d}t} + w_s L_m i_{md},\\
R_{Fe} i_{qFe} &= L_m \frac{\mathrm{d}i_{mq}}{\mathrm{d}t} + w_s L_m i_{mq},\\
C_{em} &= p \frac{L_m}{L_r}\left[\psi_{rd}\left(i_{sq} - i_{qFe}\right) - \psi_{rq}\left(i_{sd} - i_{dFe}\right)\right],
\end{aligned} \tag{1}$$

where U, i, and ψ denote voltage, current, and flux vector, respectively. r, s, and m stand for rotor, stator, and air-gap, respectively. p is the number of pole pairs. w_s is the speed of the reference axis. $p\Omega$ is the rotor speed. Cem is the electromagnetic torque. R_s, R_r, L_{ls}, L_{lr}, and L_m can be determined directly from conventional tests: DC test, no-load test, and locked-rotor test. For operation in transient state, a mechanical model is coupled to the electrical system via the electromagnetic torque (Cem) by the equation of motion given as follows:

$$J\frac{d\Omega}{dt} + f\Omega = C_{em} - T_L, \quad (2)$$

where J is the moment of inertia, f is the coefficient of friction, and T_L is the load torque.

The state representation of the machine model is as follows:

$$\begin{aligned} \dot{x} &= f(x, U), \\ y &= Cx = \begin{bmatrix} i_{sd} & i_{sq} \end{bmatrix}^T, \end{aligned} \quad (3)$$

where

$$x = \begin{bmatrix} i_{sdq} & i_{rdq} & i_{dqFe} & \Omega & R_s & R_r \end{bmatrix}^T,$$

$$[U] = \begin{bmatrix} U_{sdq} & 0_{2\times1} & 0_{2\times1} & 0 & 0 & 0 \end{bmatrix}^T,$$

$$\underbrace{\begin{pmatrix} \dot{i}_{sd} \\ \dot{i}_{sq} \\ \dot{i}_{rd} \\ \dot{i}_{rq} \\ \dot{i}_{dFe} \\ \dot{i}_{qFe} \\ \dot{\Omega} \\ \dot{R}_s \\ \dot{R}_r \end{pmatrix}}_{\dot{x}=(\dot{i},\dot{\Omega},\dot{R}_s,\dot{R}_r)} = \underbrace{\begin{pmatrix} \frac{1}{L_{ls}} f_1 \\ \frac{1}{L_{ls}} f_2 \\ \frac{1}{L_{lr}} f_3 \\ \frac{1}{L_{lr}} f_4 \\ f_5 \\ f_6 \\ f_7 \\ 0 \\ 0 \end{pmatrix}}_{f(i,\Omega,R_s,R_r)} + B \underbrace{\begin{pmatrix} U_{sd} \\ U_{sq} \end{pmatrix}}_{U_s}, \quad (4)$$

with

$$B = \begin{pmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \\ 0 & 0 \\ \frac{1}{L_{ls}} & 0 \\ 0 & \frac{1}{L_{ls}} \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{pmatrix},$$

$$\begin{aligned}
f_1 &= (k_2 w_s - R_s) i_{sd} + (w_s L_s - k_1 w_s) i_{sq} \cdots + k_2 w_s i_{rd} + (w_s L_m - k_1 w_s) i_{rq} \cdots - \left(k_1 \frac{R_{Fe}}{L_m} + k_2 w_s \right) i_{dFe} \cdots \\
&\quad + \left(w_s (k_1 - L_m) - k_2 \frac{R_{Fe}}{L_m} \right) i_{qFe}, \\
f_2 &= (L_1 - L_s) w_s i_{sd} + (R_s - k_2 w_s) i_{sq} \cdots + (L_1 - L_m) w_s i_{rd} - k_2 w_s i_{rq} \cdots + \left(w_s (L_m - L_1) - k_2 \frac{R_{Fe}}{L_m} \right) i_{dFe} \cdots \\
&\quad + \left(w_s k_2 - L_1 \frac{R_{Fe}}{L_m} \right) i_{qFe}, \\
f_3 &= k_2 w_s i_{sd} + (w_{sl} L_m - k_1 w_s) i_{sq} \cdots + (k_2 w_s - R_r) i_{rd} + (w_{sl} L_r - k_1 w_s) i_{rq} \cdots - \left(k_1 \frac{R_{Fe}}{L_m} + k_2 w_s \right) i_{dFe} \cdots \\
&\quad + \left(w_s k_1 - w_{sl} L_m - k_2 \frac{R_{Fe}}{L_m} \right) i_{qFe}, \\
f_4 &= (L_1 w_s - L_m w_{sl}) i_{sd} - k_2 w_s i_{sq} \cdots + (L_1 w_s - L_r w_{sl}) i_{rd} - (k_2 w_s + R_r) i_{rq} \cdots + \left(w_{sl} L_m - w_s L_1 - k_2 \frac{R_{Fe}}{L_m} \right) i_{dFe} \cdots \\
&\quad + \left(w_s k_2 - L_1 \frac{R_{Fe}}{L_m} \right) i_{qFe}, \\
f_5 &= \left(k_2 w_s \varpi - \frac{R_s}{L_{ls}} \right) i_{sd} \cdots + \left(w_s \frac{L_s}{L_{ls}} - k_1 w_s \varpi - w_s \right) i_{sq} \cdots + \left(k_2 w_s \varpi - \frac{R_r}{L_{lr}} \right) i_{rd} \cdots + \left(w_s \frac{L_m}{L_{ls}} - k_1 w_s \varpi + w_{sl} \frac{L_r}{L_{lr}} - w_s \right) i_{rq} \cdots \\
&\quad - \left(\left(k_1 \frac{R_{Fe}}{L_m} + k_2 w_s \right) \varpi + \frac{R_{Fe}}{L_m} \right) i_{dFe} \cdots \\
&\quad + \left(w_s k_1 \varpi - k_2 \frac{R_{Fe}}{L_m} \varpi + w_s \left(1 - \frac{L_m}{L_{ls}} \right) - w_{sl} \frac{L_m}{L_{lr}} \right) i_{qFe}, \\
f_6 &= \left(w_s + \varpi L_1 w_s - \frac{L_s}{L_{ls}} w_s - w_{sl} \frac{L_m}{L_{lr}} \right) i_{sd} \cdots + \left(\frac{R_s}{L_{ls}} - k_2 w_s \varpi \right) i_{sq} \cdots + \left(w_s + L_1 w_s \varpi - w_s \frac{L_m}{L_{ls}} - w_{sl} \frac{L_r}{L_{lr}} \right) i_{rd} \cdots - \left(\frac{R_r}{L_{lr}} + k_2 w_s \varpi \right) i_{rq} \cdots \\
&\quad + \left(\left(w_s (L_m - L_1) - k_2 \frac{R_{Fe}}{L_m} \right) \varpi - P\Omega \frac{L_m}{L_{lr}} + w_s \right) i_{dFe} \cdots \\
&\quad + \left(\left(w_s k_2 - L_1 \frac{R_{Fe}}{L_m} \right) \varpi - \frac{R_{Fe}}{L_m} \right) i_{qFe}, \\
f_7 &= P \frac{L_m}{J} \left(i_{sq} i_{rd} - i_{sd} i_{rq} \right) - \frac{f}{J} \Omega - \frac{T_L}{J},
\end{aligned} \tag{5}$$

where

$$\varpi = \frac{1}{L_{ls}} + \frac{1}{L_{lr}},$$
$$k_1 = L_{dy}\cos^2\mu + L_m\sin^2\mu,$$
$$k_2 = \cos\mu\sin\mu\left(M_{dy} - L_m\right),$$
$$L_1 = L_{dy}\sin^2\mu + L_m\cos^2\mu. \tag{6}$$

With $w_{sl} = w_s - P\Omega$,

$$L_d = L_{dy}\cos^2\mu + L_m\sin^2\mu,$$
$$L_q = L_{dy}\sin^2\mu + L_m\cos^2\mu,$$
$$L_{dq} = \left(L_{dy} - L_m\right)\cos\mu\sin\mu,$$
$$\cos\mu = \frac{i_{md}}{i_m};\ \sin\mu = \frac{i_{mq}}{i_m},$$
$$L_m = \frac{\psi_m}{i_m};\ M_{dy} = \frac{d\psi_m}{di_m}, \tag{7}$$

where L_m and L_{dy} are the static and dynamic mutual inductances, respectively. μ is the angle between the magnetizing current i_m the axis d. L_m and L_{dy} consider that i_m changes as a function of the magnetizing state of the machine; they depend on the instantaneous values of ψ_m and i_m and are variable. L_{dq} explains the *cross effect* between the d and q axes [26, 27].

3. Adaptive Moving Horizon Estimation Formulation

This section introduces the adaptive moving horizon estimation formulation to make self-contained this paper [25].

$$x_{k+1} = f\left(x_k, u_k\right) + Dw_k$$
$$y_k = Cx_k + v_k, \tag{8}$$

where the state vector is $x_k \in X_\ell \subseteq \mathbb{R}^n$, the process noise vector is $w_k \in W_\ell \subseteq \mathbb{R}^p$, the measurement vector is $y_k \in Y_\ell \subseteq \mathbb{R}^m$, and the measurement noise vector is $v_k \in V_\ell \subseteq \mathbb{R}^m$. The process and measurement noises (w_k, v_k) are assumed to be bounded and/or unknown, i.e., $w \in W_\ell(\vartheta_{W_\ell \max})$ and $v \in V_\ell(\vartheta_{V_\ell \max})$ for $(\vartheta_{W_\ell \max}, \vartheta_{V_\ell \max}) \in \mathbb{R}^2_+$, with X_ℓ, Y_ℓ, W_ℓ, and V_ℓ convex and/or compact sets considered closed with $0 \in X_\ell$, $0 \in Y_\ell$, $0 \in W_\ell$, and $0 \in V_\ell$. The adaptive moving horizon estimation can be formulated as the following constrained optimization problem at time T:

$$\min_{\widehat{w}_k, \widehat{x}_{k-N|k}} \Psi = \Gamma_{k-N|k}\left(\widehat{x}_{k-N|k}\right) + \sum_{j=k-N}^{k-1} \left\|\widehat{w}_{j|k}\right\|^2_{Q^{-1}} + \sum_{j=k-N+1}^{k} \left\|\widehat{v}_{j|k}\right\|^2_{R^{-1}}$$
$$\text{s.t.} \begin{cases} \widehat{x}_{j+1|k} = f\left(\widehat{x}_{j|k}\right) + \widehat{w}_{j|k}, \\ y_j = C\widehat{x}_{j|k} + \widehat{v}_{j|k}, \\ \widehat{x}_{j|k} \in X_\ell, \widehat{w}_{j|k} \in W_\ell, \widehat{v}_{j|k} \in V_\ell, \end{cases} \tag{9}$$

where $\widehat{x}_{k-j|k}$ is the optimal estimated, and the process noise estimate is $\widehat{w}_{j|k}$, which is based on available measurements at time k (y_k). The estimation residuals are $\widehat{v}_{j|k} = y_j - C\widehat{x}_{j|k}$. To ensure a suitable stability of the MHE, it is necessary to make an adequate choice of $\Gamma_{k-N|k}(\cdot)$ and its parameters [28].

It is quite arduous for constrained moving horizon estimation problems to find an analytical expression of the arrival cost; therefore, an approximation of the arrival cost used for the constrained problem will be highlighted and this approximation quadratic takes the form as follows:

$$\Gamma_{k-N} = \left\|\widehat{x}_{k-N} - \widetilde{x}_{k-N}\right\|^2_{P^{-1}_{k-N}}, \tag{10}$$

where $\widetilde{x}_{k-N}$ is the initial state and P_{k-N} is the weighting matrix. They define the approximation of the arrival cost. In this work, the approach proposed for the update of the arrival cost function, based on an adaptive algorithm, is formulated as an update of the following elements: P_{k-N} and $\widetilde{x}_{k-N}$. In this case, the update of the initial state $\widetilde{x}_{k-N}$ will be done by a so-called smooth update, which implies that once the estimate has left the estimate horizon, the state constraints will not change [29–31].

$$\widetilde{x}_{k-N} = \widehat{x}^*_{k-N|k-1}. \tag{11}$$

About the update of the weighting matrix P_{k-N}, it is important to note that the weighting matrix can be considered as the covariance of the state x_{k-N}, following a stochastic interpretation of the MHE problem [4]. Analytical solutions exist to calculate the weighting matrix for unconstrained linear systems, on the other hand, for constrained linear systems, a deduction of the approached solutions is necessary, they are fundamental and based on a process of recursive updating of the useful information of the process at a given time. In the adaptive estimation method highlighted, we use a recursive updating process based on measures and states [32, 33].

$$P^{-1}_{k-N} = \lambda_k\left(P^{-1}_{k-N-1} + \frac{\alpha_k}{\lambda_k}\widehat{x}_{k-N|k-1}\widehat{x}^T_{k-N|k-1}\right), \tag{12}$$

where α_k is a function called *the dead zone*, varying between 0 and 1, andλ_k is the forgetting factor $(0 < \lambda_k \leq 1)$, with $P_0 > 0$. A recursive real-time estimate of P_{kN} is produced by (12). P_{k-N-1} being the previous estimate is updated from the matrix $\hat{x}_{k-N|k-1}\hat{x}_{k-N|k-1}^T$. This mechanism can be qualified as a dynamic temporal filter update with P_0, the initial condition, and $\hat{x}_{k-N|k-1}\hat{x}_{k-N|k-1}^T$ the input.

Lemma 1. *Let a matrix $G > 0$, then an invertible matrix M exists such that $M^T G M = I$, with I the identity matrix. Then, $MM^T = G^{-1}$ exists.*

Proof. (cf. Lemma 7 in [34]).

The function α_k and the forgetting factor λ_k, each has a particular role. In P_{k-N-1}, when $\lambda_k \approx 1$, the algorithm keeps the old information, and all information is included in this case, enhancing the estimation problem. Moreover, when $\lambda_k \ll 1$, the algorithm tends to discard the old data in P_{k-N-1}, considering actual data to estimate P_{k-N} [35].

This case makes it possible to discard many old data which could negatively hinder the performance of the estimator. To ensure robustness, the dead zone function α_k is used, when estimating (12) can be rewritten by the matrix inversion Lemma as follows:

$$P_{k-N} = \frac{1}{\lambda_k} P_{k-N-1} - \frac{\alpha_k P_{k-N-1}\hat{x}_{k-N|k-1}\hat{x}_{k-N|k-1}^T P_{k-N-1}}{\lambda_k + \hat{x}_{k-N|k-1}^T P_{k-N-1}\hat{x}_{k-N|k-1}}. \quad (13)$$

By this way a feedback loop is introduced into the MHE problem to compute P_{k-N}, the convergence of the estimates is ensured in this way $\hat{x}_{k-N|k}$ and $\hat{w}_j\,(j = k-N, \ldots, N)$ and to adjust P_{k-N}^{-1} according to the amount of available data. The proposed algorithm used, proposes two crucial elements, a variable forgetting factor, which varies between 0 and 1, and a dead zone function, both enabling P_{k-N} to be updated under certain conditions to be respected as follows [32]:

$$\lambda_k = \begin{cases} \dfrac{\left(N_0 + \Delta_k^2\right)}{\left(N_0 + M_{1k}\right)} & \text{if } \dfrac{\Delta_k^2}{M_{1k}} < 1, \\ 1 & \text{otherwise,} \end{cases} \quad (14)$$

$$\alpha_k = \begin{cases} 1 & \text{if} \Delta_k^2\left(1 + \dfrac{\mu_k}{\lambda_k}\right) \leq e_k^2, \\ 0 & \text{otherwise,} \end{cases} \quad (15)$$

withN_0 is a positive parameter. $M_{1k} = e_k^2/1 + \mu_k$,

$$\begin{aligned} \mu_k &= \hat{x}_{k-N|k-1}^T P_{k-N-1}\hat{x}_{k-N|k-1}, \\ e_k &= y_{k-N} - \hat{y}_{k-N}, \end{aligned} \quad (16)$$

where $\Delta_k = \|\hat{x}_{k-N|k-1}\| d_1 + d_2/n_{k-1}$, with $n_{k-1} = \max(1, \|\hat{x}_{k-N|k-1}\|)$, and d_1 and d_2 are design parameters too, chosen positive notably. The dead zone size $\Delta_k^2(1 + \mu_k/\lambda_k)$ is bounded because μ_k is a bounded function [32] proposed a forgetting factor, which is based on the constant data principle; moreover, it is judicious for external and unmodelled disturbances. Algorithm 1 summarizes the adaptive moving horizon estimation. □

4. Results and Discussion

Numerical simulations have been carried out to show the performance of the adaptive MHE on the induction machine. Table 1 presents the parameters of the machine used in the simulations and Table 2 presents the parameters and initial values of the estimator. The sampling frequency chosen for the execution of the simulations is $10K_{hz}$ and the optimization problems have been solved using the Matlab Optimization Toolbox™. A sequence of independent normally distributed random values with zero mean and covariance equal to 0.1 for measurement noises and a sequence of normally distributed random values with zero mean and covariance equal to 1 for process noises.

The proposed moving horizon estimation formulation for induction machine state estimation is compared with the performance of conventional moving horizon estimation, extended Kalman filter and unscented Kalman filter. Figures 1(a) and 1(b) show the estimation of the stator currents in the d and q axis. It can be seen that the estimation of the stator currents by the MHE_{AD} is better than that provided by the others estimators. Despite the extension of the machine model to the crucial parameters notably R_s and R_r, the adaptive estimator follows the real state by its ability to adapt to changes and this estimator shows its great robustness to the given model, which assumes that the parameters have slow dynamics. Figures 2(a) and 2(b) show the estimation of the rotor currents in the d and q axis. Just like the estimate of the stator current, it can be seen a very good estimate especially during the steady state. Moreover, we also note that the convergence speed of the adaptive estimator is obviously greater than that of the MHE, EKF and UKF. Figures 3(a) and 3(b) show the estimation of the iron currents in the d and q axis. The estimate of the iron current along the d axis is significantly better than the estimate of the iron current along the q axis. It can also be noted that at the level of Figure 3(b), the estimated state reaches stability at a greater time than that of Figure 3(a), on the other hand the estimate of other estimators diverge exponentially. Figures 4(a) and 4(b) show the estimation of the stator and rotor resistance. Thanks to its ability to adapt due to the variable forgetting factor and the dead zone function, the formulated adaptive estimator guarantees a good estimation of the parameters. We can also appreciate the high speed of convergence of the adaptive estimator on the moving horizon estimator, EKF and UKF. Note that the other estimators were not designed to estimate the parameters of nonlinear systems in an efficient way, which explains its slow convergent speed and its poor parametric estimation. The proposed adaptive estimator overcomes almost all the problems of others. Figure 5 shows the estimation of the rotor speed. Once again, we can appreciate the good estimation and the good convergence speed of the MHE^{AD}. Also we can note the divergence of the MHE^{KF} which tries somehow to rebuild the speed but without ever succeeding. As for EKF and UKF, they provide an estimate of very poor

$\tilde{x}_0$, $P_0, Q, R > 0$, $d_1, d_2, N_0 > 0$ *and* $N \geq 2$
Initialization
$\tilde{x}_{k-N} \leftarrow \tilde{x}_0$
$P_{k-N} \leftarrow P_0$
for $k = 0, 1, 2 \ldots$ ***do***
Get measurements y_k
if $k < N$ ***then***
$y \leftarrow [y_0, y_1, \ldots, y_k]^T$
Solve Ψ_k *with* $\tilde{x}_0$, P_0 *and* y
else
$y \leftarrow [y_{k-N}, \ldots, y_k]^T$
Solve Ψ_k^N *with* $\tilde{x}_{k-N}$, P_{k-N} *and* y
$\tilde{x}_{k-N} \leftarrow \hat{x}_{k-N+1|k}$
Updating P_{k-N} *using* (13), (14) *and* (15)
end if
Get current estimates $\hat{x}_{j|k}$ $(j = k - N, \ldots, k)$
end for

Algorithm 1: AD-MHE Algorithm.

Table 1: Parameters of induction motor model.

Parameters	Values
Motor power	$2.2kw$
Nominal voltage	$380/230V$
Nominal current	$4.7A$
Stator resistance R_s	2.05Ω
Rotor resistance R_r	4.05Ω
Iron resistance R_{Fe}	160Ω
Stator self-inductance L_{ls}	$274mH$
Rotor self-inductance L_{lr}	$274mH$
Mutual inductance L_{mo}	$810mH$
Rotor inertia J	$0.081kg.m^2$
Number of pole pair p	2
Friction coefficient f	$0.003N.m.s.rad^{-1}$

Table 2: Estimator settings.

Parameters	Values
Number of outputs measured	2
Number of estimated states	9
Horizon length N	8
Covariance matrix Q	Diagonal 15
Covariance matrix R	Diagonal 10
Weighting matrix P_0	Diagonal 1
d_1	10^{-2}
d_2	10
N_0	0.5
Initial values of estimated states	
Stator current (A)	0, 5
Rotor current (A)	0, 5
Iron loss current (A)	0, 1
Rotor speed (tr/min)	0, 3
Stator resistance (Ω)	0, 15
Rotor resistance (Ω)	2, 5

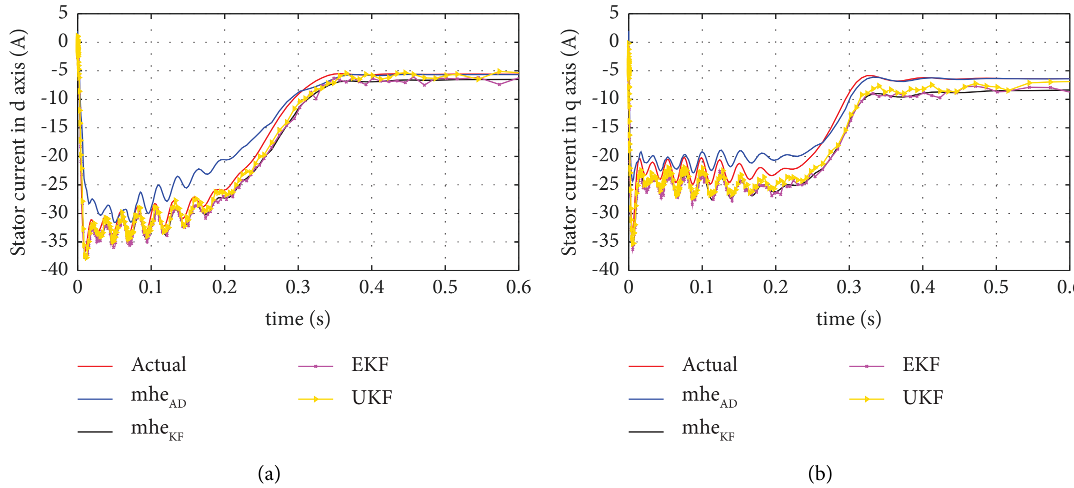


Figure 1: (a) Estimation of stator current in d axis. (b) Estimation of stator current in q axis.

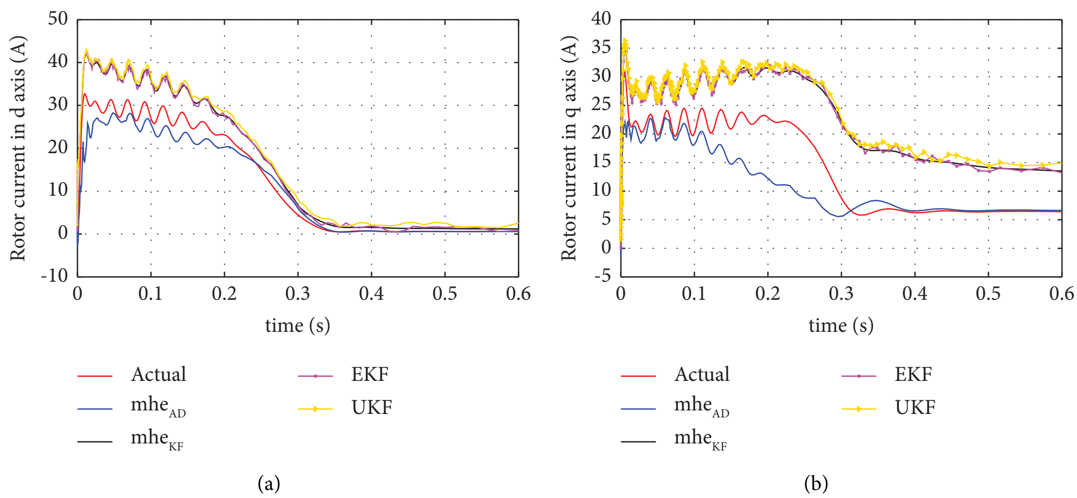


Figure 2: (a) Estimation of rotor current in d axis. (b) Estimation of rotor current in q axis.

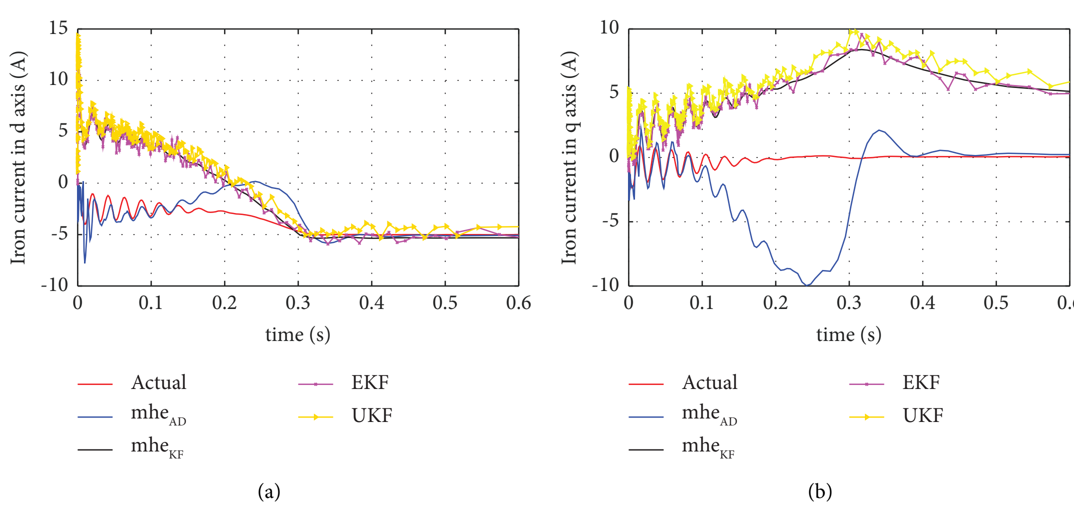
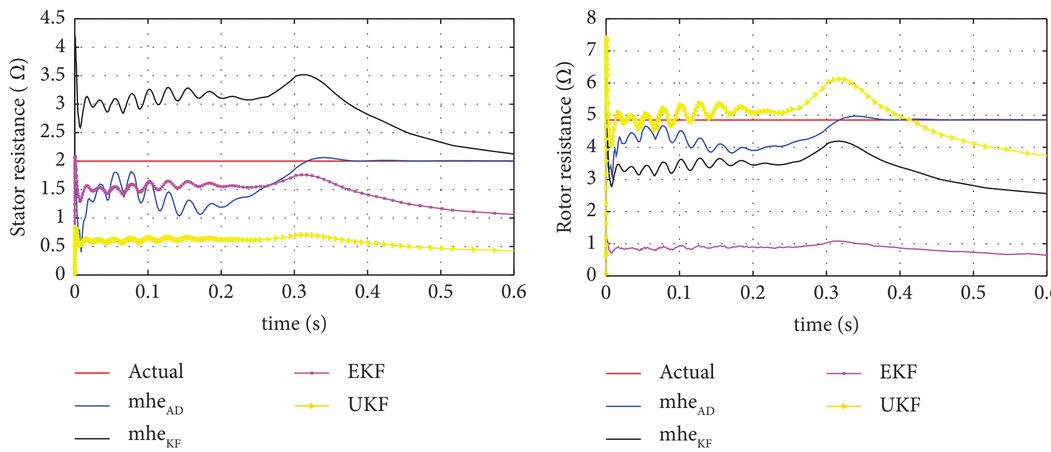


Figure 3: (a) Estimation of iron current in d axis. (b) Estimation of iron current in q axis.



(a) (b)

Figure 4: (a) Estimation of stator resistance. (b) Estimation of rotor resistance.

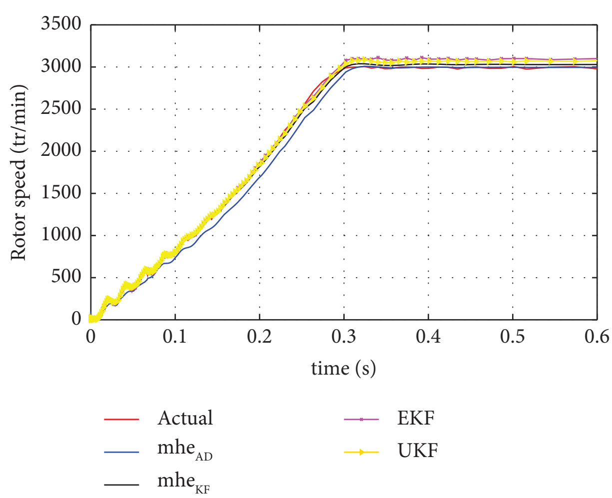
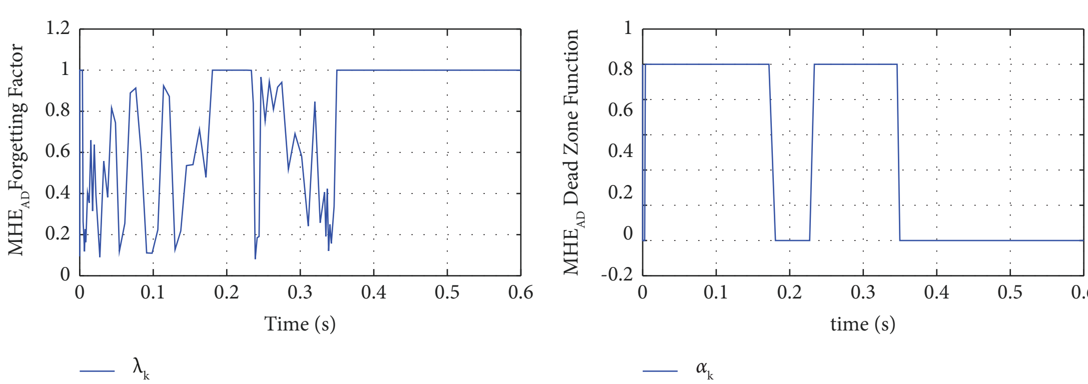


Figure 5: Estimation of rotor speed.



(a) (b)

Figure 6: Evolution of the sequence of (a) forgetting factor and (b) dead zone function.

quality with estimation disparities on both sides. In steady state, the estimation error between the real state and the state estimated by the adaptive estimator is very small compared to the error between the real state and the state estimated by the other estimators. Figures 6(a) and 6(b) present the evolution of the variable forgetting factor and the dead zone function, respectively. The forgetting factor is variable that varying between 0 and 1, providing a quite good adaptation ability and allowing the proposed MHE^{AD} to insert judicious information into the data and enable sudden variations, it tries to adapt to variations in the transient state while keeping its value between 0 and 1. The dead zone function makes variations between 0 and 1 to enable a fast adaptation of the weighting matrix when a sudden change happens. It can note that when the estimate error is relatively large, the dead zone function is equal to 1, and when the error is low relatively, the dead zone function takes the value 0. Additionally, it can be seen that the adaptive estimator with mechanical equation included, can correctly estimate the states and parameters of the induction machine and demonstrated a faster convergence transient comparing with classic MHE. Moreover the adaptive moving horizon estimation can successfully incorporate jointly the states and parameters estimation and give a quite good converging estimation despite the existence of parametric errors of the initial model.

5. Conclusion

This paper presented an adaptive moving horizon estimation scheme for the joint estimation of states and parameters, in particular the stator and rotor resistances of the induction machine. The formulated estimation algorithm is based on a least squares algorithm including a dead zone function ensuring robustness and a variable forgetting factor, which is based on the principle of constant information. The results obtained show that the adaptive estimation scheme allows a relatively good approximation of the cost of arrival for the estimation of the moving horizon, this can be explained by the fact that the variable forgetting factor and the function of dead zone can follow slow and/or sudden changes and provide good adaptability. The results of the adaptive moving horizon estimation tests for the induction machine sufficiently show that the presented estimation scheme can achieve suitable convergent estimation performance when the model parameters are biased from the start and the results show that the mhe_{ad} has a much higher convergence speed than the classical mhe and we notice a root mean square error of 75.37 for the mhe^{ad} and 185.10 for the conventional mhe. The crucial elements of the mhe^{ad} provide robustness against disturbances and uncertainties of the unmodelled model.

Notations

$x(t)$: States vector
y_k: Measurement outputs
Ψ_k: Objective function
G: Noise weighting matrix
w: Process noise vector
v: Measurement noise vector
f: Process vector
h: Measurement vector
A: matrix with respect to x_{k}
C: Jacobian matrix of h with respect to x_{k}
N: Horizon length
$\Gamma(.)$: Arrival cost
Q: Weighting matrix representing the confidence in the dynamic model
R: Weighting matrix representing the confidence in the measurements
$\hat{x}$: Estimates vector
$\tilde{x}_0$: Initial state
$\tilde{x}_{k-N}$: Initial state
P_{k-N}: Weighting matrix
λ_ℓ: Forgetting factor
α_ℓ: Dead zone function
N_0: Design parameter
e_k: Estimation error
$d_{1,2}$: Design parameters
R_s, R_r: Stator and rotor resistances
R_{Fe}: Iron loss resistance
L_m: Mutual inductance
ψ_s, ψ_r: Stator and rotor flux vectors
U_s, U_r: Stator and rotor voltage vectors
I_s, I_r: Stator and rotor currents vectors
ψ_m, I_m: Magnetizing flux and current vectors
w_s, w_{sl}: Synchronous and slip angular speeds
p: Number of pole's pair
C_{em}: Electromagnetic torque
J: Moment of inertia
T_L: Load torque.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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