DESIGN AND MATLAB SIMULATION OF MODEL REFERENCE ADAPTIVE SYSTEM (MRAS) FOR SPEED CONTROL OF THREE PHASE INDUCTION MOTOR

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Abstract: It is the paper that presents a new predictive model reference adaptive system (MRAS) speed estimator for speed control of sensor-less induction motor (IM) drives. The specified estimator depends on the finite control set model predictive control (FCS-MPC) principle [1]. A search-based optimization algorithm is used to calculate the rotor position which guarantees a minimum speed tuning error signal at each sampling period. This eliminates the need for a proportional–integral (PI) controller which is conventionally employed in the adaptation mechanism of MRAS estimators. A large number of experimental tests have been carried out in order to study the performance of the proposed estimator using a 1 HP IM with a field-oriented control (FOC) scheme employed as the motor control strategy. Experimental results show improved performance of the MRAS scheme at low speeds and with different loading conditions. The proposed scheme also helps to improve the system rigidness against motor parameter variations and the maximum bandwidth of the speed loop controller increases.

Index terms: Induction motor (IM) drive, vector control, speed estimation, model reference adaptive system (MRAS), classical rotor-flux MRAS, proposed predictive MRAS control.

I. INTRODUCTION

Induction motors (IMs) are widely used in many industrial applications due to their self-starting capability, simple structure, mechanical robustness and low cost. Most of the drives for industrial process and domestic appliances have been designed to operate at constant speed. But, it is well known that in the mechanical system a variable speed drive provides improved performance and energy efficiency. So, more and more emphasis is given to find out means of precise speed and torque control of induction motors. Various speed control techniques applied by modern age VFD are mainly classified into two categories: scalar control and vector control.

The scalar speed control method of IM includes volts per hertz (V/f), slip-power recovery and Direct Torque Control (DTC). In scalar control, voltage regulated voltage source inverter (VSI) is used. Hence, we go for Space Vector Pulse Width Modulation (SVPWM) in order to generate the gate pulses [1].

The vector speed control method of IM includes Rotor Flux Oriented Vector Control, Stator Flux Oriented Vector Control and Mutual Flux Oriented Vector Control. Among these, Rotor Flux Oriented Vector Control gives natural decoupling effect whereas air-gap or stator flux control gives coupling effect. Due to coupling effect, IM cannot give an as fast response as DC machine. The performance similar to DC machine can be obtained from IM if we use the system in the synchronously rotating reference frame.

Vector control, also called field-oriented control (FOC) of induction motors (IM) has established an increasing popularity in a wide range of applications and acceptance in the electric drives markets worldwide. In general, a speed sensor is required in the closed loop operation for both V/f control and FOC control. The speed sensor or tachometer is mounted on the motor shaft. The elimination of the speed sensor has been one of the important features in the modern motor control systems [2]. This project presents a novel method of controlling the speed of induction motors without the speed sensor. Although sensor-less control has been successfully applied in medium- and high-speed operating regions, operation at very low speeds still remains a significant problem for IM drives [3]. The information of the rotor speed can be obtained by processing the stator voltages and currents measured at the motor terminals.

In sensor-less IM drives, a number of techniques have been introduced for speed estimation. Among these techniques, model reference adaptive system (MRAS) based estimators have gained great popularity for estimating rotor speed because of their relative simplicity and ease of application. Rotor flux-based MRAS has been extensively studied and it has been demonstrated that these estimators can have an excellent performance down to 5% of rated speed [4]. However, rotor flux-based MRAS schemes suffer from many problems which become dominant at a low speed including sensitivity to machine parameter variation, pure integration effects, inverter nonlinearity, and the quality of stator voltage and current being measured [2],[4].

In general, a proportional–integral (PI) controller with fixed-gain is utilized in the adaptation mechanism of MRAS schemes in order to produce the estimated position or speed. This is because of its simple structure and ability to generate a satisfactory performance over a wide range of speeds. However, inverter nonlinearities and machine parameter variation become more dominant at low speeds. Hence, the PI with fixed-gain may not be able to maintain the system stability or do not give the required performance. Also, the tuning of these PI gains is difficult. Therefore we go for other solutions in order to offer an alternative approach to the design of the adaptation mechanism for MRAS estimators. These solutions have focused on replacing the conventional fixed-gain PI adaption mechanism with more advanced algorithms [5]-[7].

In order to replace PI adaptation mechanism, a sliding mode (SM) algorithm was suggested in [5] and [6]. Although this scheme is shown to improve the estimator dynamic response, it causes a considerable amount of disturbances in the estimated speed signal, and a low-pass filter is needed to smooth out the estimated rotor speed. In [7], another solution was proposed where the PI controller is replaced by a fuzzy logic (FL)-based adaption mechanism. This scheme shows improvement in the estimator dynamic response, but the computational complexity of the FL controller is the main drawback of this scheme.

During the last few years, interest has grown in the use of sensor-less based applications for predictive control techniques. A predictive current controller for a sensor-less speed control system for an IM has been proposed in [8], where it has been claimed against motor parameter variations this combination can improve the system robustness. In [9], an encoder-less predictive torque control is proposed with a rotor flux MRAS estimator to reduce the system cost. In general, model predictive controllers (MPC) can be classified into classical MPC and finite control set-model predictive controllers (FCS-MPC) [10]. In classical MPC, the controller generates a continuous voltage vector and a modulator is used to apply this voltage to the inverter, whereas in FCS-MPC the controller directly produces a switching state of the inverter [11]. FCS-MPC has gained popularity and has been applied in many different applications because of its compact design, simplicity, and flexibility. For example in [12], an FSC-MPC was applied to drive an IM fed by a matrix converter to increase the system efficiency.

This paper presents an ideal MRAS speed estimator for sensor-less vector control of IM drives for solving the problems related to the adaptation mechanism design. The FCS-MPC control concept is incorporated in the estimator design. For this scheme, the adaptation mechanism is based on solving an optimization problem with the objective of minimizing the speed tuning error signal of the MRAS estimator over a finite number of rotor position angles. A rotor position search algorithm is developed to ensure that the optimal position is obtained at each sampling time [13]. The computational complexity of the proposed scheme is evaluated and a modified method is employed to reduce its execution time to make it suitable for practical implementation. The performance of the proposed predictive estimator is experimentally tested using a 1HP IM drive which employs FOC as the motor control strategy. Comparison between the classical rotor flux MRAS estimator and the proposed scheme has been carried out in detail. Results show the superior performance of the proposed scheme at different low-speed operating conditions and improved robustness against motor parameter variations.

II. MRAS ESTIMATOR FOR CLASSICAL ROTOR FLUX

The classical method for MRAS estimator is mainly based on rotor flux as shown in Fig. 1 Schauder introduced it for the first time [4]. It mainly consists of two mathematical models, the reference and adaptive models, and an adaptation mechanism to produce the estimated speed. This scheme is one of the most common rotor speed estimators and many attempts to improve its performance can be found in the literature. The reference model represents the stator voltage equation in the stationary reference frame which can be written as follows.

$$Vs\alpha = Rs \,.\, is\alpha + \alpha Ls\left(\frac{dis\alpha}{dt}\right) + \left(\frac{Lm}{Lr}\right) . \left(\frac{d\psi r\alpha}{dt}\right)$$

$$Vs\beta = Rs \,.\, is\beta + \alpha Ls\left(\frac{dis\beta}{dt}\right) + \left(\frac{Lm}{Lr}\right) . \left(\frac{d\psi r\beta}{dt}\right) \quad \ldots (1)$$

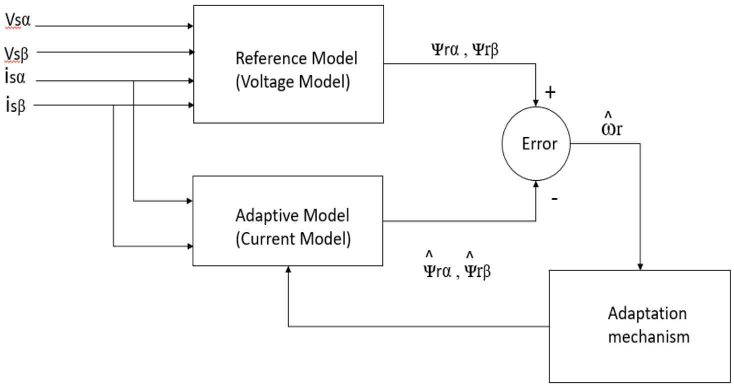

Fig. 1: The MRAS structure based on rotor flux

Here,

vsα , vsβ = stator voltage components

isα , isβ = stator current components

ψsα, ψsβ = reference rotor flux linkage components

All above quantities are expressed in the stationary reference frame.

Lm = machine mutual inductance

Rs = stator resistance

Ls = stator self-inductance

Lr = rotor self-inductance

The leakage coefficient i.e. σ is given by,

$$\boldsymbol{\alpha = 1 - \mathrm{Lm}^2/(\mathrm{LsLr})}$$

The adaptive model represents the rotor voltage equation of the IM in the stationary reference frame which can be written as

$$0 = \frac{1}{Tr}\vec{\Psi}r\alpha + \frac{Lm}{Tr}is\alpha + \frac{d\vec{\Psi}r\alpha}{dt} + \overrightarrow{\omega}\overrightarrow{\Psi}r\beta$$

$$0 = \frac{1}{Tr}\vec{\Psi}r\beta + \frac{Lm}{Tr}is\beta + \frac{d\vec{\Psi}r\beta}{dt} + \overrightarrow{\omega}\overrightarrow{\Psi}r\alpha \qquad \text{... (2)}$$

where, Tr is the rotor time constant, $\vec{\omega}r$ is the estimated rotor speed, $\vec{\Psi}$rα and $\vec{\Psi}$rβ are the adaptive rotor flux linkage components in the stationary reference frame.

The cross-coupling presence of the speed-dependent components in the adaptive model (2) can lead to an instability issue [32]. Therefore, it is common for the rotor flux equation represented in the rotor reference frame to be used

$$\vec{\Psi}rd = \frac{Lm}{1 + Tr\,.s}\,\mathrm{isd}$$

$$\vec{\Psi}rd = \frac{Lm}{1 + Tr\,.s}\,\mathrm{isq} \qquad \text{... (3)}$$

where, isd and isq are the stator current components, $\vec{\Psi}$rd and $\vec{\Psi}$rq are the rotor flux components all expressed in the rotor reference frame. The implementation of the rotor frame-based flux model is shown in Fig. 2. The adaption mechanism design is based mainly on the hyperstability theory [2], and as a result of applying this theory, the speed tuning error signal ε can be written as

$$\varepsilon = \vec{\Psi}r\alpha\,.\,\psi r\beta - \vec{\Psi}r\beta\,.\,\psi r\alpha \qquad \text{… (4)}$$

A PI controller is used to minimize this error, which in turn generates the estimated speed at its output

$$\vec{\omega}r = \left(Kp + \frac{Ki}{s}\right)\varepsilon \qquad \text{… (5)}$$

III. PROPOSED PREDICTIVE MRAS ESTIMATOR

The principle of the proposed predictive MRAS estimator is derived from the FCS-MPC concept. In contrast to the conventional MPC, FCS considers the discrete nature of the inverter in solving the control optimization problem. The cost function is evaluated at each single switching state of the inverter, and the state with the minimum cost function is chosen to be applied in the next sampling instant. This method, therefore, has the advantages of both simplicity and design flexibility making it attractive to electric drives applications [11].

The FCS-MPC approach is applied in this paper to design the adaptation mechanism in MRAS speed estimators. An optimization problem is formulated to find the rotor position in order to minimize a cost function, which is the speed tuning signal ε (4) in the case of the MRAS estimator.

In contrast to the FCS-MPC, the rotor position, which varies continuously between 0◦ and 360◦, does not have the same discrete nature as the inverter output. Therefore, a search method is to be applied to discretize the rotor position into a finite number of positions to allow evaluating the cost function at each of these discrete positions. This search is performed within an iteration-based process. The block diagram of the proposed predictive MRAS estimator is shown in Figure 3. The flowchart of the proposed search algorithm is shown in Fig.4. The algorithm starts by calculating the reference model outputs ψrα, ψrβ from the stator voltages and currents. The discretization of the rotor position begins by starting from an initial base angle θbase,0 and then displacing this angle by a displacement (Δθi) which is calculated as follows:

$$\Delta\theta i = 45^\circ * 2{-}i \qquad \text{… (6)}$$

where, i is the order of the current iteration. The displacement of the base angle θbase within each iteration is carried out to get eight discrete rotor positions as follows:

$$\theta i,j = \theta base + \Delta\theta i.(j - 4) \qquad \text{… (7)}$$

where, j is the order of the displacement.

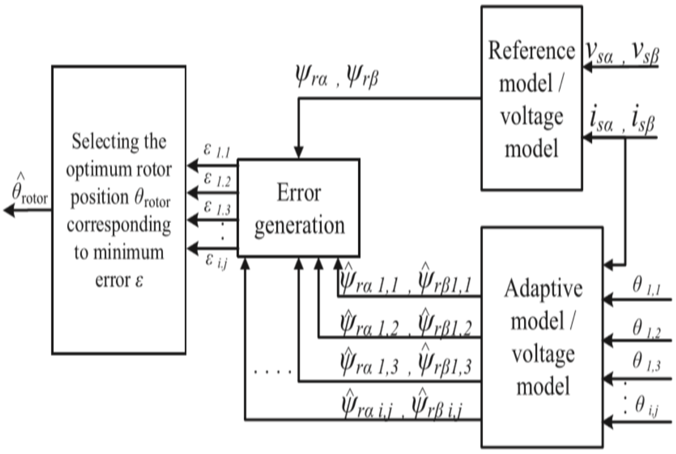

Fig. 2: Block diagram of the proposed MRAS estimator

For the first iteration (i = 0), the base angle θbase is chosen to be 0◦ with Δθ = 45 ◦ according to (6). After applying (7) it will produce eight discrete positions: 0◦, 45◦, 90◦, 135◦, 180◦, −45◦, −90◦, and −135◦. Each of these discrete positions (θi,j) is used to calculate the adaptive model outputs corresponding to each individual position ($\vec{\Psi}_{r\alpha i,j}$ and $\vec{\Psi}_{r\beta i,j}$). Consequently, the cost function, εi,j in (4), is calculated for each position as follows:

$$\varepsilon_{i,j} = \vec{\Psi}_{r\alpha i,j} * \psi_{r\beta} - \vec{\Psi}_{r\beta i,j} * \psi_{r\alpha} \qquad \dots (8)$$

This leads to eight different cost functions corresponding to each of these angles. The angle corresponding to the minimum cost function of the eight positions is chosen as the base or starting point θbase,1 for the next iteration.

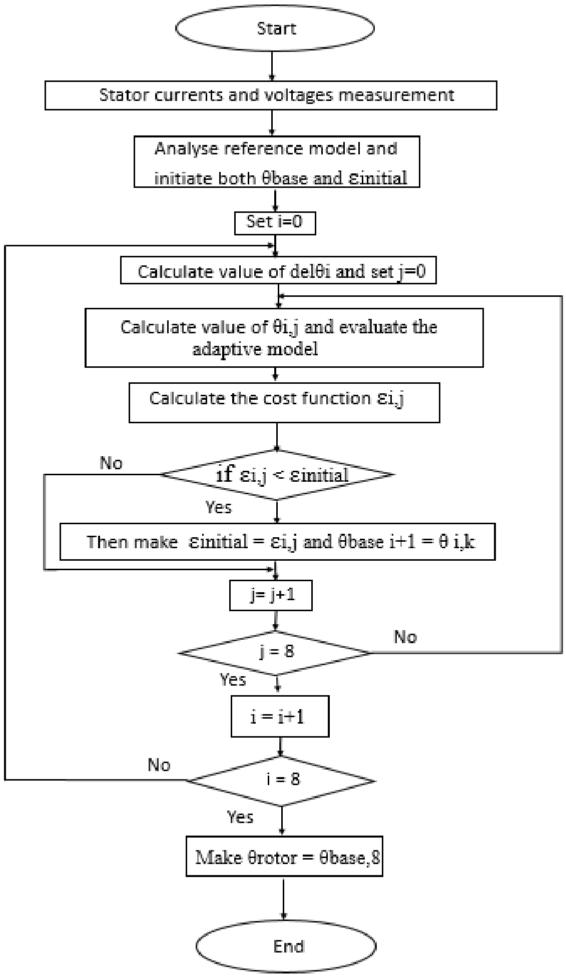

Fig. 3: Flowchart of the proposed rotor position search algorithm

At the next iteration (i = 1), the angular displacement is decreased to Δθ1 = 45◦*2−1 = 22 .5◦, which increases the search accuracy by a factor of 2. The search then starts again from the new base angle θbase,1 to find the angle that generates the minimum cost function in the second iteration. Figure 3. 3. shows the initial and first steps of the search algorithm.

After each iteration, the search algorithm gets closer to the optimal solution, and by the end of the eighth iteration (i = 7 and Δθ7 =0 .35◦), the optimal rotor position can be found with 0.35◦ accuracy. Therefore, by running this algorithm, it can be assured that the optimal rotor position, which produces the minimum cost function throughout the search space, is selected as the output of the estimator.

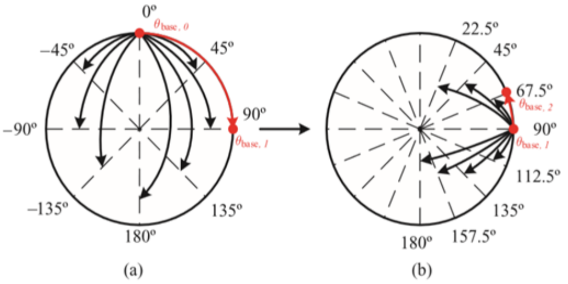

Fig. 4: Schematic representation of the first two steps of the proposed search algorithm.
(a) Initial iteration. (b) First iteration.

As described previously, the output of the proposed scheme is the rotor position, and to extract the speed signal the following procedure is applied.

The change in rotor position over the last sampling period is calculated from

$$\Delta\theta = \theta rotor\ (k) - \theta rotor\ (k-1) \qquad \ldots (9)$$

where. K is the current time sample. This change is recorded over 200 samples and the average value is obtained by applying

$$\Delta\theta ave = \frac{1}{200}\sum_{n=1}^{200}\Delta\theta n \qquad \ldots (10)$$

The speed is finally found by dividing the average by the sampling period, the conversion to rad/s is considered here also

$$N = \frac{2\pi}{60}\,\frac{\Delta\theta ave}{Ts} \qquad \ldots (11)$$

where, N is the rotor speed in r/min.

A drawback of the proposed method is the high computational effort required to run the search algorithm eight times in each sampling period. However, the rotor position, as a mechanical variable, changes relatively slowly and hence it does not vary significantly between two-time samples. Therefore, instead of initiating the search algorithm in each sampling period with zero angle (θbase,0 = 0), it can be initialized by the output of the algorithm in the last sampling instant θbase,0 = θrotor (k−1). As a result, the number of the iterations required by the search algorithm to find the optimal solution can be significantly reduced as the search is performed only around the previous rotor position. This simplified scheme is referred to as “modified-predictive.”

IV. DESIGN OF EXPERIMENTAL SYSTEM

The experimental platform used to validate the proposed estimator (Fig. 5) consists of a 0.75-kW, 415-V, star-connected, four-pole, three-phase squirrel cage IM. The motor parameters for 1 HP IM are presented in Table I. The motor is loaded by a belt arrangement. The load allows independent control of the load torque. The ac drive consists of a three-phase diode bridge rectifier, and an insulated-gate bipolar transistor (IGBT)-based three-phase bridge inverter. To control the ac drive, an interfacing medium called dSpace1104 which is a research and development controller board is used. It can be used for real-time simulation. The control algorithm, based on the FOC scheme, is written in MATLAB Function which is a user-defined function. The maximum inverter switching frequency is 10 kHz with a dead-time period of 3μs and the FOC algorithm is executed with the same sampling frequency.

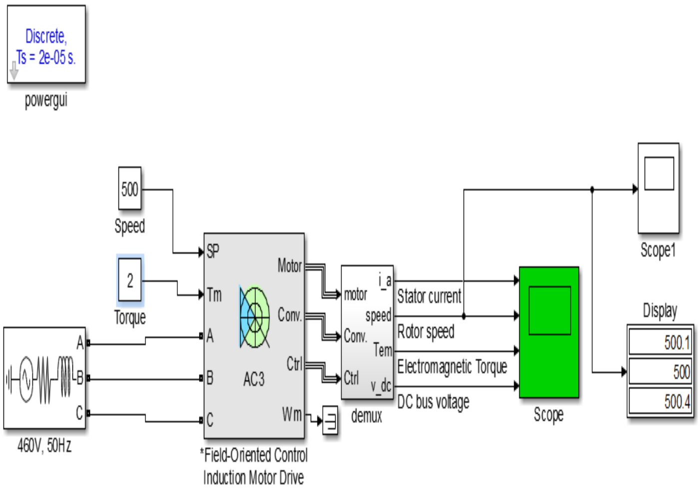

Fig. 5. The main system block diagram

To evaluate the performance of the classical rotor flux-based MRAS scheme, extensive tests are carried out using FOC scheme as the IM control strategy.

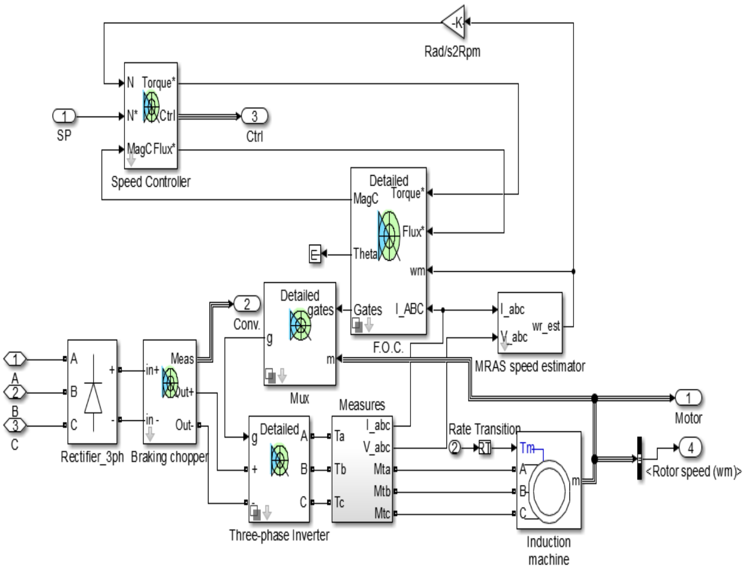

Fig. 6: The high-level schematic diagram

The high-level schematic shown above in Fig. 6 is built from seven main blocks. They are induction motor, three-phase inverter, three-phase diode rectifier, braking chopper, F.O.C., speed controller, MRAS speed estimator models.

A proximity sensor is used to measure the actual motor speed, and three LA 25-NP current sensors are used to measure the motor phase currents. In addition, three LV 20-P voltage sensors are used to measure motor phase voltages and one LV 20-P voltage sensor applied to monitor the dc-link voltage. In order to practically implement MRAS scheme, the integrator in the reference model was replaced by a low-pass filter with a cut- off frequency of 16 Hz to minimize drift and initial condition problems associated with pure integration.

V. SIMULATION RESULTS

The simulation results for the various type of response are obtained using MATLAB Simulation. *With no load test, block rotor test and dc test parameters of the induction motor are calculated. Induction machine rating and parameters are shown below* in the Table I.

Table I. Induction Motor (1 HP) rating and parameters

Symbol	Meaning	Values
-	Motor power	1 HP
-	Line to line voltage	415V(RMS)
-	Rated speed	1410 rpm
P	Pole pair	2
Ls	Stator self-inductance	0.0502 H
Lr	Rotor self-inductance	0.0754 H
Lm	Magnetizing Inductance	0.601 H
Rs	Stator Resistance	10.33 Ω
Rr	Rotor Resistance	6.18 Ω
J	Inertia	0.009413 Kg-m^2

In Fig. 7 shown below, there is stator current of the motor, the comparison between estimated speed, reference speed and actual speed, load torques of the motor and dc bus voltage at a torque of 5Nm and speed of 100 rpm.

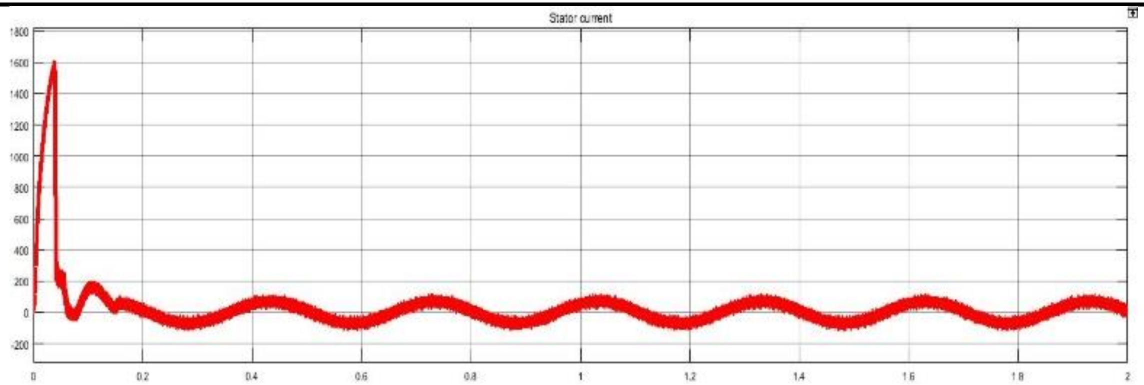

Fig. (a)

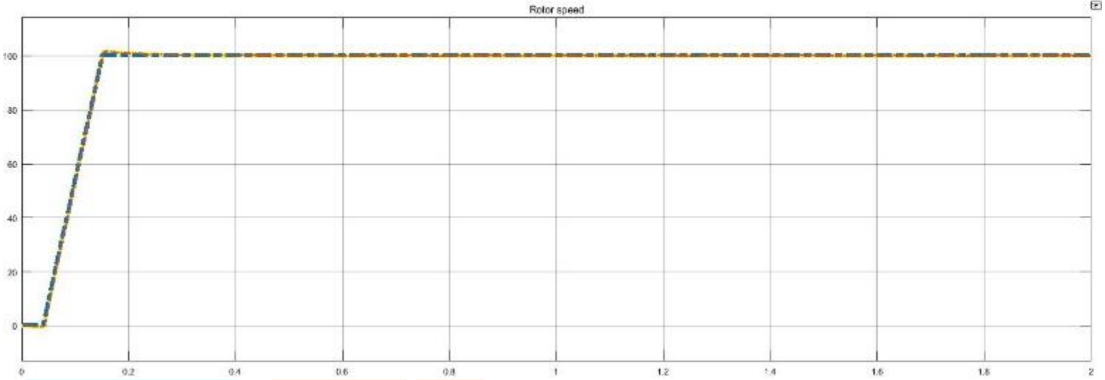

Fig. (b)

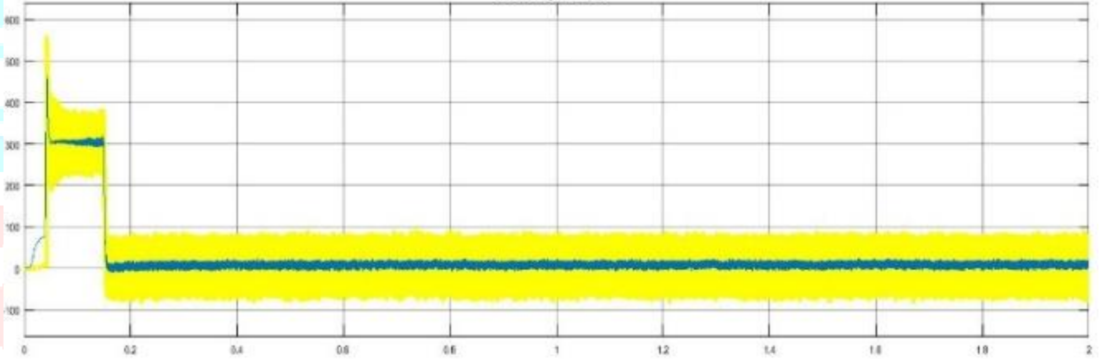

Fig. (c)

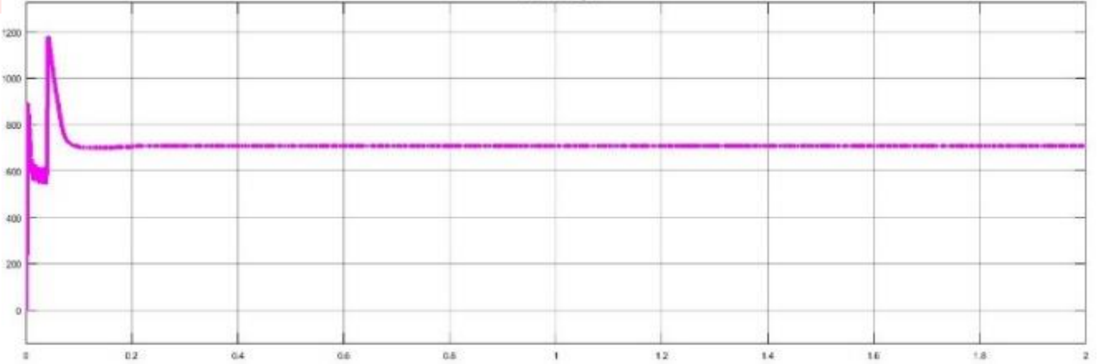

Fig. (d)

Fig. 7: Waveforms of (a) Stator current, (b) The comparison between estimated speed, reference speed and actual speed, (c) Load torques of the motor and (d) DC bus voltage at a speed of 100 rpm and torque of 5Nm.

From stator current and electromagnetic torque waveform, it is seen that initially the starting current and torque are high and after 0.18sec when the motor attains 70-80% of rated speed both the current and torque reduces.

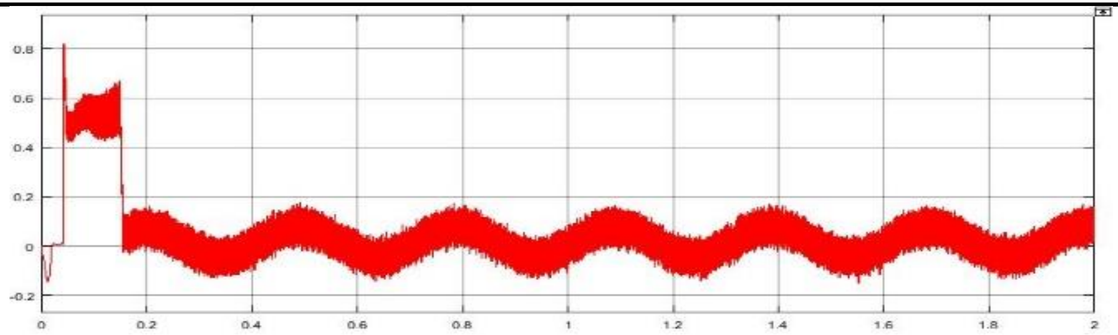

Fig. (a)

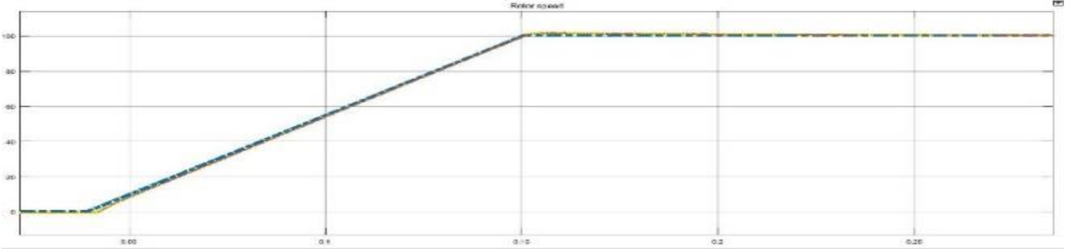

Fig. (b)

Fig. 8: Error and comparison between estimated speed, reference speed and actual speed

In model predictive MRAS method, the error between estimated rotor speed and the actual speed of the motor is very less compared to an error with classical MRAS method.

VI. CONCLUSION

In this paper, a novel predictive MRAS rotor speed estimator has been proposed for sensor-less IM drives. The new estimator is based on the finite control set-model predictive control principle and applies an optimization approach to minimize the speed tuning error signal of the MRAS scheme. This eliminates the need for a PI controller in the adaptation mechanism. A search algorithm is employed to ensure that optimal rotor position is achieved in each sampling period that minimizes the error signal. A modification has been introduced to the proposed algorithm to reduce its computational complexity compared to the conventional PI controller. Detailed experimental tests were carried out to compare the performance of the proposed and the classical rotor flux based MRAS schemes. Results show a better estimation quality of the rotor speed with a significant reduction in steady-state oscillations without affecting the dynamic response as a minimum speed tuning signal is ensured in both transient and steady-state conditions. Improved robustness against motor parameter variations was also demonstrated for the proposed scheme.

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