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Performance analysis of a robust MF-PTC strategy for induction motor drive

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ABSTRACT

The load model-based conventional predictive torque control (PTC) strategy performs as a high-performance controller at transient and steady-state conditions. However, its performance is poor on the issue of parameters variation. A robust model-free PTC (MF-PTC) strategy has been proposed in this paper to overcome the aforementioned drawback. An auto-regressive exogenous (ARX) model instead of a load model has been used to establish a model-free controller. This model is usually formed based on their input-output transfer function. A recursive least square algorithm has been employed to estimate the unknown parameters of the ARX model. Then, an observable canonical state-space model uses those estimated parameters to achieve an accurate prediction of the control variables. The performance of the proposed scheme can be affected by the variation of resistance. A resistance estimator based on the model reference adaptive system observer has been applied to improve the robustness of the system against variation of the stator and rotor resistance, and inductance measurement uncertainty. Simulation results show that the proposed MF-PTC scheme is robust against parameters uncertainty and works well at transient and steady-state conditions.

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1. INTRODUCTION

In recent years, the model predictive control (MPC) strategy has achieved the most popularity in the application areas of power converters and motor drives, and academic research communities. As per the name of the controlled variables, this strategy may be divided into predictive torque control (PTC) [1], predictive current control (PCC) [2], predictive flux control (PFC) [3], [4], and predictive voltage control (PVC) [5]. The advantages of the control strategies are found as a simple control structure, fast dynamic response, easy implementation, and flexible inclusion of system nonlinearities and system constraints [6]. However, researchers have found some drawbacks to it, which are computational burden, non-constant switching frequency, high sampling frequency requirement, issue of parameter variation, and tuning of nontrivial weighting factors [7]. The effectiveness of the MPC scheme is highly dependent on the system modeling and parameter mismatch [8]. A model-free PCC (MF-PCC) scheme has been proposed in [9] to achieve a good steady-state performance of induction motor (IM) drive against parameter variation. Its performance is satisfactory compared to the PCC scheme, even though the used model parameters are inaccurate. However, its total harmonic distortion (THD) in stator current is not satisfactory. In [10], a conventional MF-PCC method is applied to avoid parameters mismatch between a real system and controller. The method uses an ultra-local (UL) model instead of an IM model, and its state is represented by Heun's theory. The UL model is constructed by a simple function that is only valid within a short time. To estimate an unknown function of the ultra-local model, a linear extended state observer (LESO) is used in conventional MF-PCC. Therefore, its control performance is robust against parameter mismatch of the machine, but tuning controller parameters and tuning of observer gains are not easy task [11]. The estimation error of the unknown function for an ultra-local model can be enhanced due to its time-varying and nonlinear nature. To reduce the estimation error, the well-known integral sliding mode observer (ISMO) is implemented for the model-free predictive control whereas a Lyapunov theory is utilized to maintain the observer's stability. However, it is complicated to design and the performance of the controller is highly affected by the chattering problem [12], [13]. Nowadays, the model-free control approaches have been presented widely for a resistive-inductive (R-L) load to achieve robust control performance against parameter uncertainties and parameter variations. Detailed knowledge about the system and system modeling are not needed in the model-free approaches. These approaches use an auto-regressive exogenous (ARX) structure instead of the load model, whereas the coefficients of the ARX structure are identified by using the recursive least squire (RLS) algorithm. These model-free approaches require high sampling frequency for yielding high-performance control [14]–[16] behavior. A new model-free state-space neural network (ssNN) has been proposed in [17] for the R-L load to mitigate parameter mismatch between the real system and controller, where all the weights in ssNN are updated through the particle swarm optimization (PSO) approach. However, the load current quality is not satisfactory for the controller. The model-free control approach has been spread for the deadbeat predictive current control (DPCC) [18], deadbeat predictive speed control (DPSC) [19], and predictive voltage control (PVC) [20] to achieve a reliable control operation under the external disturbance and parametric uncertainties. The aforementioned three techniques require an algebraic parameter identification to compute an unknown part of the ultra-local model.

The model-free predictive control for motor drives has two main variants: one is model-free PCC (MF-PCC), which is discussed in the above paragraphs, and another one is model-free predictive torque control (MF-PTC). Both strategies can effectively control the torque, flux, and speed under different operating conditions. In MF-PCC, the motor flux and torque are controlled indirectly by controlling the motor current. On the other hand, in MF-PTC, the motor flux and torque are controlled directly; thus, comparatively faster torque response is achieved [21], and less mathematical calculation is required. Furthermore, the torque control is more significant because an efficient torque controller for motor drive produces good torque/current and reduces current harmonics, thus increasing the lifetime of the motor. However, a few works on MF-PTC of IM drive have been published in the literature. Recently, a model-free parallel PTC has been proposed in [22]. The controller is designed to mitigate the model uncertainty and to avoid the weighting factor for permanent magnet synchronous motor (PMSM). However, the ripples in torque and flux are still high under the operation of model parameter mismatch.

A recursive least square (RLS) parameter identifier for an ARX model is applied to construct a new model-free PTC proposed in [23]. A resistance estimator is developed based on a support vector regression (SVR) [24] and a sliding mode observer (SMO) [25]. The estimated resistance is used for computing stator flux. It is only parametric robustness under no-load and rated speed operation, and its control structure is more complicated for using several complex mathematical calculations. Another new model-free PTC proposed in [26] is applied to improve the performance under the rated-load and rated speed operation, where it is designed based on the fed forward neural network (FFNN) [27] approach. However, the FFNN requires redundant calculations. As a result, its computational burden is high. In addition, the stator flux estimation may be inaccurate. It is because the voltage model-based flux estimation depends on the stator resistance variation. Hence, the controller performance will be degraded against variation of the motor parameters.

Therefore, this paper proposes a new MF-PTC scheme for the two-level voltage source inverter (2L-VSI) fed 3-phase IM to improve its robustness against stator and rotor resistance variation and also inductance measurement uncertainty. The proposed scheme uses an ARX model instead of an IM model, an RLS algorithm for unknown parameter identification of the ARX model, and a computationally simple MRAS observer-based resistance estimator. Finally, an observable canonical state–space model is used for the prediction step. This paper is arranged as follows; the proposed robust MF-PTC scheme with ARX model, RLS parameters identification algorithm, a resistance estimator, and an observable canonical state-space model are discussed in section 2. The simulation results of this proposed scheme are presented in section 3. At last, a conclusion is stated in section 4.

2. PROPOSED ROBUST MF-PTC STRATEGY

The proposed robust MF-PTC for 2L-VSI fed IM drive is depicted in Figure 1. The control strategy mainly consists of a minimization cost function, prediction based on an observable canonical state-space model and parameter estimation with RLS algorithm, and estimation of stator flux. In order to design a model-free approach, an ARX model instead of the IM model has been employed, which is formed based on a basic relationship between past input and past output. The proposed strategy is described in the subsequences as follows.

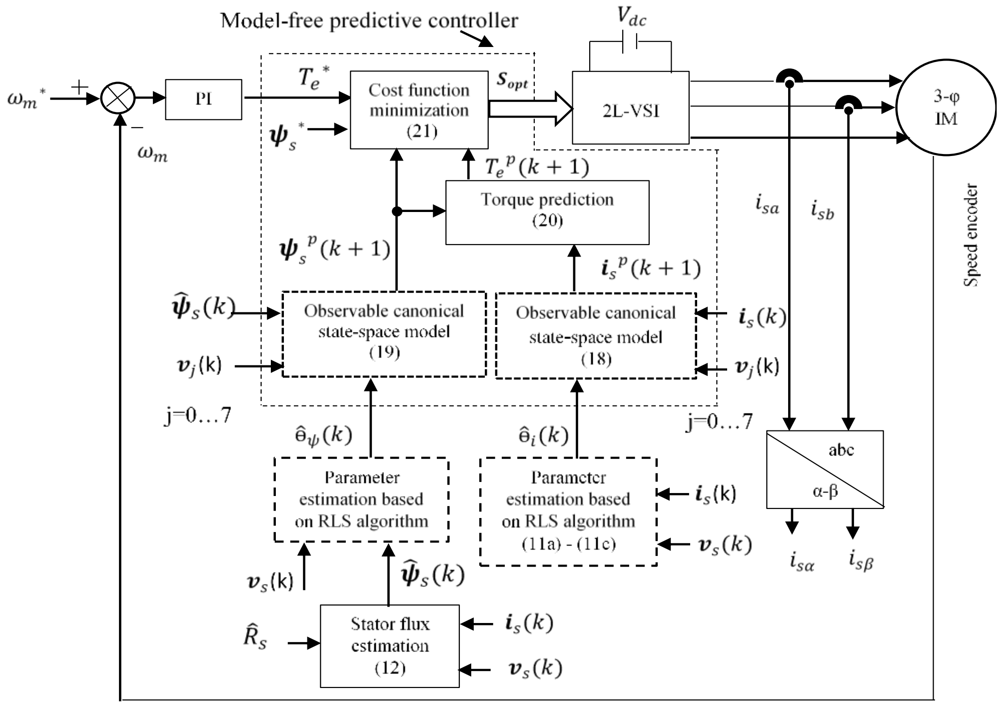

Figure 1. Proposed robust MF-PTC for 2L-VSI fed IM drive

2.1. ARX model structure

A discrete transfer function of an unknown system for output and input is represented by using ARX model. Here, the output stator current and stator flux are estimated as (1) and (2),

$$\hat{i}_s(k) = \frac{B(z^{-1})}{A(z^{-1})} \mathrm{v}_s(k) \tag{1}$$

$$\hat{\psi}_s(k) = \frac{N(z^{-1})}{M(z^{-1})} \mathrm{v}_s(k) \tag{2}$$

where $\mathrm{v}_s(k)$ is an input voltage vector which is generated by 2L-VSI. The included polynomials $A(z^{-1}), B(z^{-1})$, $M(z^{-1})$ and $N(z^{-1})$ in the ARX model are written as (3) and (4).

$$\left.\begin{aligned} A(z^{-1}) &= 1 + a_1 z^{-1} + a_2 z^{-2} \ldots + a_{n_A} z^{-n_A} \\ B(z^{-1}) &= b_1 z^{-1} + b_2 z^{-2} \ldots + b_{n_B} z^{-n_B} \end{aligned}\right\} \tag{3}$$

$$\left.\begin{aligned} M(z^{-1}) &= 1 + m_1 z^{-1} + m_2 z^{-2} + \cdots + m_{n_M} z^{-n_M} \\ N(z^{-1}) &= n_1 z^{-1} + n_2 z^{-2} + \cdots + n_{n_N} z^{-n_N} \end{aligned}\right\} \tag{4}$$

The unknown parameters of the system in (3) and (4) are defined as a_{n_A}, b_{n_B}, m_{n_M} and n_{n_N}; where n_A, n_B, n_M and n_N are marked as an order of polynomials. At first, (3) and (4) are substituted into (1) and (2), then the simplified equations are rewritten as (5) and (6).

$$\hat{\imath}_s(k) = -a_1 i_s(k-1) + \cdots - a_{n_A} i_s(k-n_A) + b_1 v_s(k-1) + \cdots + b_{n_B} v_s(k-n_B) \tag{5}$$

$$\hat{\psi}_s(k) = -m_1 \psi_s(k-1) + \cdots - m_{n_M} \psi_s(k-n_M) + n_1 v_s(k-1) + \cdots + n_{n_N} v_s(k-n_N) \tag{6}$$

The unknown parameters in (5) and (6) are gathered in vectors θ_i and θ_ψ respectively as (7) and (8).

$$\theta_i = \left[a_1 \dots a_{n_A}\; b_1 \dots b_{n_B}\right]^T \tag{7}$$

$$\theta_\psi = \left[m_1 \dots\dots m_{n_M}\; n_1 \dots n_{n_N}\right]^T. \tag{8}$$

Similarly, the past known input and output data in (5) and (6) are stored in vectors φ_i and φ_ψ, which are introduced as regression vectors shown in (9) and (10).

$$\varphi_i = [-\mathrm{i}_s(k-1), \dots, -\mathrm{i}_s(k-n_A), \mathrm{v}_s(k-1), \dots, \mathrm{v}_s(k-n_B)]^T \tag{9}$$

$$\varphi_\psi = [-\psi_s(k-1), \dots, -\psi_s(k-n_M), \mathrm{v}_s(k-1), \dots, \mathrm{v}_s(k-n_N)]^T \tag{10}$$

The gathered unknown parameters in (7) and (8) are easy to estimate by using a RLS algorithm.

2.2. RLS algorithm-based parameter estimation

In this research, the RLS algorithm has been used to estimate the unknown parameters of the ARX model. No inverse matrix is used in this algorithm; thereby a computational complexity has been reduced. A mathematical plat form of the RLS algorithm is expressed by a set of equations that is solved recursively. The estimation of parameters vector $\hat{\theta}_i(k)$, gain matrix $G_i(k)$ and covariance matrix $P_i(k)$ are expressed as follows only for the step of current estimation.

$$\hat{\theta}_i(k) = \hat{\theta}_i(k-1) + G_i(k)(i_s(k) - {\varphi_i}^T(k)\, \hat{\theta}_i(k-1)) \tag{11a}$$

$$G_i(k) = \frac{P_i(k-1)\varphi_i(k)}{{\varphi_i}^T(k)\, P_i(k-1)\varphi_i(k)+\lambda} \tag{11b}$$

$$P_i(k) = \frac{1}{\lambda}\left[P_i(k-1) - \frac{P_i(k-1)\varphi_i(k){\varphi_i}^T(k)P_i(k-1)}{{\varphi_i}^T(k)\, P_i(k-1)\varphi_i(k)+\lambda}\right] \tag{11c}$$

Where λ is a forgetting factor that is selected by running a heuristic computer simulation. In the same way, parameters vector $\hat{\theta}_\psi(k)$ has been estimated for the step of flux estimation. From (11a), it can be seen that the parameters vector estimation is an easy task because the instantaneous measured stator current $i_s(k)$ is available from current sensor. However, instantaneous stator flux is unavailable, which is needed to estimate the parameters vector in the RLS algorithm. So, in this work, the stator voltage model is applied for the estimation of stator flux. However, the flux estimation is dependent on the stator resistance. In addition, the temperature rise changes the stator resistance. As a result, the estimation of the stator flux will not be accurate. Hence, a MRAS observer-based resistance estimator has been used in order to overcome the aforementioned problem.

2.3. Stator flux estimation with a resistance estimator

A model reference adaptive system (MRAS) observer presented in [28], [29] has been modified in the proposed controller to build a resistance estimator as shown in Figure 2, where both the rotor and stator resistance have been estimated. For the modeling of the resistance estimator, two models are considered which are adjustable model and reference model. The rotor flux calculation from the stator voltage model is introduced as a reference model. The expression of the estimated stator flux is defined as (12):

$$\hat{\psi}_s = \int\left(v_s - \hat{R}_s i_s\right)dt \tag{12}$$

where $\hat{R}_s$, v_s and i_s are the estimated resistance, voltage vector, and current vector with respect to the stator frame. The reference rotor flux calculation based on the above expression can be written as (13):

$$\hat{\psi}_{rV} = \frac{L_r}{L_m}\hat{\psi}_s + (L_m - \frac{L_r L_s}{L_m})i_s \tag{13}$$

where, L_m, L_s, and L_r are the mutual inductance, stator inductance, and rotor inductance. Similarly, the rotor flux calculation based on the current model is considered as an adjustable model, which can be expressed as (14):

$$\hat{\psi}_{rI} = \int (\frac{L_m}{\hat{\tau}_r} i_s - \hat{\psi}_{rI} (\frac{1}{\hat{\tau}_r} - jp\omega_m))dt \tag{14}$$

where, $\hat{\tau}_r = \frac{L_r}{\hat{R}_r}$ is the estimated rotor time constant and $\hat{R}_r$ is the estimated rotor resistance; p and ω_m denote as number of pole pairs and motor speed. An adaptation mechanism for the stator resistance is expressed as (15).

$$e_{R_s} = Re\{(\hat{\psi}_{rV} - \hat{\psi}_{rI})^* . i_s\} \tag{15}$$

A proportional-integral (PI) controller is used for estimating the stator resistance, which is presented as (16).

$$\hat{R}_s = k_{pRs} e_{R_s} + k_{iRs} \int e_{R_s} \, dt \tag{16}$$

The values of k_{pRs} and k_{iRs} are 0.8 and 10 which are chosen by running a heuristic computer simulation. The estimation of rotor resistance may be written as (17),

$$\hat{R}_r = R_r + k_r . R_r \frac{\hat{R}_s - R_s}{R_s} \tag{17}$$

where R_r and R_s are the nominal value of the rotor and stator resistances, and k_r is defined as a constant multiplier which is the ratio of R_s and R_r.

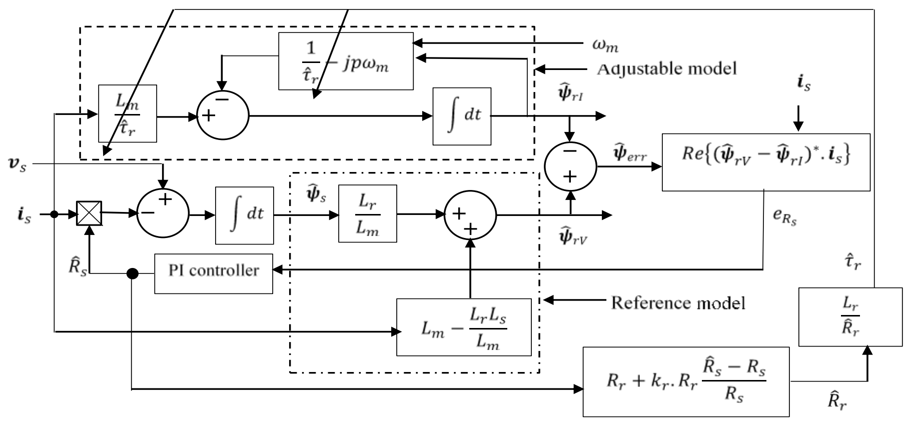

Figure 2. Resistance estimator based on the MRAS observer

2.4. Prediction based on observable canonical state-space model

Finally, ARX model (1) and (2) are expressed as an observable canonical state-space model. The state-space ARX model is shown in (18) and (19).

$$\begin{aligned} \mathrm{i}_s(k+1) &= \begin{bmatrix} -a_1 & 1 & 0 & \dots & 0 \\ -a_2 & 0 & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ -a_{n_A} & 0 & 0 & \dots & 0 \end{bmatrix} \mathrm{i}_s(k) + \begin{bmatrix} b_1 \\ \vdots \\ b_{n_B} \end{bmatrix} \mathrm{v}_j(k) \\ \mathrm{i}_s{}^p(k+1) &= [1 \quad 0 \quad \dots \quad 0]\, \mathrm{i}_s(k+1) \end{aligned} \tag{18}$$

$$\begin{aligned} \psi_s(k+1) &= \begin{bmatrix} -m_1 & 1 & 0 & \dots & 0 \\ -m_2 & 0 & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ -m_{n_M} & 0 & 0 & \dots & 0 \end{bmatrix} \hat{\psi}_s(k) + \begin{bmatrix} n_1 \\ \vdots \\ n_{n_N} \end{bmatrix} \mathrm{v}_j(k) \\ \psi_s{}^p(k+1) &= [1 \quad 0 \quad \dots \quad 0]\, \psi_s(k+1) \end{aligned} \tag{19}$$

Where $\mathrm{v}_j(k)$ is the possible voltage vectors. The predictive torque expression is written in terms of predictive stator flux and stator current as (20).

$$T_e{}^p(k+1) = \frac{3}{2}pIm\{\psi_s{}^p(k+1)^* i_s{}^p(k+1)\} \quad (20)$$

To generate the reference torque T_e^*, the error between the measure speed ω_m and the command speed $\omega^*{}_m$ is processed by an anti-windup PI speed controller. The stator reference flux $\psi_s{}^*$ is computed from the motor rating. The model-free cost function is defined as (21).

$$g_{MF} = |T_e{}^* - T_e{}^p(k+1)| + \eta_p\big||\psi_s{}^*| - |\psi_s{}^p(k+1)|\big| \quad (21)$$

Where η_p is a weighting factor which is selected by running a heuristic computer simulation.

3. SIMULATION RESULTS AND DISCUSSION

The simulation of this drive system is done by using MATLAB/Simulink platform. The different blocks (model-free controller, inverter and induction motor) of Simulink model are depicted in Figure 1. A sampling time T_s is considered as 40 μs. The stator reference flux $\psi_s{}^*$ is set to 1.0 Wb. The polynomial orders in (3) and (4) are chosen by running heuristic computer simulation, those are $n_A = 3$, $n_B = 2$, $n_M = 3$, $n_N = 2$. The parameters of the proposed controller and parameters of a 1.1 KW, 3-φ, 415 V, 50 Hz induction motor are shown in Table. 1.

Table 1. Motor and controller parameters

Motor parameter	Value	Controller parameter	Value
R_s, R_r	6.03 Ω, 6.085 Ω	K_p, K_i for speed controller	0.6, 9.056
L_s, L_r, L_m	0.5192 H, 0.5192 H, 0.4893 H	λ, η_p	3, 35
T_{nom}, ω_m, N_p, J	7.4 N m, 1415 rpm, 2, 0.011787 Kg m^2	I_{max}	4.5 A

Figure 3 shows the performance of the MF-PTC scheme for the increment of stator resistance by 130% in the motor model applied at time t=2 s. The effect of stator resistance is analyzed with the rated-load and rated speed as shown in Figure 3. It can be seen that the motor speed is satisfactory before and after the increment of stator resistance. Moreover, the estimated torque and stator flux follow their respective references accurately when stator resistance is considered as 100% R_s in the motor model. When the stator resistance is increased by 130%, the estimated stator flux is decreased gradually and the flux level remains constant at a lower value. As a result, both the estimated torque and flux do not follow accurately their respective references. It is also noticeable that THD of the stator current is a slightly big for 130% increment of the stator resistance. Hence, the controller is not robust in case of stator resistance variation. Therefore, a resistance estimator has been used with the MF-PTC strategy to make the controller robust against the motor resistance variation.

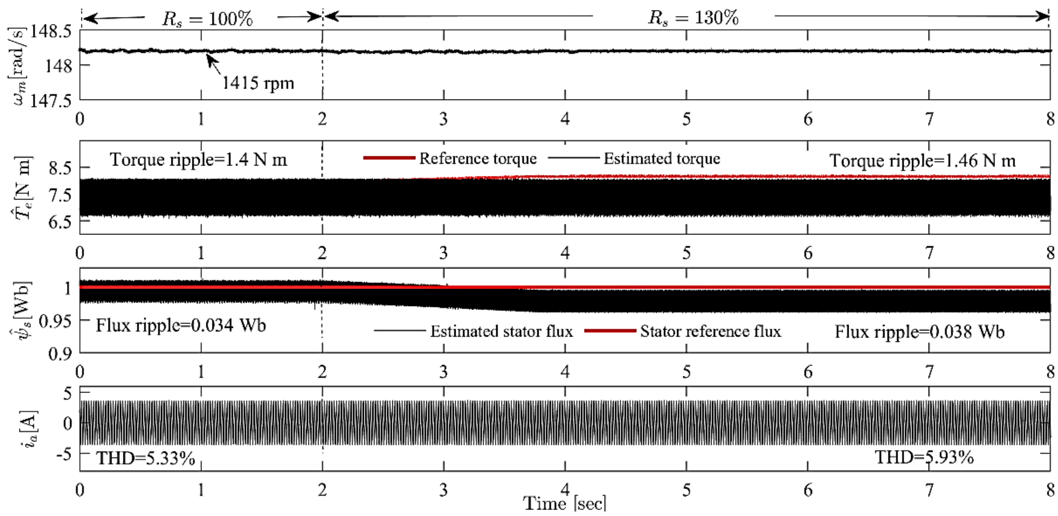

Figure 3. Behavior of the motor speed, estimated torque, estimated stator flux, and stator current for 130% of R_s at time t=2 sec

Figure 4 presents the effectiveness of this proposed MF-PTC scheme for 130% variation of rotor and stator resistances in the motor. The motor is operated at full-load and rated speed. Initially, the estimator is kept ‘on’. It is turned ‘off’ at time 0.8 sec. It is observed that the motor speed response is satisfactory with and without estimator. However, a small speed dip is seen when estimator is turned off at time 0.8 sec. The motor speed come backs to its nominal speed of 148.2 r/s within a short time (i.e., 0.13 sec). It can be seen that the estimated torque and stator flux track properly their respective references because the controller works with the estimator ‘on’. However, when estimator is ‘off’, the torque and flux are unable to track their respective references, and their ripples are higher. Moreover, it is noticed that THD of the stator current is slightly bigger after turning ‘off’ the estimator. It can be seen that the estimated stator and rotor resistance are very close to 130% of R_s and R_r while estimator is kept ‘on’. Hence, the proposed MF-PTC scheme ensures that motor’s speed, torque, stator flux and current are unaffected by the variation of stator and rotor resistances.

The performance of the proposed MF-PTC scheme for the uncertainty of inductances with 100% of R_s and R_r is shown in Figure 5. An inductance mismatch of $\pm 10\%$ is considered in L_s, L_r and L_m. Initially, the controller is operated for 100% of L_s, L_r and L_m. Then, 90%, 100%, and 110% of L_s, L_r, and L_m are applied respectively at time 0.2 sec, 0.6 sec, and 1.0 sec. It can be observed that no disturbance and oscillation is seen in speed for these mismatches. Moreover, a constant flux and torque response is noticed in the estimated flux and torque, and they have good tracking behavior. It can be seen that the THD of the stator current is similar in the inductance mismatch situations. Therefore, the proposed MF-PTC scheme with a resistance estimator shows good robustness against inductance measurement uncertainty.

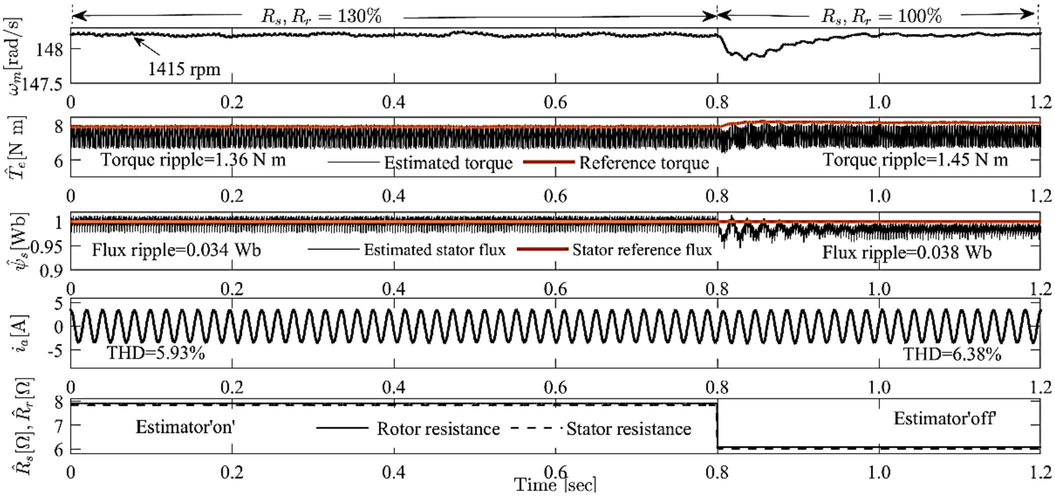

Figure 4. Behavior of the motor speed, torque, stator flux, stator current, and estimated resistances when estimator is ‘on’ and ‘off’

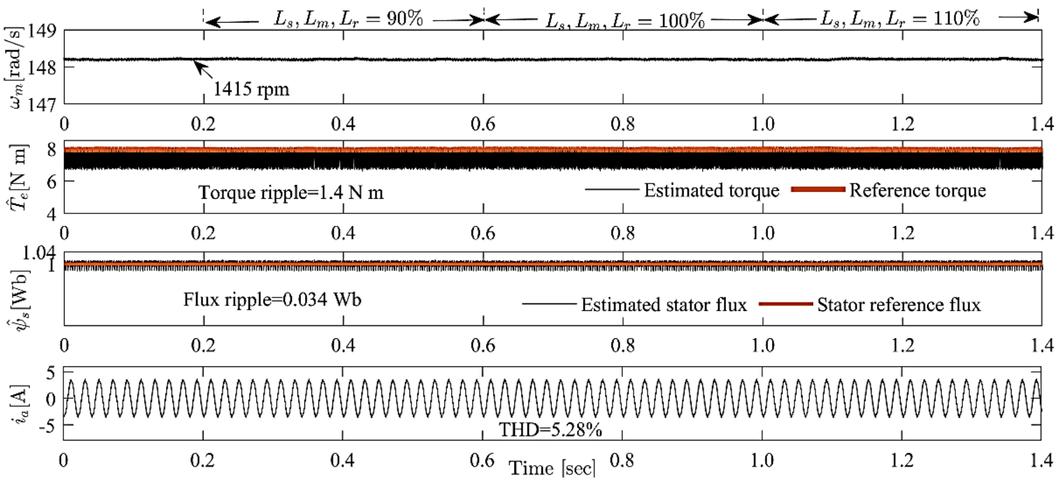

Figure 5. Behavior of the motor speed, torque, stator flux, and stator current for the inductance mismatch

Figure 6 presents the performance of the proposed robust MF-PTC scheme for the rated speed reversal with full-load. It is analyzed for 130% of R_s and R_r with estimator 'on'. It can be observed that the quality of the estimated torque and flux is similar and satisfactory after reverse speed applied at time 0.4 sec. The estimated torque and flux follow their respective references. However, a small oscillation is seen in the estimated torque and flux during speed reversal, and then their oscillation becomes stable within a short time of 0.15 sec. This scenario is existed for flowing high current in motor winding and also changing motor speed suddenly. Moreover, it can be observed that the THD of the stator current in the steady-state region is slightly low after speed reversal. It is also noticed that the speed response in both directions is satisfactory.

Figure 7 shows the performance of the proposed MF-PTC scheme against load disturbance. The controller is executed up to t=0.1 s with the load torque of 3 N-m at rated speed of 148.2 r/s. The load torque is changed suddenly from 3 N-m to 7.4 N-m (rated load) at time t=0.1 sec. It is noticed that no oscillation is present in speed after adding full-load. However, a small speed dip is observed in speed curve when full-load is applied. The motor speed comes back to its nominal speed of 148.2 r/s within a short time (0.18 s). The estimated torque tracks the reference torque perfectly before and after a step change of load torque, and its ripple is similar around 1.4 N-m. The estimated stator flux remains constant at nominal flux during the load change, and its ripple is almost similar before and after a step change of load torque. Moreover, it can be seen that the current THD is low in full-load operation. Hence, the proposed MF-PTC is robust for changing load torque suddenly.

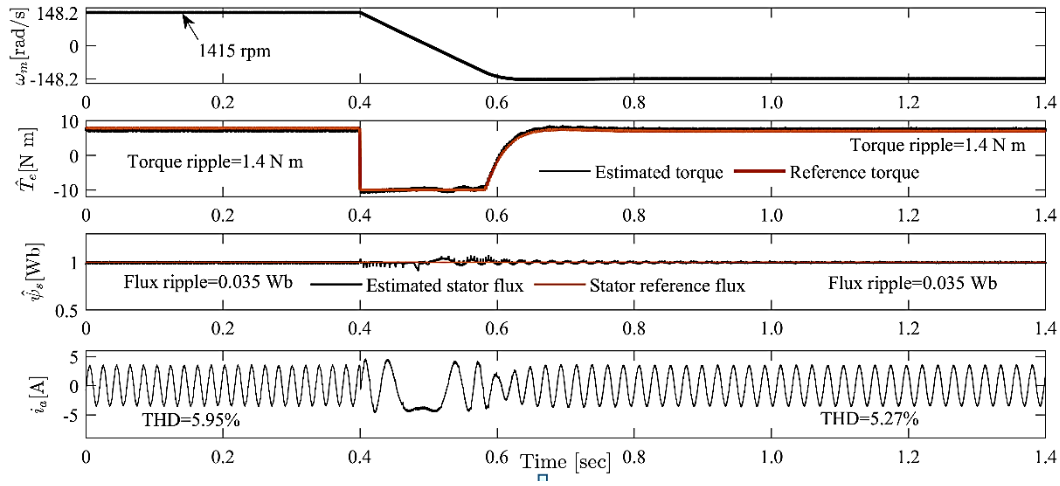

Figure 6. Behavior of the motor speed, torque, stator flux, and stator current for the reversal speed

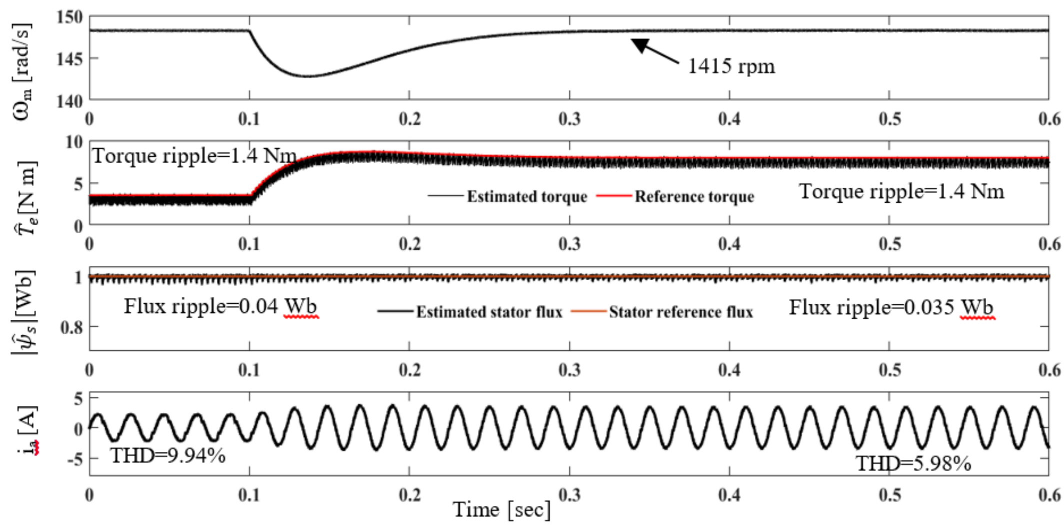

Figure 7. Behavior of the motor speed, torque, stator flux, and stator current for a step change of load torque at time t=0.1 sec

4. CONCLUSION

This paper has proposed a robust MF-PTC strategy for a 2L-VSI fed IM drive. The strategy used an ARX model instead of IM model. A standard parameter identifier RLS algorithm has been employed to estimate the parameters of ARX model. To obtain an accurate prediction, an observable canonical state-space model has been used. However, the stator flux estimation of the proposed strategy is dependent on the stator resistance. Hence, a computationally simple resistance estimator has been used to get a satisfactory performance of the proposed MF-PTC scheme. Simulation results confirm that the controller is robust against variation of stator and rotor resistances, inductance measurement uncertainty, and load-disturbance. It is also shown that the performance of the proposed scheme is satisfactory for the reverse speed operation.

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