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Online Stator and Rotor Resistance Estimations of IM by Using EKF

GKF ile ASM'nin Eş-zamanlı Stator ve Rotor Direnci Kestirimleri

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Abstract

In this paper, a state and parameter observer, based on a novel extended Kalman filter (EKF), is designed to solve the parameter variations dependent estimation performance deterioration of induction motor (IM) drive systems. The proposed EKF based observer algorithm performs online estimation of the rotor mechanical speed, stator stationary axis component of the stator currents and rotor fluxes, stator resistance, rotor resistance, reciprocal of the total inertia of the system, and load torque including viscous friction term in a single EKF by using measured rotor mechanical speed and stator currents. Thus, frequency and temperature-dependent variations of the resistances are estimated to be updated in the observer, which leads to control performance enhancement of the IM drive. Moreover, to rise the dynamic performance of the observer, the load torque and reciprocal of the total inertia of the system which are mechanical parameters are also estimated. To verify the robustness of the IM drive and the estimation performance of the proposed observer, they have been tested under challenging scenarios including changes in parameters and speed reference. Moreover, the estimation performance of the proposed ninth order observer is compared with that of a sixth order EKF estimating the same electrical parameters by using directly measured speed. Ultimately, the simulation results obviously reveal the efficacy of the proposed IM drive.

Keywords: Extended Kalman filter, Induction motor, Rotor and stator resistance estimation, State and parameter estimation

Öz

Bu makalede, asenkron motor (ASM) sürücü sistemlerinin parametre değişimlerine bağlı kestirim başarımlarının kötüleşmesi problemini çözmek için genişletilmiş Kalman filtresine (GKF) dayalı yeni bir durum ve parametre gözlemleyicisi tasarlanmıştır. Önerilen GKF tabanlı gözlemleyici algoritması, ölçülen stator akımları ve rotor mekanik hızı kullanılarak stator akımlarının ve rotor akılarının stator duran eksen bileşenlerinin, rotor mekanik hızının, viskoz sürtünme terimi dahil yük momentinin, rotor direncinin, stator direncinin ve sistemin toplam eylemsizliğinin tersinin eş-zamanlı kestirimlerini gerçekleştirmektedir. Böylece, dirençlerin frekans ve sıcaklık bağımlı değişimlerinin gözlemleyicide güncellenmek üzere kestirilmesi ASM sürücüsünün kontrol başarımının iyileştirilmesi sağlar. Ek olarak, gözlemleyicinin dinamik başarımını artırmak için mekanik parametreler olan yük momenti ve sistemin toplam eylemsizliğinin tersi de kestirilmektedir. Önerilen gözlemleyicinin kestirim başarımı ve ASM sürücüsünün sağlamlığı, hız referansı ve parametrelerdeki değişimleri içeren zorlu senaryolar altında test edilmektedir. Ayrıca, dokuzuncu dereceden önerilen gözlemleyicinin kestirim başarımı, ölçülen hızı doğrudan kullanarak aynı elektriksel parametreleri kestiren altıncı dereceden GKF'nin kestirim başarımı ile karşılaştırılmıştır. Özetle, benzetim sonuçları önerilen ASM sürücüsünün etkinliğini açıkça ortaya koymaktadır.

Anahtar kelimeler: Genişletilmiş Kalman filtresi, Asenkron motor, Rotor ve stator direnci kestirimi, Durum ve parametre kestirimi

1 Introduction

In literature, there are many sophisticated studies on high-performance control applications of the induction motors (IMs) performed by the vector control (VC) [1], [2], the direct torque control (DTC) [3], [4], and the model predictive control [5], [6]. These control methods require the correct values of the control variables/states. However, the highly nonlinear structure of the IM model and parameter variations that are caused by its working conditions make obtaining the correct values of control variables challenging. Thus, for the researchers concentrating on the improvement of control performance by estimating states and parameters, it is a research area that is still open. In literature, there are deterministic and stochastic based various methods proposed to solve this problem which can be classified as full order observers [6], model reference adaptive systems (MRAS) [7], Luenberger observers [8], sliding mode observers (SMO) [9], and nonlinear Kalman filter based observers [1], [3], [10].

Considering the deterministic based approaches concentrating on the parameter estimation of the IM, [11] introduces a neural network estimator utilizing the flux estimation of a programmable cascade filter for rotor resistance (R_r) estimation and a fuzzy logic based estimator for stator resistance (R_s) estimation. [12] considers an adaptive observer to perform online estimations of R_r and R_s by utilizing one phase current measurement. In order to perform R_r estimation, motor torque and reactive power based MRAS algorithms are performed in [13]. Online estimations of R_r and magnetizing inductance (L_m) are realized in [14] by using MRAS algorithm which utilizes the rotor flux obtained by SMOs series implemented. In order to attain improved dynamic performance, [15] presents a decoupling mechanism for the R_r and L_m estimations performed in [14]. [16] presents reactive and active power based-MRAS (Q-MRAS and P-MRAS) algorithms to perform simultaneous R_r and R_s estimations. The parameter and noise sensitivity of the deterministic based methods affect their estimation performances. Contrary to the

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deterministic approaches, stochastic ones such as the extended Kalman filter (EKF), a commonly used methods for the state and parameter estimations of IMs despite its computational load, take into account noises called the measurement (**R**) and process (**Q**) noises.

There are many EKF based studies focusing on the state and parameter estimation of the IMs in the current literature. For the speed-sensorless case, it is stated in [17] that the estimation performance deteriorations occur when a limited number of measurement is used in a single EKF to estimate a high number of parameters. In [18], an eight-order EKF is designed to perform simultaneous estimation of R_r and R_s in a single EKF; however, when simultaneous changes are performed in R_r and R_s, the eight-order EKF fails to realize the correct estimation of one of the estimated R_r and R_s values in simulations. The experimental results demonstrate that R_s is not estimated correctly while R_r is estimated successfully in the eight-order EKF. In the literature, to overcome the simultaneous estimation problem of R_r and R_s, EKF observer structures, known as switching EKF [19], [20], braided EKF [17], [21] and bi-input EKF [22], [23] are proposed for estimation of the high number of states and the other parameters together with R_r and R_s. Moreover, to perform estimation of more states and parameters with a lower computational burden, a hybrid structure of the EKF and the MRAS algorithms is proposed in [4]. Even if these structures enable high number of estimated parameters, the main drawbacks of these methods can be given as follows:

- The switching of the different EKF algorithms in [20], [21] and different IM models in [22] lead to computational load increase as well as the tuning difficulty and design complexity as in hybrid structure in [4].
- Increased memory requirement in [4], [20]–[22] compared to the standard EKF.

Along with the proposed EKF studies for speed-sensorless operation, there are also some studies using EKF algorithm in state and parameter estimations of the IM when the rotor speed is measured. For this case, [24] presents the online estimation of stationary axis ($\alpha\beta -$ axis) component of the rotor fluxes and stator currents ($\varphi_{r\alpha}$, $\varphi_{r\beta}$, $i_{s\alpha}$, and $i_{s\beta}$,) together with the R_r and R_s by an EKF algorithm for direct VC (DVC) based IM drive. As opposed to the [24], [25] proposes a DTC based IM drive, which uses EKF algorithm estimating $i_{s\alpha}$, $i_{s\beta}$ $\varphi_{s\alpha}$, $\varphi_{s\beta}$, R_r, and R_s by using the six-order the stator flux based dynamic model of the IM. Furthermore, [26] presents a reduced-order EKF based observer, which performs the online estimation of $\varphi_{r\alpha}$, $\varphi_{r\beta}$, R_r and L_m both in real-time experiments and simulation. In these studies, The EKF algorithm directly uses the measured rotor speed (ω_m), which results in the only use of the electrical subsystem in the IM model. Thus, it is not possible for these studies to perform online estimation of the mechanical states, resulting in dynamic performance enhancement, with the electrical ones. For this purpose, an EKF algorithm that simultaneously performs the estimations of $i_{s\alpha}$, $i_{s\beta}$, $\varphi_{r\alpha}$, $\varphi_{r\beta}$, ω_m, t_L, R_r, and L_m in a single EKF algorithm without switching operation is proposed in [27], and the proposed EKF algorithm is compared to the six-order EKF directly using the measured ω_m. The experimental results show that with the help of equation of motion and measurement matrix (**H**) extension, t_L estimation improves the dynamic performance of the EKF algorithm compared to the six-order EKF. Furthermore, [1] proposes an EKF observer performing the online estimations of $i_{s\alpha}$, $i_{s\beta}$ $\varphi_{r\alpha}$, $\varphi_{r\beta}$, ω_m, t_L, R_r, L_m, and γ_T by using the ninth-order extended model of the IM. Therefore, thanks to the **H** matrix extension used as in [27], both the mechanical parameters and the electrical parameters except for R_s, rotor leakage inductance (L_{lr}), and stator leakage inductance (L_{ls}) are estimated both in real-time experiments and simulations by using measured $i_{s\alpha}$, $i_{s\beta}$, and ω_m values.

The main contribution of this paper is to perform simultaneous estimation of $i_{s\alpha}$, $i_{s\beta}$ $\varphi_{r\alpha}$, $\varphi_{r\beta}$, ω_m, t_L, R_r, R_s, and γ_T, in a single EKF without any model/EKF switching operation or hybrid method. To perform the estimation of overall all nine states and parameters in a single EKF, the **H** matrix is extended by the measured ω_m, which leads to use of the priori estimation error in rotor speed together with the currents in the posteriori estimations in the proposed EKF, similar to recent study [1] estimating $i_{s\alpha}$, $i_{s\beta}$ $\varphi_{r\alpha}$, $\varphi_{r\beta}$, ω_m, t_L, R_r, L_m, and γ_T. Thus, this paper aims to obtain enhanced estimation performance of the EKF and thus the control performances of the IM drive specifically at very low and up to rated speed operations which are sensitive to variations in R_r and R_s. Furthermore, compared to the other speed-sensored EKF studies, using directly the measured ω_m in [24]–[26], the proposed EKF is also estimates the mechanical parameters (t_L and γ_T) to increase the dynamic performance. By performing t_L estimation with the proposed observer, it is also possible to use the estimated t_L value in the feed forward control loop to improve the torque response, as in [28]. γ_T estimation is also required for the position control system to perform robust control, as demonstrated in [1]. Moreover, in order to demonstrate the effectiveness of the proposed ninth order observer, its estimation performance is compared with that of a sixth order observer, proposed in [24], directly using the measured ω_m to perform $i_{s\alpha}$, $i_{s\beta}$ $\varphi_{r\alpha}$, $\varphi_{r\beta}$, R_r, and R_s estimations. Therefore, the estimation performance deteriorations based on the effect of the frequency and temperature variations on resistances as well as the unknown mechanical parameters is eliminated by estimating t_L, R_r, R_s, and γ_T parameters.

This study organized as five sections, the detailed literature analysis is given in section I. The ninth-order IM model development is presented in Sections II. EKF algorithm with the effect of **H** matrix extension is detailed in Sections III. Section IV presents the simulation studies of the proposed EKF based IM drive. Lastly, section V clarifies the results of the paper.

2 Development of the Extended IM Model

So as to perform simultaneous estimation of overall nine states and parameters ($i_{s\alpha}$, $i_{s\beta}$ $\varphi_{r\alpha}$, $\varphi_{r\beta}$, ω_m, t_L, R_r, R_s, and γ_T), the rotor flux based dynamic IM model is extended. From this point of view, with the assumption of slow changes in t_L, R_r, R_s, and γ_T values against operation conditions and time [27], these values are determined as additional constant states in the IM model. The steady state representation of the rotor flux based ninth-order dynamic model of the IM is given in (1) and (2) in continuous form.

$$\begin{aligned}\dot{\mathbf{x}}_\mathbf{t} &= \mathbf{f}(\mathbf{x}_\mathbf{t}, \mathbf{u}_\mathbf{t}) + \mathbf{w}\\ \dot{\mathbf{x}}_\mathbf{t} &= \mathbf{A}(\mathbf{x}_\mathbf{t})\mathbf{x}_\mathbf{t} + \mathbf{B}\mathbf{u}_\mathbf{t} + \mathbf{w}\end{aligned} \tag{1}$$

$$\begin{aligned}\mathbf{z}_t &= \mathbf{h}(\mathbf{x}_\mathbf{t}) + \mathbf{v}\\ \mathbf{z}_t &= \mathbf{H}\mathbf{x}_\mathbf{t} + \mathbf{v}\end{aligned} \tag{2}$$

Here, the nonlinear state and input function is represented by $\mathbf{f}$ while the output function is referred by $\mathbf{h}$. $\mathbf{A}$ and $\mathbf{B}$ extended system and control input matrix, respectively. The measurement matrix extended by measured ω_m in this paper as in [1], [27] is represented by $\mathbf{H}$. $\mathbf{x}$, $\mathbf{z}$, and $\mathbf{u}$ are the extended state, measurement, and control input vectors, respectively. the measurement and process noises are referred by $\mathbf{v}$ and $\mathbf{w}$, respectively. The details of ninth-order rotor flux based IM model whose general form is presented in (1) and (2) can be given as follows:

$$\mathbf{x}_t = [i_{s\alpha} \quad i_{s\beta} \quad \varphi_{r\alpha} \quad \varphi_{r\beta} \quad \omega_m \quad t_L \quad R_r \quad R_s \quad \gamma_T]^T$$

$$\mathbf{u}_t = [u_{s\alpha} \quad u_{s\beta}]^T \qquad \mathbf{h}(\mathbf{x}_t) = [i_{s\alpha} \quad i_{s\beta} \quad \omega_m]^T$$

$$\mathbf{H} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$\mathbf{f}(\mathbf{x}_t, \mathbf{u}_t) = \underbrace{\begin{bmatrix} -\left(\frac{R_s}{L_\sigma} + \frac{R_r L_m^2}{L_\sigma L_r^2}\right) i_{s\alpha} + \frac{R_r L_m}{L_\sigma L_r^2}\varphi_{r\alpha} + \frac{L_m p_p}{L_\sigma L_r}\omega_m \varphi_{r\beta} + \frac{u_{s\alpha}}{L_\sigma} \\ -\left(\frac{R_s}{L_\sigma} + \frac{R_r L_m^2}{L_\sigma L_r^2}\right) i_{s\beta} - \frac{L_m p_p}{L_\sigma L_r}\omega_m \varphi_{r\alpha} + \frac{R_r L_m}{L_\sigma L_r^2}\varphi_{r\beta} + \frac{u_{s\beta}}{L_\sigma} \\ \frac{R_r L_m}{L_r} i_{s\alpha} - \frac{R_r}{L_r}\varphi_{r\alpha} - p_p \omega_m \varphi_{r\beta} \\ \frac{R_r L_m}{L_r} i_{s\beta} + p_p \omega_m \varphi_{r\alpha} - \frac{R_r}{L_r}\varphi_{r\beta} \\ \frac{3 p_p L_m \gamma_T}{2 L_r}\left(\varphi_{r\alpha} i_{s\beta} - \varphi_{r\beta} i_{s\alpha}\right) - t_L \gamma_T \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}}_{\mathbf{A}(\mathbf{x}_t)\mathbf{x}_t + \mathbf{B}\mathbf{u}_t}$$

where, L_s is the stator inductance; $L_\sigma = L_s - L_m^2/L_r$ represents stator transient inductance; L_r is the rotor inductance; $u_{s\alpha}$ and $u_{s\beta}$ represent the $\alpha\beta-$ components of stator voltages, respectively; p_p is the number of pole pairs. It should be emphasized that the viscous friction term is not included in the presented IM model, which means that it is counted in the estimated t_L. Here, the steady state form of the IM model presented in (1) and (2) is discretized by the use of the first-order forward Euler approximation presented in (3), and the obtained discretized model of the IM can be given as in (4) and (5).

$$\dot{\mathbf{x}}_t \approx \frac{\mathbf{x}_{k+1} - \mathbf{x}_k}{T} \tag{3}$$

$$\begin{gathered} \mathbf{x}_{k+1} = \boldsymbol{T} \times \mathbf{f}(\mathbf{x}_k, \mathbf{u}_k) + \mathbf{I}_{9\times 9} \times \mathbf{x}_k + \mathbf{w} \\ \mathbf{x}_{k+1} = \mathbf{A}(\mathbf{x}_k)\mathbf{x}_k + \mathbf{B}\mathbf{u}_k + \mathbf{w} \end{gathered} \tag{4}$$

$$\begin{gathered} \mathbf{z}_k = \mathbf{h}(\mathbf{x}_k) + \mathbf{v} \\ \mathbf{z}_k = \mathbf{H}\mathbf{x}_k + \mathbf{v} \end{gathered} \tag{5}$$

Here, $\mathbf{I}$ is the identity matrix. The EKF algorithm proposed in this paper is constituted by using the discretized IM model in (4) and (5) in the EKF algorithm presented below.

3 The EKF Observer

In this paper, in order to estimate $i_{s\alpha}$, $i_{s\beta}$ $\varphi_{r\alpha}$, $\varphi_{r\beta}$, ω_m, t_L, R_r, R_s, and γ_T in a single EKF without any hybrid approach or switching operation, the $\mathbf{H}$ matrix is extended by the measured ω_m, which means that ω_m is both measured and the estimated by the proposed EKF just as $i_{s\alpha}$ and $i_{s\beta}$ as in [1], [27]. Instead of direct usage of the measured ω_m in EKF, this extension enables using of the speed error, the difference between the measured and priori estimated speed, along with the current errors to obtain posterior values of the estimations in the measurement update step of the standard EKF. Moreover, due to the definition of ω_m in the IM model as a state thanks to the equation of motion, the dynamic performance increase is provided thanks to the estimation of t_L and γ_T as in [1], [27]. Due to the fact that t_L estimation is performed in this paper, it can be used to obtain enhanced torque response as in [28]. With the advantages of $\mathbf{H}$ matrix extension and the use of the equation of motion, the standard EKF algorithm presented in (6) and (11) is used to perform simultaneous estimation of the total nine states and parameters.

$$\mathbf{F}_{k|k-1} = \left.\frac{\partial \mathbf{f}(\mathbf{x}, \mathbf{u}_k)}{\partial \mathbf{x}}\right|_{\mathbf{x}=\hat{\mathbf{x}}_{k-1}} \tag{6}$$

$$\hat{\mathbf{x}}_{\mathbf{k}}^- = \mathbf{f}(\hat{\mathbf{x}}_{\mathbf{k-1}}, \mathbf{u}_{\mathbf{k}}) \tag{7}$$

$$\mathbf{P}_{\mathbf{k}}^- = \mathbf{F}_{\mathbf{k|k-1}}\mathbf{P}_{\mathbf{k-1}}\mathbf{F}_{\mathbf{k|k-1}}^{\mathbf{T}} + \mathbf{Q} \tag{8}$$

$$\mathbf{K}_{\mathbf{k}} = \mathbf{P}_{\mathbf{k}}^- \mathbf{H}^{\mathbf{T}}[\mathbf{H}\mathbf{P}_{\mathbf{k}}^- \mathbf{H}^{\mathbf{T}} + \mathbf{R}]^{-1} \tag{9}$$

$$\hat{\mathbf{x}}_{\mathbf{k}} = \hat{\mathbf{x}}_{\mathbf{k}}^- + \mathbf{K}_{\mathbf{k}}(\mathbf{z}_{\mathbf{k}} - \mathbf{H}\hat{\mathbf{x}}_{\mathbf{k}}^-) \tag{10}$$

$$\mathbf{P}_{\mathbf{k}} = (\mathbf{I} - \mathbf{K}_{\mathbf{k}}\mathbf{H})\mathbf{P}_{\mathbf{k}}^- \tag{11}$$

Here, $\mathbf{F}$ is the function that is used in the linearization of the nonlinear IM model. $\mathbf{P}_{\mathbf{k}}^-$ and $\mathbf{P}_{\mathbf{k}}$ are the priori and the posteriori estimation error covariance matrices. $\hat{\mathbf{x}}_{\mathbf{k}}^-$ and $\hat{\mathbf{x}}_{\mathbf{k}}$ are the priori and the posteriori estimations of the state vector, respectively. $\mathbf{K}$ is the Kalman gain which is used to correct and update the outputs of the estimation stage. $\mathbf{R}$ and $\mathbf{Q}$ are the covariance matrices for the measurement and process noises. $\mathbf{I}$ is the Identity matrix.

4 Simulations Studies

In simulation studies, the proposed EKF algorithm, simultaneously estimating $i_{s\alpha}$, $i_{s\beta}$ $\varphi_{r\alpha}$, $\varphi_{r\beta}$, ω_m, t_L, R_r, R_s, and γ_T in a single EKF, and the proposed drive are verified under the challenging scenarios. Furthermore, the estimation performance comparison of the proposed ninth order observer and a sixth order observer proposed in [24] is performed. While the proposed ninth order observer utilizes the $\mathbf{H}$ extension to perform estimations of nine states and parameters, the sixth order observer proposed in [24] directly uses the measured ω_m to realize online estimations of $i_{s\alpha}$, $i_{s\beta}$ $\varphi_{r\alpha}$, $\varphi_{r\beta}$, R_r, and R_s. To perform simulations, the proposed DVC based IM drive demonstrated in Figure 1 is implemented and realized in Matlab/Simulink. Therefore, by using the DVC based IM drive, the close loop comparison of the proposed ninth order and the sixth order observers are carried out. In Figure 1, the required phase angle $\hat{\theta}_{rf}$ and the magnitude of the rotor flux is obtained by the use of estimated rotor flux components. Moreover, trial and error method based tuned conventional PI controllers are used in the drive system presented in Figure 1. Table I presents the rated parameter values of the IM used in Figure 1, which are the same as in previous studies to make an easy comparison with the previous ones. As it can be seen directly in Figure 1, the estimations of t_L, R_r, R_s, and γ_T are only realized to eliminate the performance deteriorations of the proposed EKF algorithm and thus the drive system.

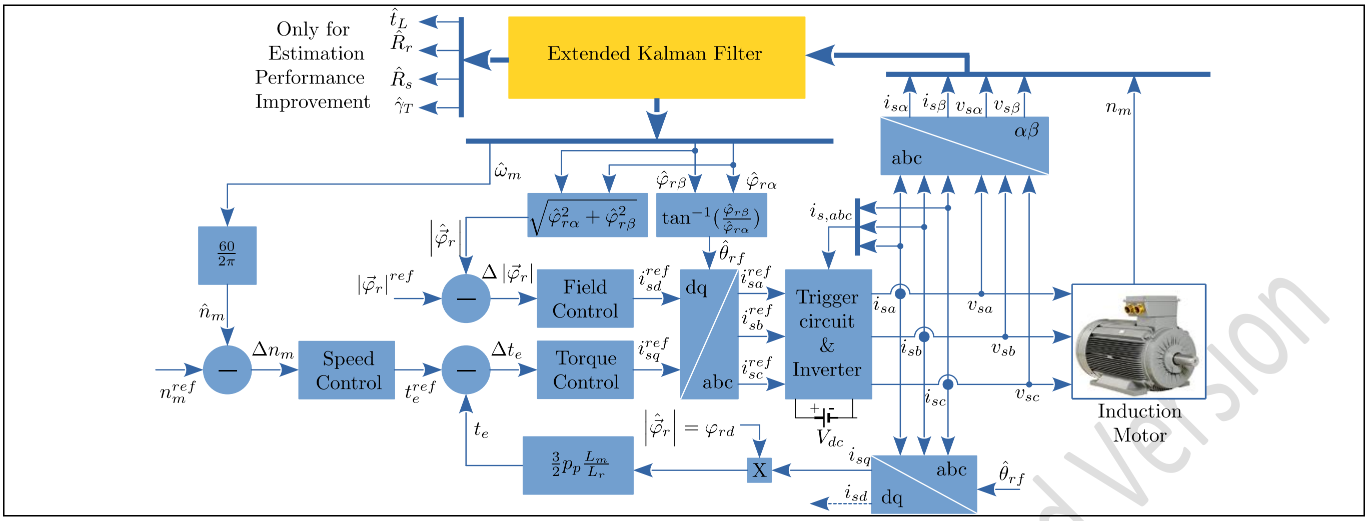

Figure 1. The proposed DVC based drive.

In order to verify both estimation accuracy of the proposed EKF based observer and the robustness of the proposed IM drive, they are verified under a comprehensive scenario, which is specially designed to show their capability against varying parameters as seen in Figure 2. In order to make a fair comparison, the six order observer is also tested under same scenario given in Figure 2. Whole details of the designed comprehensive scenario are given below.

- This scenario includes the wide speed range operation of the IM, which can be summarized as rated speed at clockwise and counterclockwise directions (1500 r/min and -1500 r/min), low speed (-100 r/min), and the continuously zero-speed operation.
- t_L applied to the IM is changed to its rated value (20 Nm), half of its rated value (10 Nm), and unloaded condition (0 Nm) by step-like and linear variations.
- R_r and R_s values of the IM are doubled (4.266 and 4.566 respectively) and decreased to their nominal values in the different operating conditions of the IM.
- γ_T value is changed to its halved value (27.3 1/kg.m^2) and increased to rated one in different speed regions.
- So as to make estimations more difficult, the initial conditions for estimations are chosen as zero, and the DC condition is included in the different parts of the scenario.

Table 1. IM parameters

$P(kW)$	$f(Hz)$	$V(V)$	$I(A)$
2	50	380	6.9
R_s (Ω)	R_r (Ω)	L_s (H)	L_r (H)
2.283	2.133	0.2311	0.2311
L_m (H)	n_m (rpm)	T_L (Nm)	p_p
0.22	1430	20	2
$J_L(kg\ m^2)$		$B_L(Nm/(rad/s))$	
0.0183		0.001	

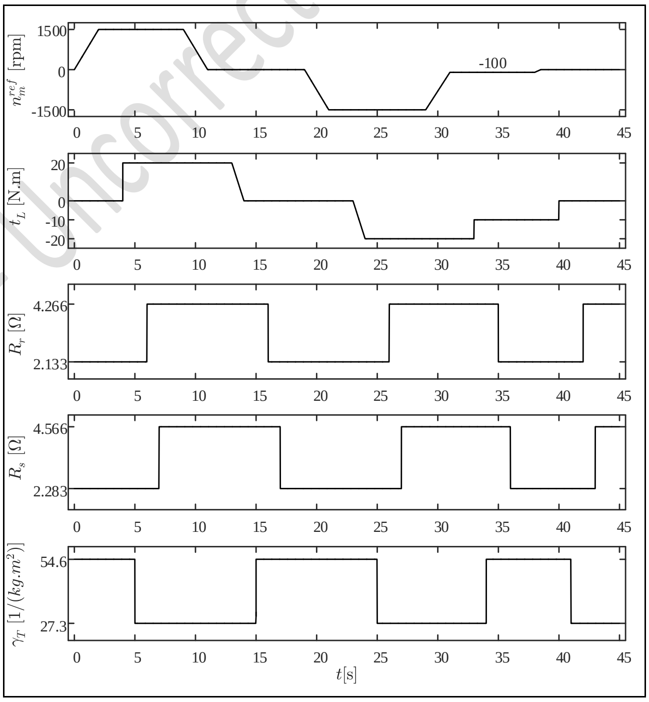

Figure 2. n_m^{ref} variation and applied t_L, R_r, R_s, and γ_T for DVC based IM system.

The applied IM values and reference signals for the IM drive to obtain this detailed comprehensive scenario are presented in Figure 2. Here, "$.^{ref}$" represents the reference value applied to the drive system. Figure 3 shows the resulting estimation performances of the proposed ninth order EKF and the control performance proposed EKF based IM drive. Figure 4 indicates the estimation results of the sixth order observer proposed in [24] and control performance of sixth order observer based IM drive. Figure 5 demonstrates the resulting estimation errors for proposed observer which is obtained by calculating the difference between estimated and actual values. Figure 6 shows the corresponding estimation errors for sixth order observer. Here in Figure 3 and 4, "$\hat{.}$" represents the estimations. In Figure 5 and 6, "$e_{(.)}$" represents the estimation error between actual and estimated values. In simulations, **Q** and **R** matrices that are crucial for the EKF algorithm are chosen as diagonal, and their diagonal elements are selected by the trial and error method. Moreover, to perform a fair comparison between the proposed ninth order observer and sixth order observer in [24], the elements of $\mathbf{Q}$ and $\mathbf{R}$ matrices are used as the same in both observers for corresponding states.

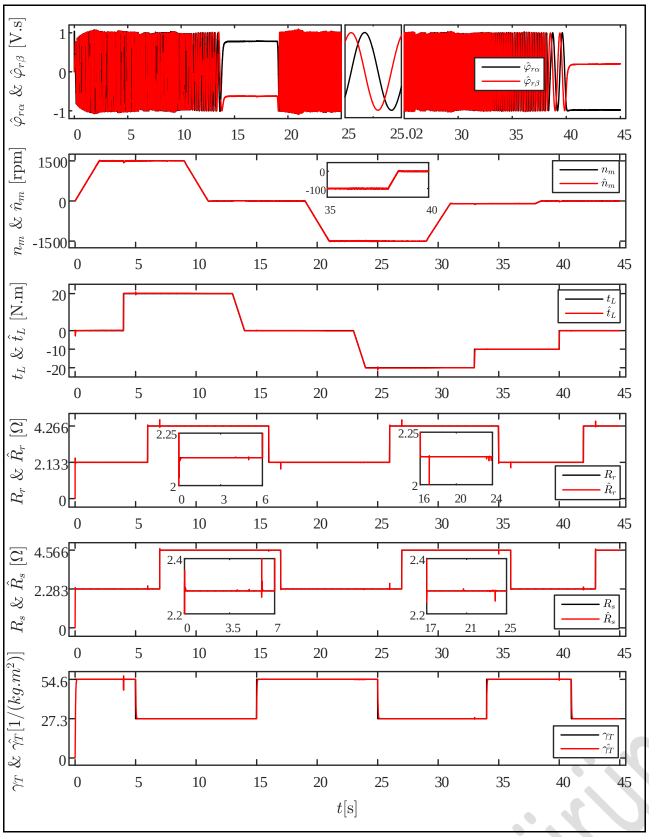

Figure 3. The tracking performance of the proposed drive and the proposed ninth order EKF estimations.

The resulting selected noise covariance matrices for the proposed ninth order EKF observer are given below.

$$\mathbf{P}^{\text{Proposed EKF}} = \text{diag}\{10 \quad 10 \quad 10 \quad 10 \quad 10 \quad 10 \quad 10 \quad 10 \quad 10\}$$

$$\mathbf{Q}^{\text{Proposed EKF}} = \text{diag}\{10^{-10} \quad 10^{-10} \quad 10^{-12} \quad 10^{-12} \quad 10^{-5} \quad 10^{-4} \quad 10^{-5} \quad 10^{-5} \; 5\text{x}10^{-4}\}$$

$$\mathbf{R}^{\text{Proposed EKF}} = \text{diag}\{10^{-6} \quad 10^{-6} \quad 10^{-6}\}$$

The corresponding noise covariance matrices used in the sixth order observer are as follows:

$$\mathbf{P}^{\text{6th order EKF}} = \text{diag}\{10 \quad 10 \quad 10 \quad 10 \quad 10 \quad 10\}$$

$$\mathbf{Q}^{\text{6th order EKF}} = \text{diag}\{10^{-10} \quad 10^{-10} \quad 10^{-12} \quad 10^{-12} \quad 10^{-5} \quad 10^{-5}\}$$

$$\mathbf{R}^{\text{6th order EKF}} = \text{diag}\{10^{-6} \quad 10^{-6}\}$$

The mean square error (MSE) values for R_r and R_s estimations of both the proposed ninth order observer and sixth order observer are presented in Table 2. Here, R_r and R_s parameters are the only parameters that are estimated by both observers, which is the main reason why the corresponding MSE values are presented for only R_r and R_s parameters.

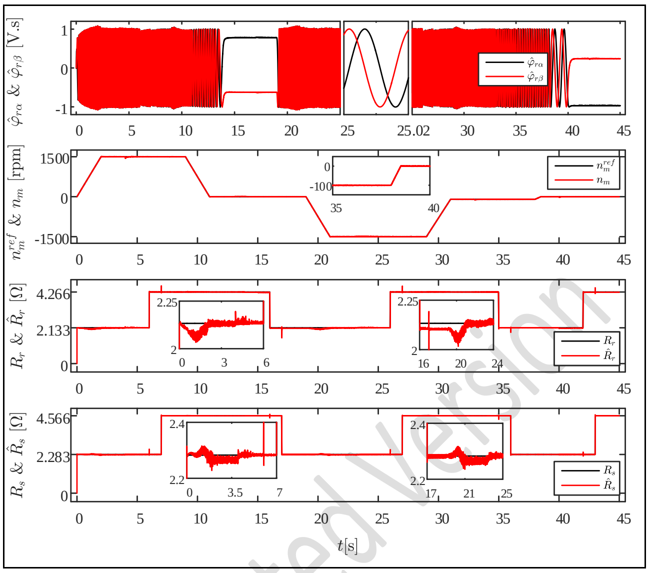

Figure 4. The sixth order EKF estimations and tracking performance of the sixth order EKF based drive.

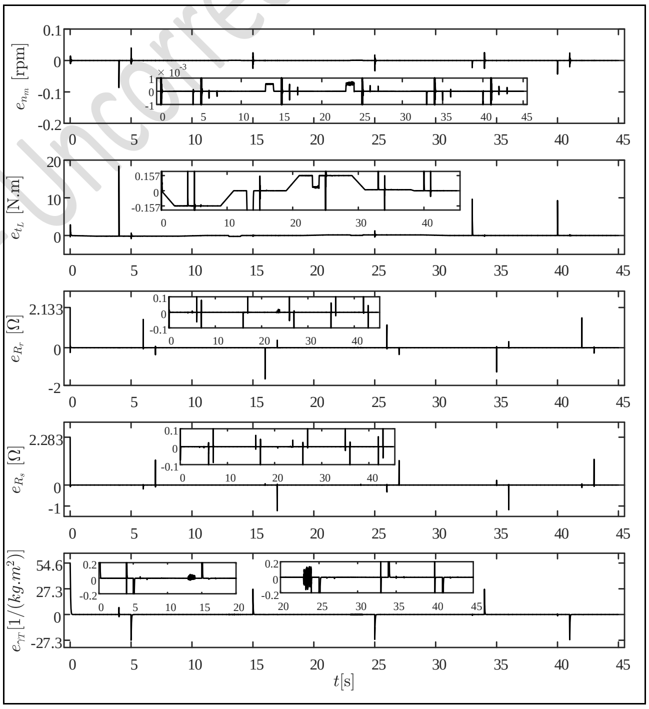

Figure 5. Resulting estimation errors for proposed ninth order observer.

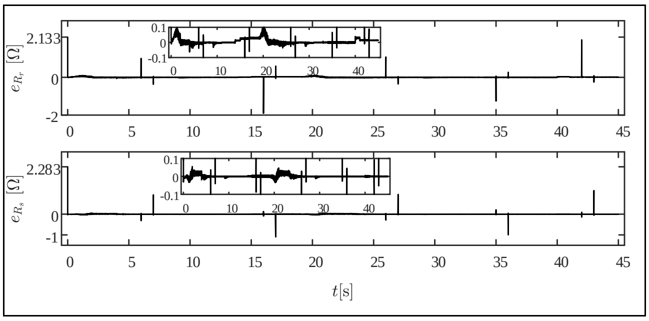

Figure 6. Estimation errors for sixth order observer.

Table 2. MSE values related to estimations

Figure 5		Figure 6	
$e_{R_r}(\Omega)$	$e_{R_s}(\Omega)$	$e_{R_r}(\Omega)$	$e_{R_s}(\Omega)$
$4.44\text{x}10^{-5}$	$1.65\text{x}10^{-5}$	$8.13\text{x}10^{-4}$	$1.60\text{x}10^{-4}$

As to the estimation results of the proposed EKF, the effectiveness of the proposed IM drive, and comparison studies given in Figures 3-6, it can be convenient to deduce the following remarks:

- While all initial conditions are zero, the estimations of the proposed EKF observer converge to their actual values in a swift manner. In the obtained results, the transient state is nearly completed for $\hat{R}_r$, $\hat{R}_s$, and $\hat{\gamma}_T$ values in $0.2\ s$ ($e_{R_r} = 7.19\text{x}10^{-4}$ [Ω]), $0.15\ s$ ($e_{R_s} = -7.13\text{x}10^{-4}$ [Ω]), and $0.3\ s$ ($e_{\gamma_T} = 8.62\text{x}10^{-4}$ [$1/(kg.m^2)$]), respectively. Furthermore, it is clear that the proposed EKF based observer can easily handle the DC condition occurring in the time interval of $14s \leq t \leq 19s$ and $40s \leq t \leq 45s$.
- The estimation accuracy and thus the control robustness of the proposed IM drive is highly impressive against this challenging scenario for all speed regions.
- Although a fair comparison, meaning test under same scenario with the same **Q** and **R** matrices elements for corresponding states, is performed between the proposed ninth order observer and sixth order observer in [24], it is clear from Table 2 and Figure 3-6 that the proposed ninth order observer has better estimation performance for both R_r and R_s, which are the estimated parameters for both observers. The proposed ninth order observer has also advantages over the sixth order observer in [24] since t_L and γ_T estimated by the proposed ninth order observer are able to improve control performances as shown in [28] and [1], respectively.
- Even if there are challenging changes in t_L, R_r, R_s, and γ_T parameters, the proposed EKF still presents magnificent estimation performance with instantaneous small peaks, which are caused by the transients at momentary parameter changes.
- Although the trial and error method is chosen in the determination of the **R** and **Q** matrices, highly promising estimation results for proposed EKF and robust control performance for proposed IM drive is obtained against the changes in t_L, R_r, R_s, and γ_T.
- In Figure 5, it is clear that there is a DC bias in e_{t_L}. However, as it is stated in Section II, the viscous friction term is estimated in t_L in the proposed EKF observer. Hence, the DC bias in e_{t_L} represents the viscous friction term. It can be proven as follows:

$$e_{t_L} \cong -\beta_T \omega_m(\infty) \tag{12}$$

$$-0.157 \cong -0.001\text{x}\frac{1500 \text{ x } 2 \text{ x } \pi}{60} \tag{13}$$

$$-0.157 \cong -0.15707 \tag{14}$$

Overall, these simulation results for proposed observer show how effectively all these states and parameters, which are also estimated in [23] by using bi-input EKF resulting in IM model switching requiring for an extra difficulty in determining the values of the additional **R** and **Q** matrices, are estimated in a single EKF without using a hybrid structure or a switching operation.

5 Conclusion

In this study, a DVC based IM drive, which contains an EKF algorithm estimating $i_{s\alpha}$, $i_{s\beta}$ $\varphi_{r\alpha}$, $\varphi_{r\beta}$, ω_m, t_L, R_r, R_s, and γ_T, is proposed. So as to verify the proposed IM drive in simulation, a comprehensive and challenging scenario is designed. The estimation performance of the proposed ninth order observer is compared with that of a sixth order EKF, proposed in [24], using directly measured ω_m. Thanks to the extension made in the **H** matrix and the use of the equation of motion in the IM model, the proposed EKF algorithm can easily estimate overall nine states and parameters. The obtained results demonstrate the impressive estimation accuracy of the proposed ninth order EKF and the highly satisfactory tracking results of the IM drive as opposed to the challenging variations in t_L, R_r, R_s, and γ_T as well as the speed reference and show superior performance over the sixth order EKF, proposed in [24]. Another striking point of the study is that the estimation of all nine states and parameters are performed in a single EKF observer without using a hybrid structure or a switching operation, it reveals the superiority of this study over the previous one that estimates the same parameters and states. Thus the simulations prove that the proposed IM drive is reliable in order to solve the high performance control problem by updating parameter variations in the proposed EKF. As a future study, to increase the robustness of the proposed EKF based observer in the field-weakening region, inductance values in IM model can be estimated and thus updated in both the observer and control system.

6 Author contribution statements

Authors 1 and 2 proposed the idea of the observer algorithm. Authors 1 and 3 reviewed the current literature. Author 1 designed and tested the observer in simulations. All authors prepared the manuscript together by analyzing and interpreting the simulation results of the observer.

7 Ethics committee approval and conflict of interest statement

There is no need to obtain an ethics committee approval for the article prepared.

There is no conflict of interest with any person / institution in the article prepared.

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