Improving the speed estimation by load torque estimation in induction motor drives: an MRAS and NUIO approach

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***Abstract*— This paper proposes the application of the NUIO inside a FOC induction motor drive for the simultaneous estimation of the load torque and the rotor speed. The idea is to estimate at first the speed with the current model in parallel with a reference model developed on the basis of the voltage model of the induction machine. Then, the estimated speed is given as input to a nonlinear unknown input observer (NUIO) to estimate the load torque. This estimation is then used to correct the previous estimation of the speed. Simulation and experimental results confirm the goodness of the method for an extended range of speed and different load torque, and they confirm the reduction of error in transient and steady state with respect to a simple MRAS scheme without NUIO.**

Keywords—Observers, FPGA, AC electrical drives, Induction Motor, disturbance rejection.

I. INTRODUCTION

Sensorless techniques in AC motor drives are, of course, a prominent area of research over 30 years now and there is a huge literature[1]-[3]. In these approaches, one of the main goals of the control system is their improvement in performance; with this regard, tuning the control algorithm is not very complicated, but it heavily depends on the analytical model of the system, including the power converter structure[4]-[6]. Indeed, as pointed out in [7] and [11], high performance, both in terms of speed accuracy and load torque compensation, needs the estimation of the load torque, since it cannot be easily measured or predicted. As a matter of fact, one of the major external disturbances that have an impact on the performance of the motor is the load acting on the shaft. In this case, any perturbation on the speed is reflected on the back emf with resulting variations of the stator current and perturbation on the control action. Indeed, the capability of rejection of control strategies to load disturbances to the motor shaft has been addressed in the literature, especially in induction motor drives.

One effective idea to make the system more robust to load disturbances is to try to predict them so as to obtain better rejection capabilities, with resulting improved performance through proper dynamical compensation. This problem, in the case of induction motor drives, has been addressed in [7], where the load torque is estimated by using the mechanical equation, but considering a load torque with slow dynamics. This approach has also been followed in other subsequent works [8].

The literature presents some ways of estimating the load torque in the case of induction motor drives. For instance, [12] addresses it by using the mechanical equation, but only when considering a load torque signal with slow dynamics; moreover, this same approach is present in other papers[13],[14]. Another strategy is to use a Kalman Filter or an Unscented Kalman Filter (KF) [15],[16], which however require assumptions about the dynamical behavior of the load torque, with resulting increase of the computational burden.

Recently, a new technique in control systems has been developed to reconstruct unknown inputs, based on the theory of Unknown Input Observers (UIO), which can overcome the limitations above [17]-[21]. Traditional disturbance estimation approaches, based on Extended Kalman Filters (EKF), suffer from known disadvantages due to the necessity to calibrate noise covariance matrices and introduce additional states, whose dynamics can only be based on the generic random walk. Beyond the fact that a convergence proof in the general scenario cannot be found, they result in over-delayed estimation or, even worse, divergent estimation behaviors (see e.g. the discussion in [22]. Furthermore, it has already been widely shown in the literature for some decades [23]-[28], that even under comparable settings, EKFs and their variations perform less or at most as much as UIO filters, which appear to have a general superior behaviour in estimating states and unknown disturbance inputs.

This paper is in the framework of speed estimation of induction motor (IM) drives based on flux and speed observers, in particular as an extension of the MRAS technique [7]. Its target is to use the speed estimation obtained with the adaptive current model of the IM and to combine it for the reconstruction of the load torque reconstructed by a Nonlinear UIO (NUIO). The estimated load torque is then used in the mechanical equation of the motor to enhance the estimated speed. Among other advantages, the solution presented here requires no a-priori information about the dynamic properties of the load disturbance signal, such as frequency content, boundedness, etc., and it avoids introducing additional variables to model uncertainty and tuning extra observer parameters.

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II. THE PROPOSED COMBINED ESTIMATOR (MRAS+UIO)

The difficulty in estimating simultaneously the rotor speed and load torque of an electrical drive system arises in the way these two quantities are dynamically coupled via the mechanical equation $\tau_e - \tau_L = J\, d\omega_m/dt$. On the one side, even if the electromechanical torque and the rotor speed were known, it would be not a practical solution to obtain the load torque by numerically differentiating the speed, since the so obtained acceleration approximation would be subject to many noise errors. On the other side, if the electromechanical torque and load torque were known, a simple numerical integration of the mechanical equation would lead to a speed estimation that is subject to drift, due to numerical integration errors, initial condition mismatch, and noise. For these reasons, achieving accurate and simultaneous estimation of rotor speed and load torque requires approaches combining together the two sources of information.

A possible way to achieve such an objective is through a nonlinear input-observer, that reconstructs load torque based on rotor speed information received from a neural network-based MRAS estimator [7], and an adaptive integrator [29] using the estimated load torque and computed electromechanical torque values, in order to dynamically refine the rotor speed estimate initially obtained.

The adopted input-state observer, so-called NUIO, derives from [19], [20]: it is a special observer that is capable of estimating the states of the system, also when the system has unknown inputs. Indeed, once the present values of the state variable have been reconstructed, the observer can also estimate the unknown inputs, with a small delay depending on the model adopted. In the following, the NUIO proposed in [19] is considered and adapted to the case of the considered Induction Motor (IM). Given a nonlinear system described by the equations, equations,

$$\begin{cases} \dot{\boldsymbol{x}}(t) = A\boldsymbol{x}(t) + \boldsymbol{f}(\boldsymbol{x}(t)) + G\boldsymbol{u}(t) + D\,\boldsymbol{v}(t) \\ \boldsymbol{y}(t) = C\boldsymbol{x}(t) \end{cases} \tag{1}$$

where $\boldsymbol{x} \in R^n$ is the state vector, $\boldsymbol{u} \in R^{\mathrm{m}}$ is a known input vector, $\boldsymbol{v} \in R^{\mathrm{d}}$ tis he unknown input vector, $\boldsymbol{y} \in R^{\mathrm{p}}$ is the measured output vector, $A \in \mathbb{R}^{nxn}$ is a dynamic matrix, and $\boldsymbol{f}(\boldsymbol{x}(t)) \in R^n$ is a nonlinear vector field, a dynamic input and state observer in the form below can be developed

$$\dot{z}(\mathrm{t}) = Nz(t) + Ly(t) + MGu(t) + Mf(\hat{x}) \tag{2}$$

where $z(t)$ is an internal vector variable of the observer, and $\hat{x}(t) = z(t) - Ey(t)$ is its output, also representing the estimated system state, and the matrices M, N and L are to be chosen so that:

$$M = I_n + EC,\; N = MA - KC,\; L = K(I_p + CE) - MAE \tag{3}$$

which are computed by considering the model of an IM. Moreover, the measured outputs are the direct and quadrature stator currents in the stationary reference frame. More precisely, the following matrices can be obtained:

$$\boldsymbol{x} = \begin{bmatrix} i_{sd} \\ i_{sq} \\ \lambda_{rd} \\ \lambda_{rq} \\ \omega \end{bmatrix} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix}, A = \begin{bmatrix} a_{11} & 0 & \frac{a_{12}}{T_r} & 0 & 0 \\ 0 & a_{11} & 0 & \frac{a_{12}}{T_r} & 0 \\ a_{21} & 0 & \frac{a_{22}}{T_r} & 0 & 0 \\ 0 & a_{21} & 0 & \frac{a_{22}}{T_r} & 0 \\ 0 & 0 & 0 & 0 & \delta_1 \end{bmatrix}, \tag{4}$$

$$G = \begin{bmatrix} b & 0 \\ 0 & b \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}, D = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ \delta \end{bmatrix}, \boldsymbol{f}(\boldsymbol{x}) = \begin{bmatrix} a_{12}\, x_4 x_5 \\ a_{12}\, x_3 x_5 \\ a_{22}\, x_4 x_5 \\ a_{22}\, x_3 x_5 \\ \gamma(x_3 x_2 - x_4 x_1) \end{bmatrix}$$

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix}$$

where $a_{11} = -\left\{\frac{R_S}{\sigma L_S} + \frac{(1-\sigma)}{\sigma T_r}\right\}$,
$a_{12} = \frac{L_m}{\sigma L_S L_r}$, $a_{21} = \left\{\frac{L_m}{T_r}\right\}$, $a_{22} = -1$ and $b = \frac{1}{\sigma L_S}$,
$\delta_1 = -\frac{B}{J}, \gamma = \frac{3}{2} p \frac{L_m}{L_r J}, \delta = -\frac{1}{J}$.

The target here is to estimate simultaneously the states of the fluxes λ_{rd} and λ_{rq} the stationary reference frame and, afterwards, the unknown load torque τ_l. By following [14] the following formula can be retrieved for the estimation of the unknown input, after discretization:

$$\hat{\tau}_l^{(u)}(k) = \boldsymbol{v}(\mathrm{k}) = [D^T D]^{-1} D^T\, [\hat{x}(k+1) - A_d \hat{x}(k) - f(\hat{x}(k)) - Gu(k))]\,. \tag{5}$$

The estimated load torque has been introduced in a classical MRAS scheme for the estimation of the rotor speed, as the one described in [7], which makes use of a neural estimator of the speed instead of a PI. Any integration in the scheme is made by using the adaptive integration method in [29] to avoid the drift and initial condition mismatch. An adaptive algorithm [30] for the estimation of the stator resistance is also included. A refined estimate of the rotor speed is finally achieved by using the following Luenberger-like estimator:

$$\widehat{\omega}^{(u)}(k+1) = -\left(D/_J + L\right)\widehat{\omega}^{(u)}(k) + T_s\left(\tau - \hat{\tau}_l^{(u)}\right)L\,\widehat{\omega}^{(m)}(k)\,, \tag{6}$$

where $\widehat{\omega}^{(m)}$ is the rotor speed estimated by the MRAS, $\hat{\tau}_{\mathrm{l}}^{(\mathrm{u})}$ is the load torque estimated by the NUIO, and finally $\widehat{\omega}^{(u)}$ is the refined rotor speed. The proposed algorithm is shown in Fig. 1.

III. SIMULATION RESULTS

The algorithm was tested in simulation by using MATLAB/Simulink software, with the model of a real 4-pole IM of 2.2 kW, rated voltage of 415 V, and rated speed of 1500 rpm. The parameters of the machine are listed in Table 1. A load torque has been simulated which in reality will be obtained by an electrical drive of a twin motor commanded in torque within a FOC strategy.

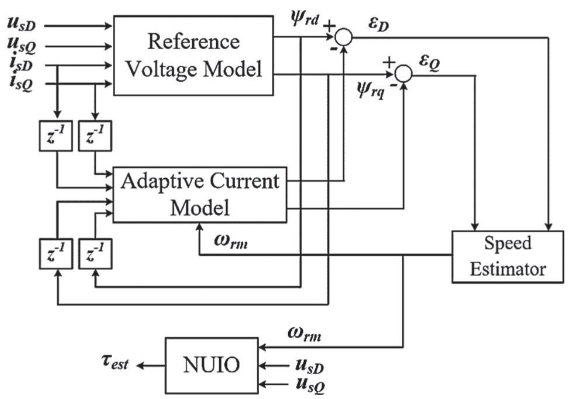

Fig. 1. Block scheme of the proposed approach

Referring to Fig 1, the commanded rotor speed is a stepwise signal (starting from 0 rad/s, it immediately goes to 100 rad/s, then to 200 rad/s at 1.5 s and finally to 150 rad/s at 4 s. The simulated applied load torque, which has to be reconstructed, is also a stepwise signal, going from 0 Nm to 3 Nm at 0.2 s and finally to 2 Nm at 2.5 s. Figs. 2, 3 and 4 shows that the proposed combined estimator is capable of reconstructing both the load torque and rotor speed. As described in Sec. 2, first the rotor speed is estimated via the neural network based MRAS shown in Fig.4, which is fed back to the NUIO, allowing it to obtain also an estimate of the load torque shown in Fig.3; finally, the difference between the electromechanical torque, computed by using the model, and the load torque, estimated by the NUIO, is used in the Luenberger-like rotor speed estimator of Eq. 6 shown in Fig. 4. As it can be observed in the figure, the refined rotor speed is less subject to chattering and indeed is much smoother than the original MRAS signal. As expected, the approach can successfully determine the current load torque and achieve higher estimation accuracy of the rotor speed.

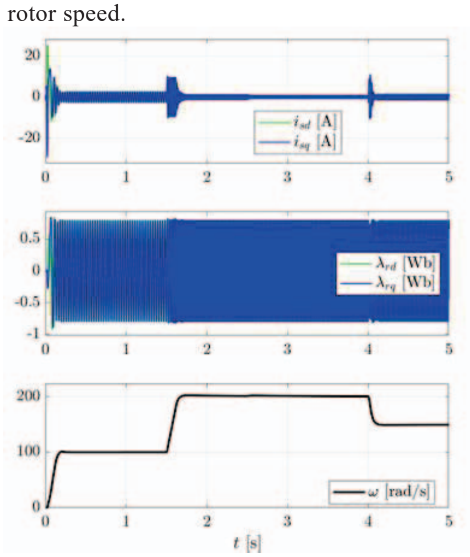

Fig. 2. Direct and Quadrature axis currents

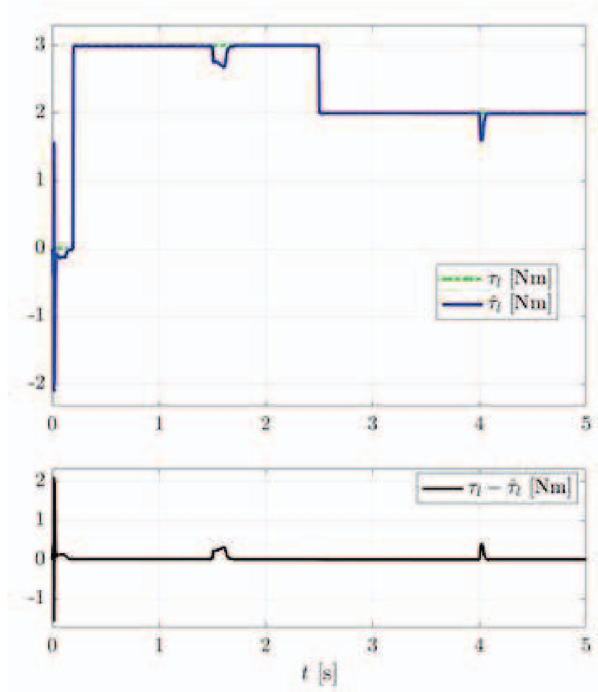

Fig. 3. Load torque estimation using NUIO

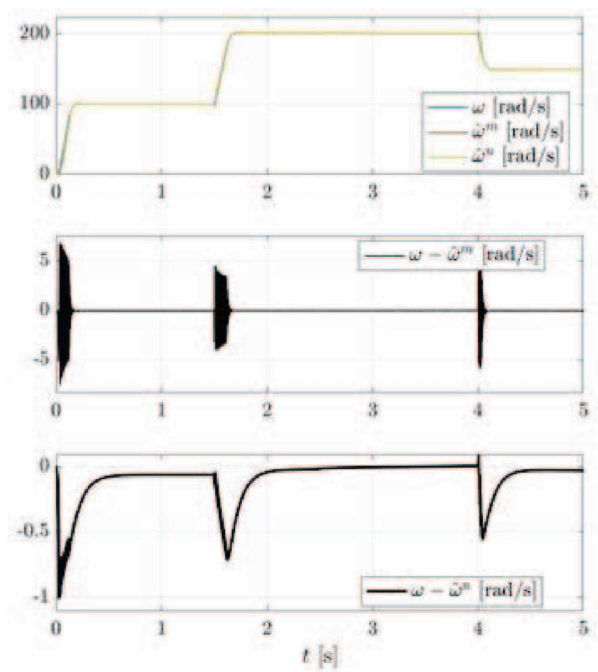

Fig. 4. Rotor speed is estimated via the neural network based MRAS+UIO

TABLE I. PARAMETERS OF THE INDUCTION MOTOR

	Unit	Value
Rated Power P_{rated}	kW	2.2
Rated Voltage U_{rated}	V	220
Rated frequency f_{rated}	Hz	50
Pole pairs		2
Stator resistance R_s	Ω	3.88
Stator inductance L_s	mH	252
Rotor resistance R_r	Ω	1.87
Rotor inductance L_r	mH	252
3-phase magnetizing inductance	mH	236
Moment of inertia J	Kg m^2	0.0266

IV. Experimental Setup

An experimental rig has been suitably developed in order to assess the high performing electrical drive with induction motor. Fig. 6 shows the experimental rig and highlights its main components.

The experimental rig consists of the following components:

• Two 3 phase induction machines, each working either as a motor or a generator.

• Two 3 phase VSI (7.5kVA Semikron IGBT inverter) supplying the motors.

• Sensors: for the voltage the LEM LV 25-P/SP5; for the current the LEM LA 55-P, and for the speed a WDG 58B incremental encoder.

• Two 3 phase Variac of 20 kVA for supplying the rectifiers connected with the inverters.

• One dSPACE autobox DS1007.

Fig. 5. Experimental rig of the IM electrical drive where the combined estimator approach is applied

The schematics of the experimental rig is described in Fig. 7, which shows the feedback signals to the dSPACE autobox (via sensors) and the gate signals that are sent to the VSI switches. The VSI DC-link voltage is supplied by the 3 phase Variac that is connected to the ac-side of the rectifier. The VSI is driven by a Space Vector-PWM.

The whole control strategy of the drive has been firstly developed in Matlab-Simulink® in simulation and then interfaced with dSPACE Board channels for input and output (I/O).

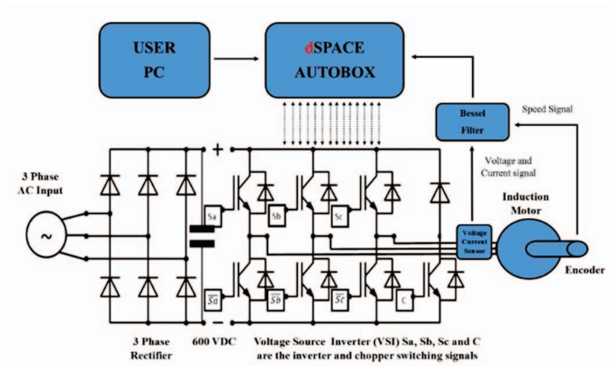

Fig. 6. *Schematics of the experimental rig*

V. Experimental Results

The algorithm proposed and developed was then tested using the experimental rig by using dSPACE Autodesk software, with the equipment's described in section IV. A load torque has been obtained by coupling two motors together and commanding one of the motors in speed and the other in torque using the FOC strategy. With the experimental results, it can be verified that using ANN-MRAS the speed can be estimated which then allows NUIO to reconstruct the torque. As seen in Fig. 7a, the motor is subject to various loads and speeds but yet with the help of UIO the response compared to the classical method is improved. Not only that but the estimation of speed using ANN-MRAS and UIO is much smother. A closer view of the transient part of Fig 7a can be inspected in Fig. 7b, 7c, 7d, 7e and 7f.

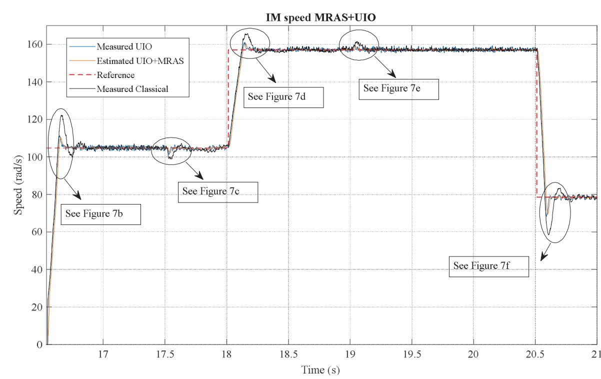

Fig. 7a *Measured and Estimated Motor Speed using Classical, UIO and MRAS + UIO at various loads and speeds*

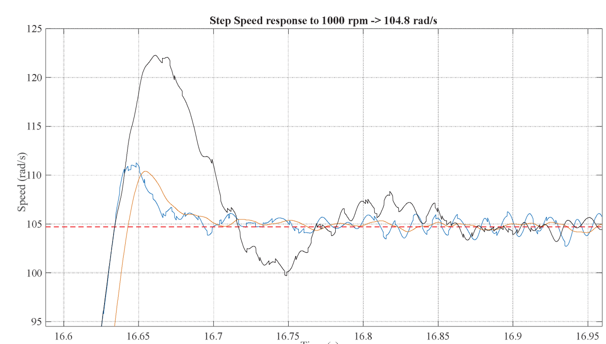

Fig. 7b *IM Rresponse to Classical, UIO and MRAS+UIO estimation to step speed response to 1000 rpm i.e. 104.8 rad/s*

Fig. 7b shows the response of Classical, UIO and MRAS+UIO estimation step speed response to 1000 rpm i.e. 104.8 rad/s. It can be visualized that UIO reduces the overshoot with respect to the classical PI method. It can also be seen that the estimation of speed has minimum to no jittering.

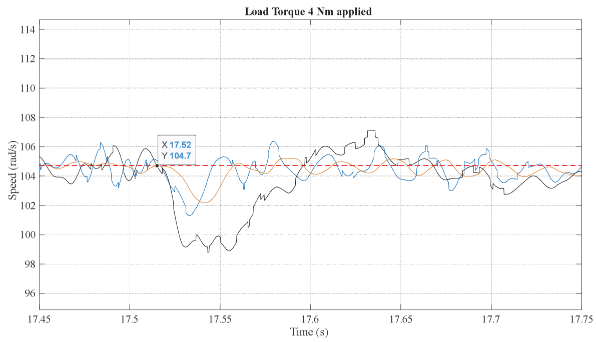

Fig. 7c *4 Nm load torque applied to the motor at 104.8 rads/s i.e. 1000 rpm.*

At time 17.45 the motor is at steady state speed of 1000 rpm then at time 17.52 a load torque of 4 Nm is applied and it can be seen that UIO is able to reject the load swiftly while the classic method is slow. On the same note, UIO+MRAS is able to perfectly reconstruct this change in speed and reject the load with less oscillation.

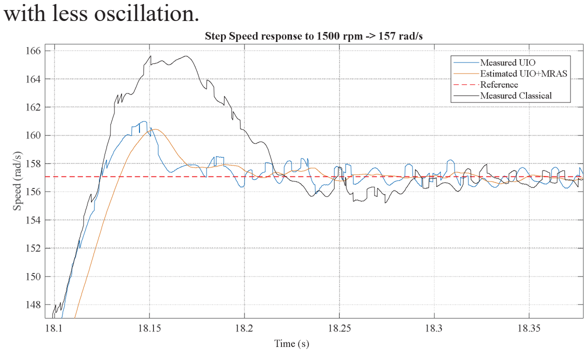

Fig. 7d *IM Rresponse to Classical, UIO and MRAS+UIO estimation to step speed response to 1500 rpm i.e. 157 rad/s*

Fig. 7d shows the response of Classical, UIO and MRAS+UIO estimation step speed response to 1500 rpm i.e. 157 rad/s. Similar to the previous step response, It can be visualized that UIO reduces the overshoot with respect to the classical PI method. It can also be seen that the estimation of speed is much smoother.

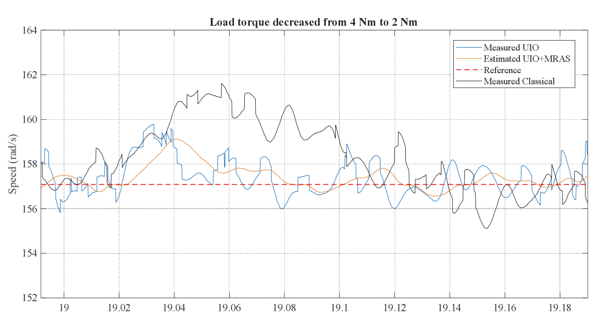

Fig. 7e *Reduction of load torque from 4 Nm to 2 Nm to the motor at 157 rads/s i.e. 1500 rpm.*

At time 19.02 of Fig. 7d the load torque of 4 Nm is reduced to 2 Nm and it can be seen again that similar to the previous results UIO is able to reject the load swiftly while the classic method is slow. On the other hand, UIO+MRAS is able to perfectly reconstruct this change in speed and reject the load with less oscillation.

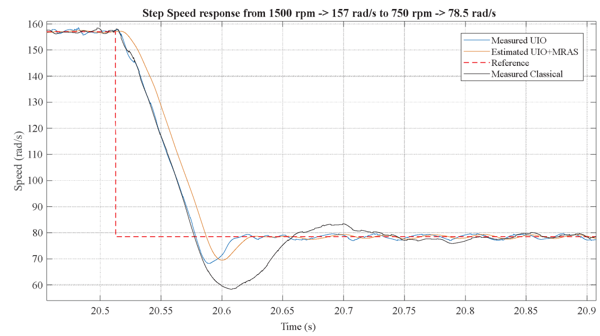

Fig. 7f *IM Rresponse to Classical, UIO and MRAS+UIO estimation to speed reduction from 1500 to 750rpm*

Fig. 7f shows the response of Classical, UIO and MRAS+UIO estimation step speed response to 1500 rpm i.e. 157 rad/s. Similar to the previous step response, it can be visualized that UIO reduces the overshoot with respect to the classical PI method. It can also be seen that the estimation of speed is much smoother.

VI. Conclusion

It can be concluded that speed estimation of induction motor drive based on flux and speed observers, in particular as an extension of the MRAS technique has been achieved and the speed estimation obtained with the adaptive model of the IM was used to reconstruct the load torque by a NUIO. Finally, the estimated load torque is used in the mechanical equation of the motor to enhance the estimated speed which has been validated by simulation and experimental results

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