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Disturbance Observer Assisted Error Sensitive Predictive Control for Induction Motors in Sensor less Environment: A Vector Field Control Model

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Abstract: *The exponential rise within the demands of Induction Motors in several applications has revitalized academia-industries to develop more robust and efficient IM drives. Amongst the main classically available IM drives efforts are made either to regulate speed or torque. However, the problem inculcated due to parametric mismatch and resulting errors have much addressed. Though, predictive control based approaches are found potential to help current and torque control; however, ensuring optimal controllability under non-linear condition remained a tedious task. Filter based approaches to impose delay that eventually impacts overall control performance. Realizing it as motivation, during this research a highly robust Disturbance Observer Assisted Error Sensitive Predictive Control Strategy for IM control is developed. Subsequently, a completely unique Disturbance Observer-based Model Predictive Control strategy is developed that performs predictive current control and torque-control during a non-linear environment. Our proposed model exploits the concept of Prediction-Error to realize transient controllability. Exploiting the error information our proposed model identified the optimal voltage vector value to be injected to the 3-Ø inverter connected to the PI-based Space Vector Pulse Width Modulation system to perform transient controllability. Structurally, our proposed system encompasses SQIM motor, 3-Ø inverter, PI controller SVPWM, Flux-observer, Torque and Speed controllers, VSI units, etc. The MATLAB 2017a based simulation has revealed that the proposed model is able to do better current control, flux-torque control and torque-ripple suppression, which broadened its employability for varied applications demands fast-torque control during a noisy environment.*

Keywords: *Induction Motor control, Model Predictive Control, Error-Prediction, Error-resilient control.*

I. INTRODUCTION

The exponential rise in electrical systems and allied demands have revitalized academia-industries to develop more efficient, productive and especially transiently controllable equipment. Amongst the major application environment ranging from the sophisticated home appliances to the industrial and /or scientific purposes, induction motors have irreplaceable significance.

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In the last few years, Alternative Current (AC) induction motors have been extensively employed in different industrial purposes, especially for motion control requirements. The key significance of employing induction motor over dc motor is rugged construction, high efficiency, and maintenance-free operation. Numerous electrical drives that need efficient dynamic performance to respond to the changes in command speed and torque. These requirements of AC

drives can be fulfilled by the vector control system. Undeniably, with the emergence of the vector control method, an induction motor has been controlled like a separately excited DC motor for high-performance applications. This approach can enable the control of the field and torque of induction motor independently by decoupling and manipulating corresponding field-oriented parameters. However, the efficiency of such systems gets limited in case of noise and interferences caused within the application environment.

In IM control, accurate and timely parameter estimation is of great significance, as it can help to achieve transient motor control. On the other hand, the predictive control paradigm too can have vital significance for IM control. Summarily, the optimal and accurate IM parameter estimation and enhanced model predictive control strategy can be of utmost significance for (adaptive) IM control. Undeniably, the optimal selection of the IM parameters and adaptive predictive control measure can be vital for IM control functions. However, estimating accurate (dynamic) parameters under interference and noisy environment, especially under a Sensorless environment is a highly complicated task. In the practical world, identifying IM parameters is a highly tedious task, which becomes even more complex due to the need for distinguishing data obtained during fast transient [1-3]. Such issues prevail even when the excitation power is exceedingly low [4]. Additionally, it impacts the functioning of the inverter drives, which are often influenced due to the intensive noise. Though authors have recommended using filters, such problems (noises) can't be alleviated or reduced by applying classical low-pass filters (LPFs). Furthermore, the signal-delay and allied (signal) deterioration too can be caused by LPF that eventually would result in estimation error and hence ineffective IM control decision.

Identifying the parameters can help to enhance dynamic control decisions by flux observers, flux estimators, speed estimators, and allied control designs [5-7].

Industries demand lightweight computational controller designs with high feasibility and low complexities. It becomes inevitable when the dynamic current measurement gets contaminated use to high interference and noises. Additionally, the literature reveals that in practice the changes in rotor resistance caused due to skin effect [8] can cause problems to the motor, even with non-load or locked rotor conditions. The majority of the conventional parameter estimation methods employ at standstill, while the recently developed inverter-fed motors employ self-estimation and control

concept which is applied in the single-phase mode. In this method self- commissioning, also called autonomous Observer and control can be applied in the single-phase mode that can maintain the motor shaft static automatically to avoid any use of rotary encoders [4]. Such control methods are also called the Sensor less method which can make overall control more computationally efficient and accurate. Considering it a motive, though efforts were made [9-11] where authors employed stator side impedances (on different frequency points) to obtain equivalent circuit parameters. However, the parameters might vary or fluctuate due to inappropriate selection of the test frequencies. As an enhanced solution, authors [12][13] designed a multi-level method in which during each phase one or two distinct parameters were selected by injecting varied excitation signals. Similarly, authors [14-17] made an effort to use the random signals and Ordinary Least Squares (OLS) method to obtain accurate IM control parameters. However, it remained vulnerable from noise presence which is common in numerous Sensorless IM application environments [4]. To alleviate such an issue, authors [18] applied a modified evaluation condition by employing non-linear least square (NLS) concepts to obtain dynamic IM parameters. However, distinguishing signal parameters from noise components remains the major issue with the state-of-art techniques. Recently, authors [19] developed an active damping based filtering model for the Rotor-Flux Oriented Control (RFOC) in IMs. Unfortunately, the delay and signal distortion introduced by such an approach might confine accuracy and might cause error-in-estimation [35]. Such limitations might affect the overall dynamic or predictive control based IM control.

To alleviate the above stated issues, in this research at first the focus is made on enhancing dynamic IM parameter estimation, which is followed by the implementation of a novel and robust Predictive Control Method for RFOC in IMs. As a solution, in this research at first, we assess the responses obtained from a step-voltage test and generate a sequence of pseudo-random signals which are injected to the stator at standstill (in single-phase mode). Noticeably, our proposed approach employs a non-linear optimization concept that reduces parameter "prediction-error" and thus minimizes the impact of measurement noise significantly. This approach not only reduces the delay but also achieves accurate IM parameters for further predictive control scheduling. In the last few years to achieve efficient controllability, especially under non-linear conditions, Model Predictive Control (MPC) methods have gained significant attention [34]. However, in MPC the focus has been made either to perform predictive current control [24] or torque control as individual tasks [36]. Additionally, authors have merely used cost-functions to predict voltage vector or magnitude of the voltage required to be injected to the inverter to perform torque or current control. However, the inclusion of classical deadbeat controllers often undergoes delay impacting overall control-efficiency or the transient control ability [32][35][40]. No significant efforts are visible which could address the parametric mismatch or measurement errors (such as flux error, current error or flux-torque error) sensitive control strategy, which seems significant for non-linear IM control purposes. Developing a vector control IM solution with MPC requires maintaining an optimal balance between computational overheads as well as multi-dimensional efficiency. To achieve it, the inclusion of a dynamic Observer control model can be significant to identify or keep track of the parametric mismatch and prediction-error. This, as a result, can help predict suitable control voltage for transient controllability. In this relation, the strategic conceptualization of the dynamic Observer model [38][39], flux controller, torque Observer and controller, speed controller (as vector control solution) with SVPWM can be vital for (prediction error-resilient) IM control in Sensorless, non-linear environment. Moreover, the inclusion of predictive current control and torque control as a combined solution can broaden the applicability of IMs in a non-liner environment. Considering the above-stated motives, in this research a novel strategic multi-phased effort has been made, where at first the focus is made on identifying optimal equivalent design parameters of the IM under predictive error condition or non-linear Sensorless environment [37]. In the subsequent research phase a novel Disturbance Observer assisted MPC control model is developed for IM vector field control. Unlike conventional efforts in this research, we focused on amalgamating both PCC as well as PTC as MPC paradigms. The overall control model has been named as "Observer Assisted Error Sensitive Predictive Control Strategy for Induction Motors in Sensorless Environment", which has been developed using MATLAB 2018a Simulink tool.

The remaining sections of the presented manuscript are given as follows. Section II discusses the snippet of the overall research contribution or intend. Section III presents the overall proposed model and its implementation, while the results obtained are discussed in Section IV. Overall research conclusion and allied inferences are presented in Section V and the references used in this research are given at the end of the manuscript.

II. RESEARCH CONTRIBUTIONS

Taking into consideration the overall research intend, existing approaches, and allied future optimization scopes, in this research the focus is made on employing a multi-phase optimization measure. In other words, in this research at first IM design parameter identification concept is derived that exploits prediction error information to achieve the optimal design parameters. In the subsequent phase, especially towards Sensorless IM control purpose with the optimally tuned IM model, a novel Model Predictive Control (MPC) concept is derived.

Noticeably, unlike conventional MPC strategies, this research intends to develop a dual objectives oriented control strategy encompassing both Predictive Current Control (PCC) as well as the Predictive Torque Control (PTC) scheme. Noticeably, in major existing efforts authors have either focused on PCC, Speed control or PTC; however, achieving a cumulative solution can be of vital significance. This research has contributed a novel approach encompassing both PTC as well as PCC under non-linear operating conditions, where there is a significantly high likelihood of

parametric mismatch and estimation errors due to non-linearity and interference/noises. The noticeable contribution of the proposed vector control strategy can be identified as the inclusion of "Prediction Error" and Parametric Mismatch based control strategy. Additionally, to consider non-linearity of the IM design, a Disturbance Observer model is introduces the tracks torque-flux changes and in conjunction with flux-controller, speed controller and torque observer ensure optimal voltage injection to the inverter for transient controllability. Structurally, the proposed system encompasses, Squirrel cage Induction Motor, fed with constant voltage VSI, in adjacency to a 3-phase inverter connected with SVPWM. The disturbance Observer model [38][39] enables the proposed model controlling injection voltage to achieve transient IM controllability.

Redefining the overall research and tentative implementation paradigm, the proposed system can be reframed as a questionnaire. These research questionnaires are given as follows:

RQ1: Can the use of the Prediction Error Method be effective to identify optimal IM design parameters so as to enable it operating efficiently under Sensorless and non-linear conditions?

RQ2: Can the use of Flux-Torque Observer unit, Flux-Torque Controller, Speed Controllers be efficient to achieve better and transient controllability of IM?

RQ3: Can the use of Disturbance Observer assisted error-sensitive MPC control model to be effective towards IM controllability under non-linear and interference/noisy conditions?

This research intends to obtain the justifiable answer for the above-stated questions and associated tentative solutions.

III. PROPOSED SYSTEM

As already stated, the predominant emphasis of this research is made on identifying optimal (control) parameters of the motor followed by dynamic Observer-based error-resilient vector control of the Induction Motor. To achieve it, we have performed a multi-phase implementation paradigm was at first the IM's design parameters are obtained while considering its use-environment as noisy and interference conditions. Additionally, to achieve a tuned design parameter "Prediction Error" information has been applied. In the later phase of implementation, a highly robust and efficient "Disturbance Observer-based Model Predictive Control (DOMPC) scheme is designed for IM control. Noticeably, our proposed DOMPC model exploits non-linear Predictive Current Control (PCC) and Predictive Torque Control (PTC) models together, which has been accomplished by means of a novel Observer unit and "Prediction Error" based control decision. DOMPC model encompasses dynamic speed and flux observer and allied controller, while the Observer model ensures exploiting error information to assist optimal (injection) voltage estimation for the three-phase inverter connected to the IM. Obtaining the error information (say, the difference between the predicted values and the estimated values), the SVPWM modulation pattern changes and thus helps to control the current and torque of the IM. This approach intends to achieve optimal (i.e., transient) current and torque controllability while assuring negligible ripple presence. The detailed discussion of the proposed dynamic "Observer Assisted Error Sensitive Predictive Control Strategy for IM in Sensorless environment" is given in the subsequent sections.

As stated, this research has been accomplished in two phases. These are:

Phase-1 Prediction Error based Dynamic IM Parameter Estimation for IM, and

Phase-2 Dynamic Observer-based Prediction-Error Sensitive Vector Control of IM.

The detailed discussion of these implementation models is given as follows.

A. Phase-1 Dynamic IM Parameter Estimation for Noise-Resilient Transient Controllability

Noticeably, the predominant motive of this inception research phase is to obtain suitable IM design parameters so as to retain reliable and dynamically controllable operating environment. Typically, the parametric mismatch in IM design often leads error in flux, speed and torque-flux information that eventually destabilizes the overall system. Unfortunately, so far authors have not addressed parameter selection followed by error-resilient control mechanism for IM. Considering it as gap and motivation, in this paper at first we focused on obtaining the optimal design parameters. For IM parameter identification we have applied the single-phase test concept. Though classically approaches like "no-load test and locked-rotor test" have been applied in a three-phase mode; however, methods like "no-load test" have been found highly intricate to perform especially when the rotor is already coupled to the loads. Furthermore, the skin effects in a locked rotor test can also impose high errors in rotor resistance that might influence the overall IM controllability. To alleviate such issues, the IM parameter update can be done in an asymmetrical manner, which is common in major IM based speed drives. Typically, to achieve it the two terminals (say B and C) of the three-phase IM are short-circuited, while a single-phase voltage is injected across the IM stator. The key significance of this method is that the rotor of the IM remains standstill as there is no electromagnetic torque generated (in offline mode). Now, replacing the value $\omega_r = 0$ in IM's dynamic model, we get the time-domain configuration as (1).

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$$IM(s) = \frac{z(s)}{u(s)} = \frac{T_r s + 1}{\sigma L_s T_r s^2 + (R_s T_r + L_s)s + R_s} \tag{1}$$

In (1), $z(s) = 1.5 i_A(s)$, where i_A states the current in phase A. The component $u(s) = U_{AB}(s)$ is the linear voltage, while L_s and R_s signify the stator inductance and resistance, correspondingly. The other constant parameter called rotor-time constant is $T_r = {}^{L_r}/_{R_r}$, where L_r and R_r are the inductance and resistance of the rotor, respectively. The parameter called leakage factor σ, which is derived as (2).

$$\sigma = 1 - \frac{{L_m}^2}{(L_s L_r)} \tag{2}$$

In (2), L_m states the magnetization inductance. Now, we discretize (1) so as to obtain the Predictive Error assisted parameter estimation, and get (3).

$$z(k) = \frac{b_1 q^{-1} + b_2 q^{-2}}{1 + a_1 q^{-1} + a_{21} q^{-2}} u(k) = \frac{B(q)}{A(q)} u(k) \tag{3}$$

In (3), q signifies an operator called the z-transformation operator. The IM parameter vector to be obtained comprises an equivalent circuit parameters defined as (4).

$$\begin{bmatrix} a_1 \\ a_2 \\ b_1 \\ b_2 \end{bmatrix} = \begin{bmatrix} 2 - \left(\frac{L_s + T_r R_s}{\sigma L_s T_r}\right) \\ -1 + \left(\frac{L_s + T_r R_s}{\sigma L_s T_r}\right).T_0 - \left(\frac{R_s}{\sigma L_s T_r}\right){T_0}^2 \\ \left(\frac{1}{\sigma L_s}\right).T_0 \\ -\left(\frac{1}{\sigma L_s}\right).T_0 + \left(\frac{1}{\sigma L_s T_r}\right){T_0}^2 \end{bmatrix} \tag{4}$$

In (4), the parameter T states the sampling interval, which has a great role in SVPWM based vector control purposes. Noticeably, estimating the values of L_s, L_r, σ and T_r is an easier task. Once obtaining the vector values of (4), the above stated four parameters can be obtained from the vector. With such motive, the parameter update can be done online by injecting specifically calibrated voltage signals to the stator and then obtaining the values of a_1, a_2, b_1 and b_2 of (3) based on the estimated voltage value U_{AB} and current i_A.

The above section put a glance on the involved parameters of the IM. The detailed discussion of the Prediction Error based IM parameter estimation is given as follows:

1. Prediction Error Based Discrete Model Parameter estimation

The predominant issue in IM parameter estimation and update, especially with inverter-driven IM motors is "electromagnetic interference," which is often imposed due to the impulses caused by the semiconductor devices. Noticeably, such issues become prevalent in the case of Sensorless a drive that eventually degrades the significant embedded information due to excessive noise. In such conditions, obtaining optimal design parameters while considering such real-time uncertainties and interference conditions is a must. With this motive, we exploited the steady-state AC waveform that makes it resilient to the noise affects. Being a self-sovereign approach and integrated with vector control concept our proposed model can be stated as the "Self-Adaptive Filtering" based parameter estimation concept. The use of steady-state waveforms often embodies the signals which are easy to process and hence avoids synchronization and DC bias problems. Considering parameter's sensitiveness in IM we designed Prediction Error based parameter estimation and adaptive vector field control by using analog and digital LPFs for signal tuning which is a better alternative of the conventional OLS based method. To achieve it, we introduced a modified model by inheriting a noise model into the original transfer function as defined in (5).

$$z(k) = \frac{B(q)}{A(q)} u(k) + \frac{1}{A(q)} v(k) = \frac{C(q)}{A(q)} e(k) \tag{5}$$

In (5), $v(k)$ equals $C(q).e(k)$, which is also called moving average sequence for the noise component. Here, $e(k)$ is considered as white noise component while $C(q)$ be the temporarily unknown filter. Mathematically,

$$C(q) = 1 + c_1 q^{-1} + c_2 q^{-2} \tag{6}$$

With the random values of $A(q)$, $B(q)$ and $C(q)$, the respective error sequence $e(k)$ has been obtained as the difference of calculated output waveform (values) and the measured one. Here, we termed a component named Total Prediction Error (TPE), which is the sum of the aforesaid error sequence, $j = \sum e$. In our proposed method, to obtain the optimal control and IM parameters, we intended to minimize predicted error by adjusting $A(q)$, $B(q)$ and $C(q)$. Implementing Parseval concept, the TPE in frequency domain (i.e., j) would be asymptotically equivalent to [21].

$$J \to \frac{1}{2\pi} \int_{-\pi}^{\pi} \left(\frac{B_0(e^{j\omega})}{A_0(e^{j\omega})} - \frac{B(e^{j\omega})}{A(e^{j\omega})}\right)^2 \frac{A^2(e^{j\omega})}{B^2(e^{j\omega})} \Phi_u(\omega) d\omega + \frac{1}{2\pi} \int_{-\pi}^{\pi} \frac{A^2(e^{j\omega})}{C^2(e^{j\omega})} \frac{\Phi_v(\omega)}{{A_0}^2(e^{j\omega})} d\omega \tag{7}$$

In (7), parameter ${}^{B_0(e^{j\omega})}/_{A(e^{j\omega})}$ signifies IM's transfer function. The other parameters $\Phi_u(\omega)$ and $\Phi_v(\omega)$ are the corresponding power spectrum of the input u and disturbance v. The angular frequency is given by ω. Similarly, in the second component of (7), the parameter $A^2(e^{j\omega})/C^2(e^{j\omega})$ states the weighing function, which is a part of LPF. It is vital as it confines noise component v transiently in the high-frequency band. In a real-time scenario, while performing optimization and update $A^2(e^{j\omega})/C^2(e^{j\omega})$ is updated dynamically that helps to eradicate the interference issue and reduction of J.

To identify the IM's parameters, we applied the above stated single-phase mode by injecting sinusoidal voltages of different frequency combinations. It enabled parameter identification based on the stator side equivalent impedance information. Though this approach can be limited due to very minute information available in the frequency domain, we used a Pseudo-Random Binary Sequence (PRBS).

In major conventional voltage injection-based approaches as stated above, R_r and L_m are highly sensitive to noise that can impact overall controllability (due to improper frequency selection. However, selecting optimal frequency with suitable parameters is an NP-hard problem. The dependency on significantly large bandwidth to accommodate more information confines the employability due to increased cost and processing time. In IM parameter estimation and allied control, the selection of the optimal shape, size and amplitude of the excitation signal is vital. Injection signal must embody the sufficient harmonics with specific or targeted frequency band. Additionally, it should be of low frequency (as high frequency might behave like interference). Considering these facts, we applied PRBS, which was generated by using Voltage Source Inverter (VSI). Here, RPBS iterated after a long interval, and during this interval the positive and negative values were generated randomly.

To achieve dynamic parameter estimation for better controllability, we generated PRBS in such a manner that it embodies ΔT (minimum interval), cycle period N and signal amplitude a. To ensure enough harmonics within the targeted frequency band or feature frequency, PRBS followed a condition given in (8) [23].

$$\begin{cases} \dfrac{2\pi}{3\Delta T} > \omega_{max} \\ N\Delta T > T_{0.95} \end{cases} \tag{8}$$

In (8), ω_{max} states the cut-off frequency of the motor while $T_{0.95}$ signifies the specific time when the step voltage response increases to 0.95 from 0. In practice $T_{0.95}$ can be obtained by means of DC voltage test, while ω_{max} too is obtained approximately as per (9).

$$\omega_{max} \approx \frac{0.7\pi}{T_{0.95}} \tag{9}$$

For ease of implementation, in the proposed model the excitation signal pattern is considered as per the IM motor responses to the DC voltage test. Additionally, the amplitude reference a is defined in such a manner that the peak value of the phase current becomes equal to the magnetization current. This approach avoids any possibility of deep saturation and over-current in IM. Thus, obtaining the tuned parameters of the IM, we designed a three-phase inverter connected IM model. The detailed discussion of the proposed IM model and its dynamic control strategy are given in the subsequent section.

B. *Phase-2 Observer assisted Model Predictive Controller for Induction Motor*

In the initial phase of the research, we focused on identifying the suitable SQIM design parameters that could make it more transiently controllable under noise and interference conditions. Our applied Predictive Error based approach resembles the "Self-Adaptive Filter" functional in between the Voltage Source Inverter (VSI) and SQIM. It intends to reduce the distortion caused in the output voltage of the VSI, surge of voltage in the motor terminal, core losses, interference, etc. Obtaining the parameter tuning, we focused on developing a novel and robust Rotor-Flux Oriented Control (RFOC) system for SQIM, which is often employed in Adjustable Speed Drives (ASD). Factually, the inclusion of filters might affect the operating point of the SQIM drives and can turn it into the unstable one, thus causing resonance frequency oscillations in stator current, voltage, etc. On the contrary, there are numerous application environments where providing fast torque response and current control is a must. To achieve it authors have proposed control strategies such as Field Oriented Control (FOC), Direct Torque Control (DTC), etc. These approaches apply controllers like Proportional-Integral (PI) controllers (PI-FOC). PI-FOC which has gained widespread attention across industries; however factors like limited bandwidth and iterative gain parameter tuning confine its applicability. In practice, the iterative gain update is a highly intricate task. Though DTC is simple, the presence of significantly large torque ripple and steady-state error confines its employability (in non-linear applications). To alleviate such limitations, in this paper a novel Disturbance Observer-based Model Predictive Control (DOMPC) model is developed. Unlike existing PI-FOC and DTC methods, our proposed "Observer Assisted Error Sensitive Predictive Control Strategy" enables transient controllability even with low computation and time consumption. Here, the prime goal is to achieve a fast dynamic response, better DC bus utilization and strong Zero-sequence current suppression along with swift Current/Torque response which is vital for the major real-time application environment.

– DOMAC: An Overview

Considering IM control purposes, MPC can be broadly classified into two types; PCC and PTC. Practically, in linear PCC model, a deadbeat controller [32][33][40] is applied especially to control and regulate the currents by generating the reference voltage using predicted current and predicted flux (EMF) [20][21]. On the other hand, for non-linear PCC, a cost-function is used that exploits the effort information between predicted current vector and the reference current that put a foundation for further switching conditions for expected controllability [22-27]. Similarly, linear PTC encompasses a deadbeat flux/torque controller [32][33][40], stator/flux and electrical torque prediction model that cumulatively generates the reference voltage for further IM control purpose. In the case of non-linear PTC, we define a cost-function that dynamically estimates the error of the values of Flux and torque so as to obtain the optimal switching pattern in SVPWM. Noticeably, in the case of non-linear PTC to perform SVPWM switching control we need an optimal set of weighing factors. Considering the significance and robustness of the non-linear PTC model, this research focus is made on designing a novel MDC (derived as a non-linear PTC) model for (RFOC) vector control. Noticeably, we implement non-linear PTC as well as Observer- based current control as well which makes our proposed system robust for numerous real-world applications.

Before discussing the proposed non-linear control model, a snippet of the IM with three-phase inverter is given as follows:

The electrical model of the IM in an arbitrary reference frame can be presented as (10).

$$\begin{bmatrix} v_s \\ v_r \end{bmatrix} = \begin{bmatrix} r_s & \\ & r_r \end{bmatrix}\begin{bmatrix} i_s \\ i_r \end{bmatrix} + p\begin{bmatrix} \psi_s \\ \psi_r \end{bmatrix} + \begin{bmatrix} J_3\,\omega_a & \\ & J_3\,(\omega_a - \omega_r) \end{bmatrix}\begin{bmatrix} \psi_s \\ \psi_r \end{bmatrix} \tag{10}$$

$$\begin{bmatrix} \psi_s \\ \psi_r \end{bmatrix} = \begin{bmatrix} L_s & L_m \\ L_m & L_r \end{bmatrix}\begin{bmatrix} i_s \\ i_r \end{bmatrix} \tag{11}$$

In (10) v_s, i_s, i_r, ψ_s and ψ_r state the state-variables with zero-sequence component. Noticeably, the term called zero-sequence component signifies that $v_s = [v_{sd} \quad v_{ssq} \quad v_{s0}]^T$. Similarly, the other parameters,R_s, R_r, L_s, L_r and L_m states the system parameters. Mathematically, these parameters, $R_s = diag[R_s \quad R_s \quad R_s]$, $L_s = diag[L_s \quad L_s \quad L_s]$ and $L_m = diag[L_m \quad L_m \quad L_0]$. Here, ω_a parameter signifies the random reference frequency, while ω_r presents the frequency of the rotor. In (10), the parameter p states the derivative operator. As depicted in (10), the coupling vector or matrix J_3 is (12).

$$J_3 = \begin{bmatrix} 0 & -1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \tag{12}$$

As depicted in the figure, different controller models apply distinct approaches to control "Inner-Controller" to achieve expected performance.

a). Predictive Current Control (PCC)

Considering above equations (10) and (11), it can be found that the derivative of the current vectors particularly under stationary frame (i.e., $i_s = 0$) can be presented as (12).

$$p\begin{bmatrix} i_s \\ i_r \end{bmatrix} = \begin{bmatrix} L_s & L_m \\ L_m & L_r \end{bmatrix}^{-1}\left(\begin{bmatrix} v_s \\ 0 \end{bmatrix} - \begin{bmatrix} r_s & \\ & r_r \end{bmatrix}\begin{bmatrix} i_s \\ i_r \end{bmatrix} - \begin{bmatrix} 0 & 0 \\ 0 & -J_3\,\omega_r \end{bmatrix}\begin{bmatrix} \psi_s \\ \psi_r \end{bmatrix}\right) \tag{13}$$

Now, applying (13), we derived stator current as (14).

$$pi_s = \frac{I_3}{L_s\sigma}\left(v_{s-}R_s i_s + \frac{I_m}{L_r}(R_r i_r - \omega_r J_3\,\psi_r)\right) \tag{14}$$

In (14), $\sigma = I_3 - \frac{L_m{}^2}{(L_s L_r)}$, while I_3 states the 3-dimensional matrix. Now, the flux (EMF) has been estimated as (15).

$$v_l = R_s i_s - \frac{L_m}{L_r}(R_r i_r - \omega_r J_3\,\psi_r) \tag{15}$$

We have applied an open loop flux estimator that measures the rotor flux using (15). Now, the rotor-flux in the rotor-reference frame ($\omega_a = \omega_r$) is obtained as (16).

$$p\psi_r = \frac{L_m}{L_r}i_s - \frac{I_3}{\tau_r}\psi_r \tag{16}$$

Noticeably, in (16), $\tau_r = {}^{L_r}/_{R_r}$. Now, assigning the values of (16) in (14), we get

$$pi_s = \frac{I_3}{L_s\sigma}(v_{s-}v_l) \tag{17}$$

Discretizing (17) by means of Forward Euler Method (FEM) results the stator current (18).

$$\hat{\imath}_{s,k+1} = i_{s,k} + T_s\frac{I_3}{L_s\sigma}(\hat{v}_{s,k-}\hat{v}_{l,k}) \tag{18}$$

In (18), T_s signifies the sampling period of the inner controller. Recalling the delay problem [35], we have estimated the sub-sequent iteration value (say, extrapolated value of (18)). Mathematically,

$$\hat{\imath}_{s,k+2} = i_{s,k+1} + T_s\frac{I_3}{L_s\sigma}(\hat{v}_{s,k+1-}\hat{v}_{l,k+1}) \tag{19}$$

Applying the Deadbeat Control Principle (DCP)[40], which states that $\hat{\imath}_{s,k+2} = i_s^*$, the reference voltage at time $t+1$ is (20).

$$\hat{v}_{s,k+1} = \frac{I_3}{T_s L_s\sigma}(i_s^* - \hat{\imath}_{s,k+1}) + \hat{v}_{l,k+1} \tag{20}$$

Here, we estimated the current reference value i_s^* from flux and torque reference values in the same way as is done with classical FOC methods. In the case of a non-linear PCC model, we applied a cost function that enabled the selection of the optimal voltage vector value to be applied to the inverter. Noticeably, in this research, the predominant focus was made on IM control with non-linear characteristics. Now, replacing $\hat{v}_{s,k+1}$ in (20) with 27 possible voltage vectors (in considered SQIM model with 3 phase inverter there are 27 feasible voltage vectors), we achieve (21).

$$\hat{\imath}_{s,k+2}(i) = \hat{\imath}_{s,k+1} + T_s\frac{I_3}{L_s\sigma}(\hat{v}_{s,k+1}(i) - \hat{v}_{l,k+1}) \tag{21}$$

where, $i = 1,\ldots,27$. For non-linear PCC we derive the cost function as (22).

$$g(i) = \omega_\alpha\left|i_{s,\alpha}^* - \hat{\imath}_{s,\alpha,k+2}(i)\right| + \omega_\beta\left|i_{s,\beta}^* - \hat{\imath}_{s,\beta,k+2}(i)\right| + \omega_0\left|i_{s,\beta}^* - \hat{\imath}_{s,0,k+2}(i)\right| \tag{22}$$

In (22), the parameters ω_α, ω_α and ω_α state the weighing factors of the current errors. Thus, with the obtained value of (22), the voltage vector (23) is obtained which was applied to the three- phase inverter for control functions.

$$v_{opt,k+1} = arg \min_{\{i=1,2,\ldots,27\}} g(i) \tag{23}$$

Unlike conventional PCC models, in this research, we have developed a novel and robust Observer-based PCC control strategy. The detailed discussion of the proposed PCC controller is given as follows:

– Disturbance Observer-based Deadbeat PCC (DO-PCC)

Being a non-linear system, IM often undergoes a situation where the measured values differ from the predicted values. On the contrary, there are numerous parameters such as rotor resistance (R_s), Magnetization Inductance (L_m), rotor-flux, etc where even a minute error might force IM to undergo adverse conditions. It can cause steady-state errors in electrical torque and rotor flux. Realizing this fact, as a contribution in this research a novel Disturbance Observer-based Deadbeat PCC (DO-PCC) Model has been developed. Noticeably, our proposed DO-PCC model intends to compensate for the errors and make control function more efficient. This section primarily discusses the proposed DO-PCC for IM. Considering the mathematical model for the stator voltage vector in terms of the stator current i_a and rotor-flux ψ_r, the stator current can be obtained as (24).

$$pi_s = \frac{1}{L_s\sigma}v_s + \left(-\frac{1}{L_s\sigma}\left(R_s + \frac{L_m^2}{L_r^2}R_r\right) - jw_e\right)i_s + \left(\frac{L_m R_r}{L_r^2 L_s\sigma} - jw_r\right)\frac{L_m}{L_r L_s\sigma}\psi_r \tag{24}$$

In above equation (24), the parameter $R = R_s + \frac{L_m^2}{L_r^2}R_r$, L=$L_s\sigma$, $k_r=\frac{L_m}{L_r}$, $\tau_r=\frac{L_r}{R_r}$. Now, for $(d-q-0)$ the rotor-flux reference frame ($\psi_{rd}=|\psi_r|, \psi_{rq}$=0) has been obtained as (25-27).

$$v_{sd}=Lpi_{sd}+Ri_{sd}-\omega_e Li_{sq}-\frac{k_r}{\tau_r}\psi_{rd} \quad (25)$$

$$v_{sq}=Lpi_{sq}+Ri_{sq}+\omega_e Li_{sd}+k_r\omega_r\psi_{rd} \quad (26)$$

$$v_{s0}=L_{ls}pi_{s0}+R_s i_{s0} \quad (27)$$

Presenting (26) and (27) in state-space formulation, we derive

$$p\begin{bmatrix} i_{sd} \\ i_{sq}\end{bmatrix}=\begin{bmatrix} -\frac{R}{L} & \omega_e \\ -\omega_e & -\frac{R}{L}\end{bmatrix}\begin{bmatrix} i_{sd} \\ i_{sq}\end{bmatrix}+\begin{bmatrix} \frac{1}{L} & \\ & \frac{1}{L}\end{bmatrix}\begin{bmatrix} v_{sd} \\ v_{sq}\end{bmatrix}+\begin{bmatrix} \frac{k_r}{\tau_r L} & \frac{k_r}{L}\omega_r \\ -\frac{k_r}{L}\omega_r & \frac{k_r}{\tau_r L}\end{bmatrix}\begin{bmatrix} \psi_{rd} \\ \psi_{rq}\end{bmatrix} \quad (28)$$

Discretizing (28) using FEM, we derived the stator d-axis and q-axis currents as (29).

$$p\begin{bmatrix} i_{sd,k+1} \\ i_{sq,k+1}\end{bmatrix}=\begin{bmatrix} 1-\frac{R}{L}T_s & \omega_e T_s \\ -\omega_e T_s & 1-\frac{R}{L}T_s\end{bmatrix}\begin{bmatrix} i_{sd,k} \\ i_{sq,k}\end{bmatrix}+\begin{bmatrix} \frac{T_s}{L} & \\ & \frac{T_s}{L}\end{bmatrix}\begin{bmatrix} v_{sd,k} \\ v_{sq,k}\end{bmatrix}+\begin{bmatrix} \frac{k_r T_s}{\tau_r L} & \frac{k_r}{L}\omega_r T_s \\ -\frac{k_r}{L}\omega_r T_s & \frac{k_r T_s}{\tau_r L}\end{bmatrix}\begin{bmatrix} \psi_{rd,k} \\ \psi_{rq,k}\end{bmatrix} \quad (29)$$

$$A=\begin{bmatrix} 1-\frac{R}{L}T_s & \omega_e T_s \\ -\omega_e T_s & 1-\frac{R}{L}T_s\end{bmatrix} \quad (30)$$

$$B=\begin{bmatrix} \frac{T_s}{L} & \\ & \frac{T_s}{L}\end{bmatrix}$$

$$F=\begin{bmatrix} \frac{k_r T_s}{\tau_r L} & \frac{k_r}{L}\omega_r T_s \\ -\frac{k_r}{L}\omega_r T_s & \frac{k_r T_s}{\tau_r L}\end{bmatrix}$$

Consider that (30) presents the discrete domain parameter matrices, then the stator current value can be predicted as (31).

$$i_{s,k+1}=Ai_{s,k}+Bv_{s,k}+F\psi_{r,k} \quad (31)$$

As already stated, inclusion of MPD and allied filtering might cause steady state error and hence we extrapolated (31) to compensate the same. Thus, we obtain (32).

$$i_{s,k+2}=Ai_{s,k+1}+Bv_{s,k+1}+F\psi_{r,k+1} \quad (32)$$

Similar to (20), considering DCP over (32) we substitute $i_{s,k+2}$ by i_s^*, and thus we get (33).

$$i_s^*=A(Ai_{s,k}+Bv_{s,k}+F\psi_{r,k})+Bv_{s,k+1}+F\psi_{r,k+1} \quad (33)$$

Now, similar to the discussion made above, the voltage (vector) to be injected at time $t+1$ is obtained as (34).

$$v_{s,k+1}=B^{-1}(i_s^*-A((Ai_{s,k}+Bv_{s,k}+F\psi_{r,k})-F\psi_{r,k+1} \quad (34)$$

In our proposed PCC model, considering the sensitivity towards error, to alleviate such issues, we designed a novel Disturbance Observer (DO) model that intends to explore and update dynamic parameters (error-resilient control) to retain better transient controllability. The detailed discussion of the proposed DO-PCC model is given in the subsequent section.

– *DO-PCC: The Design*

Considering (25) and (26), we can derive the augmented IM model as (35) and (36), respectively.

$$\begin{cases} v_{sd}=L\frac{d}{dt}i_{sd}+Ri_{sd}-\omega_e Li_{sq}-\frac{k_r}{\tau_r}\psi_{rd}+f_d \\ \frac{d}{dt}f_d=F_d\end{cases} \quad (35)$$

$$\begin{cases} v_{sd}=L\frac{d}{dt}i_{sq}+Ri_{sq}-\omega_e Li_{sd}-\frac{k_r}{\tau_r}\omega_r\psi_{rd}+f_d \\ \frac{d}{dt}f_q=F_q\end{cases} \quad (36)$$

In above equations, the parameters f_d and f_q signify the error or the disturbance imposed due to parametric differences or error. Mathematically, the disturbances are depicted in (37) and (38).

$$f_d=\Delta L\frac{d}{dt}i_{sd}+\Delta Ri_{sd}-\Delta L\omega_e i_{sq} \quad (37)$$

$$f_q=\Delta L\frac{d}{dt}i_{sq}+\Delta Ri_{sq}+\Delta L\omega_e i_{sd} \quad (38)$$

Considering the parametric mismatched or error in non-linear IM condition to retrieve the disturbances and to predict the stator currents we derived an Observer unit using (37) and (38). Mathematically, the observer can be defined as (39) and (40).

$$\begin{cases} v_{sd}=L\frac{d}{dt}\hat{\imath}_{sd}+R\hat{\imath}_{sd}-\omega_e Li_{sq}-\frac{k_r}{\tau_r}\psi_{rd}+\hat{f}_d+U_{ds} \\ \frac{d}{dt}\hat{f}_d=g_d U_{dsmo}\end{cases} \quad (39)$$

$$v_{sq}=L\frac{d}{dt}\hat{\imath}_{sq}+R\hat{\imath}_{sq}+\omega_e Li_{sd}+k_r\omega_r\psi_{rd}+\hat{f}_q+U_q \quad (40)$$

$$\frac{d}{dt}f_q=g_q U_{qsmo}$$

In the above equations (39) and (40), the parameters $\hat{f}_d$ and $\hat{f}_q$ state the values of the parameter mismatch disturbances from f_d and f_q. Similarly, $\hat{\imath}_{sd}$ and $\hat{\imath}_{sq}$ state the obtained or measured stator currents while the measured voltages in the d-axis and q-axis are given as v_{sd} and v_{sq}, respectively. In our proposed method, we have applied a "Sliding-Mode Control Function (SMCF)" which is defined for both d-axis as well as q-axis distinctly, given as U_{dsmo} and U_{qsmo}, respectively. The gains associated with each SMCF (in individual d-q axes) are g_d and g_q (for sliding mode controller). Now, subtracting (35) from (39) and (36) from (40), we derive the following.

$$\begin{cases} 0=L\frac{d}{dt}(\hat{\imath}_{sd}-i_{sd})+R(\hat{\imath}_{sd}-i_{sd})+(\hat{f}_d-f_d)+U_d \\ \frac{d}{dt}(\hat{f}_d-f_d)=g_d U_{dsmo}-F_d\end{cases} \quad (41)$$

$$0=L\frac{d}{dt}(\hat{\imath}_{sq}-i_{sq})+R(\hat{\imath}_{sq}-i_{sq})+(\hat{f}_d-f_d)+U_{qs} \quad (42)$$

$$\frac{d}{dt}(\hat{f}_q-f_q)=g_q U_{qsmo}-F_q$$

Now, we obtain the current errors in $d-q$ planes as e_{sd} and e_{sq}, respectively. The disturbance error is obtained as e_{fd} and e_{fq} for d-axis and q-axis, correspondingly. Mathematically, the errors are obtained as

$$e_{sd} = \hat{\imath}_{sd} - i_{sd} \quad (43)$$
$$e_{sq} = \hat{\imath}_{sq} - i_{sq} \quad (44)$$
$$e_{fd} = \hat{f}_d - f_d \quad (45)$$
$$e_{fq} = \hat{f}_q - f_q \quad (46)$$

The equations derived in (45) and (46) can further be given as

$$\begin{cases} \frac{d}{dt}e_{sd} = -\frac{R}{L}e_{sd} - \frac{1}{L}e_{fd} - -\frac{1}{L}U_{dsmo} \\ \frac{d}{dt}e_{fd} = g_d U_{dsmo} - F_d \end{cases} \quad (47)$$

$$\begin{cases} \frac{d}{dt}e_{sq} = -\frac{R}{L}e_{sq} - \frac{1}{L}e_{fq} - \frac{1}{L}U_{qsmo} \\ \frac{d}{dt}e_{fq} = g_q U_{qsmo} - F_q \end{cases} \quad (48)$$

In our proposed method, to implement SMC, we select a switching surface where a linear switching surface is considered. These switching surfaces are defined as (49) and (50).

$$s_d = \hat{\imath}_{sd} - i_{sd} \quad (49)$$
$$s_q = \hat{\imath}_{sq} - i_{sq} \quad (50)$$

To achieve it, we incorporated a "reaching-level", which are selected as per the following condition.

$$\frac{d}{dt}s = -k_1 sgn(s) - \lambda_s \quad (51)$$

Now, substituting (49) into (51), we get

$$\frac{d}{dt}e_{sd} = -k_1 sgn(e_{sd}) - \lambda_{esd} \quad (52)$$
$$\frac{d}{dt}e_{sq} = -k_1 sgn(e_{sq}) - \lambda_{esq} \quad (53)$$

Now, substituting the derivatives in (47) and (48) by employing (52) and (53), we get the following:

$$-\frac{R}{L}e_{sd} - \frac{1}{L}e_{fd} - \frac{1}{L}U_{dsmo} = -k_1 sgn(e_{sd}) - \lambda_{e_{sd}} \quad (54)$$

$$-\frac{R}{L}e_{sq} - \frac{1}{L}e_{fq} - \frac{1}{L}U_{qsmo} = -k_1 sgn(e_{sq}) - \lambda_{e_{sq}} \quad (55)$$

We have obtained the compensated voltages U_{dsmo} and U_{qsmo} using (56) and (57).

$$U_{dsmo} = (L\lambda - R)e_{sd} + k_1 L sgn(e_{sd}) \quad (56)$$
$$U_{qsmo} = (L\lambda - R)e_{sq} + k_1 L sgn(e_{sq}) \quad (57)$$

Discretizing (39) and (40), using FEM, we predict the stator current and parametric disturbances. The predicted values are,

$$\hat{\imath}_{sd,k+1} = \left(1 - \frac{RT_s}{L}\right)\hat{\imath}_{sd,k} + \frac{T_s}{L}v_{sd,k} + \omega_e T_s i_{sq.k} + \frac{k_r T_s}{\tau_r L}\psi_{rd,k} - \frac{T_s}{L}\hat{f}_{d,k} - \frac{T_s}{L}U_{dsmo,k} \quad (58)$$

$$\hat{f}_{d,k+1} = \hat{f}_{d,k} + T_s g_d U_{dsmo,k} \quad (59)$$

$$\hat{\imath}_{sq,k+1} = \left(1 - \frac{RT_s}{L}\right)\hat{\imath}_{sq,k} + \frac{T_s}{L}v_{sq,k} - \omega_e T_s i_{sd.k} - \frac{k_r T_s}{\tau_r L}\omega_r \psi_{rd,k} - \frac{T_s}{L}\hat{f}_{q,k} - \frac{T_s}{L}U_{qsmo,k} \quad (60)$$

$$\hat{f}_{q,k+1} = \hat{f}_{q,k} + T_s g_q U_{qsmo,k} \quad (61)$$

In major existing efforts, authors have either focuses on current control or torque control. On the contrary, applications demand efficient transient control for torque-flux as well as current that as a result can optimize the overall transient-controllability of the IM. Considering it as a motive, in this paper, we employed observer-based PTC. Noticeably, our proposed model employs flux observer, flux controller, speed controller, etc that in conjunction with PI-based SVPWM enables efficient torque control in IM. The detailed discussion of the proposed PTC model is given as follows.

b). Predictive Torque Control (PTC)

Discretizing the rotor-flux equation using FEM, we predict the rotor-flux value at $k+1$ (62).

$$\hat{\psi}_{r,k+1} = \frac{L_m}{\tau_r}T_s i_{s,k} + \left(I_3 - \frac{I_3}{\tau_r}\right)T_s\psi_{r,k} \quad (62)$$

Now, to predict the stator flux at $k+1$, we applied stator current equation. Mathematically, the stator-flux is predicted as (63).

$$\hat{\psi}_{s,k+1} = T_s v_{s,k} + \left(I_3 - T_s\left(\frac{I_3}{\tau_{s\sigma}} + J_3\omega_{\alpha,k}\right)\right)\psi_{s,k} + \frac{k_r}{\tau_{s\sigma}}T_s + \psi_{r,k} \quad (63)$$

$$\hat{T}_{e,k+2} = \frac{L_m P}{\sigma L_s L_r}\left(\hat{\psi}_{sq,k+2\hat{\psi}_{rd,k+2}} - \hat{\psi}_{sd,k+2\hat{\psi}_{rq,k+2}}\right) \quad (64)$$

In (64), P signifies the pole pairs. With the rotor-flux orientation frame we get $(\omega_\alpha - \omega_e, \psi_{rd} = |\psi_r|, \psi_{rd} = 0)$, where ω_e presents the synchronous frequency of the rotor flux. Applying the above discussed deadbeat control principle (DCP) $\hat{\psi}_{rd,k+2} = |\psi_r^*|, \hat{T}_{e,k+2} = T_e^*$, we predict the d-axis and q-axis voltages to be injected at $t+1$ (65).

$$\hat{v}_{sd,k+1} = \frac{1}{T_s}|\Psi_r^*| + \left(\frac{R_s}{\sigma L_s} - \frac{1}{T_s}\right)\hat{\psi}_{sd,k+1} - \hat{\omega}_{e,k+1}\hat{\psi}_{sd,k+1} - \frac{R_s L_m}{\sigma L_s L_m}\hat{\psi}_{rd,k+1} \quad (65)$$

In other way,

$$\hat{v}_{sd,k+1} = \frac{\sigma L_r}{PT_s}\frac{T_e^*}{|\Psi_r^*|} - \left(\frac{1}{T_s} - \frac{R_s}{\sigma L_s}\right)\hat{\psi}_{sd,k+1} + \hat{\omega}_{e,k+1}\hat{\psi}_{sd,k+1} \quad (66)$$

Considering the non-linear IM environment we consider non-linear PTC realization where we define a cost function that reduces the parameter mismatch or errors, as discussed in the above section. To achieve optimal PTC our proposed model iteratively reduces the errors of torque, flux magnitude, and zero-sequence current, respectively. Thus, applying the above discussed DO concept and error reduction measure we obtain the voltage vector to be injected to the inverter for torque control. It helps to achieving ripple suppression, fluctuation and stability that makes IM operation more reliable. To suppress the Zero-Sequence current, it can be predicted as (67).

$$\hat{\imath}_{s0,k+2}(i) = \left(1 - \frac{T_s R_s}{L_{ls}}\right)\hat{\imath}_{s0,k+1} + \frac{T_s}{L_{ls}}\hat{v}_{sd,k+1}(i) \quad (67)$$

Thus, the cost function can be derived as (68).

$$h(i) = \omega_{te}\left|T_e^* - \hat{T}_{e,k+2}(i)\right| + \omega_\psi\left||\Psi_r^*| - \hat{\psi}_{s,k+1}(i)\right| + \omega_0\left|\hat{\imath}_{s0,k+2}(i)\right| \quad (68)$$

Though, in some recent research authors recommended avoiding iterative weighing for transient controllability [28].

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In (68), the parameters ω_{te}, ω_{ψ} and ω_0 are the weight factors pertaining to the torque, flux (magnitude) and Zero-Sequence current errors respectively. Thus, employing above function, we apply the optimal voltage to the inverter for control.

$$v_{opt,k+1} = arg \min_{\{i=1,\dots,27\}} h(i) \quad (69)$$

Thus, implementing the above discussed methodology we have achieved dynamic current and torque control for IM model. The simulation results and allied inferences are discussed in the sub-sequent section.

IV. RESULTS AND DISCUSSION

The overall implementation schematic of the proposed vector control scheme for IM is given in Fig. 1. To assess the efficacy of the proposed model, we applied the MATLAB/Simulink software platform. Here, the IM was interfaced with an ideal voltage source, with a controllable noise component. Here, initially, the voltage amplitude a and time interval ΔT of the pseudo-random bit stream were estimated by means of a ramp voltage and step voltage, correspondingly. Initially the value of a was maintained at 21.57V, as at this voltage the value or i_A reached the magnetization (rated) current level. We employed IM with V_{Dc} as 480 V, operating at the frequency of 50 Hz. Noticeably, we maintained the transition time $T_{0.95}$ as 0.24 seconds. Considering real-time implementation scenario, in this research, we select ΔT in such manner that it is sufficient enough to decrease the skin-effect and has the acceptable level of delay for (real-time) data acquisition. In this simulation, we assigned $\Delta T = 0.05\ s$. It was then followed by the injection of the PRBS voltage into the IM. To emulate the noise component, we mixed colored noises to i_A along with the DC bias. Initially we applied the following detuned parameters $R_s = 2.76\,(\Omega)$, $L_s = 11.8mH$, $T_r = 0.06$, $R_r = 3.11(\Omega)$. Additionally, we applied mutual inductance of 188.2mH. We assigned the switching frequency of SVPWM as 5 kHz. In addition, we introduced dead-time compensation [25]. The DC link voltage was maintained at 480V. We interfaced motor-shaft to a DC generator, which was controlled using a DC motor speed driver so as to change in the load-torque value. To examine the performance of the proposed model, we have obtained measurements for voltage, current, rotor speed, torque, etc. To retain the efficient performance a motor requires maintaining an optimal voltage level while controlling speed and torque over a non-linear operating environment. The overall implementation schematic of the proposed IM vector control strategy is given in Fig. 1.

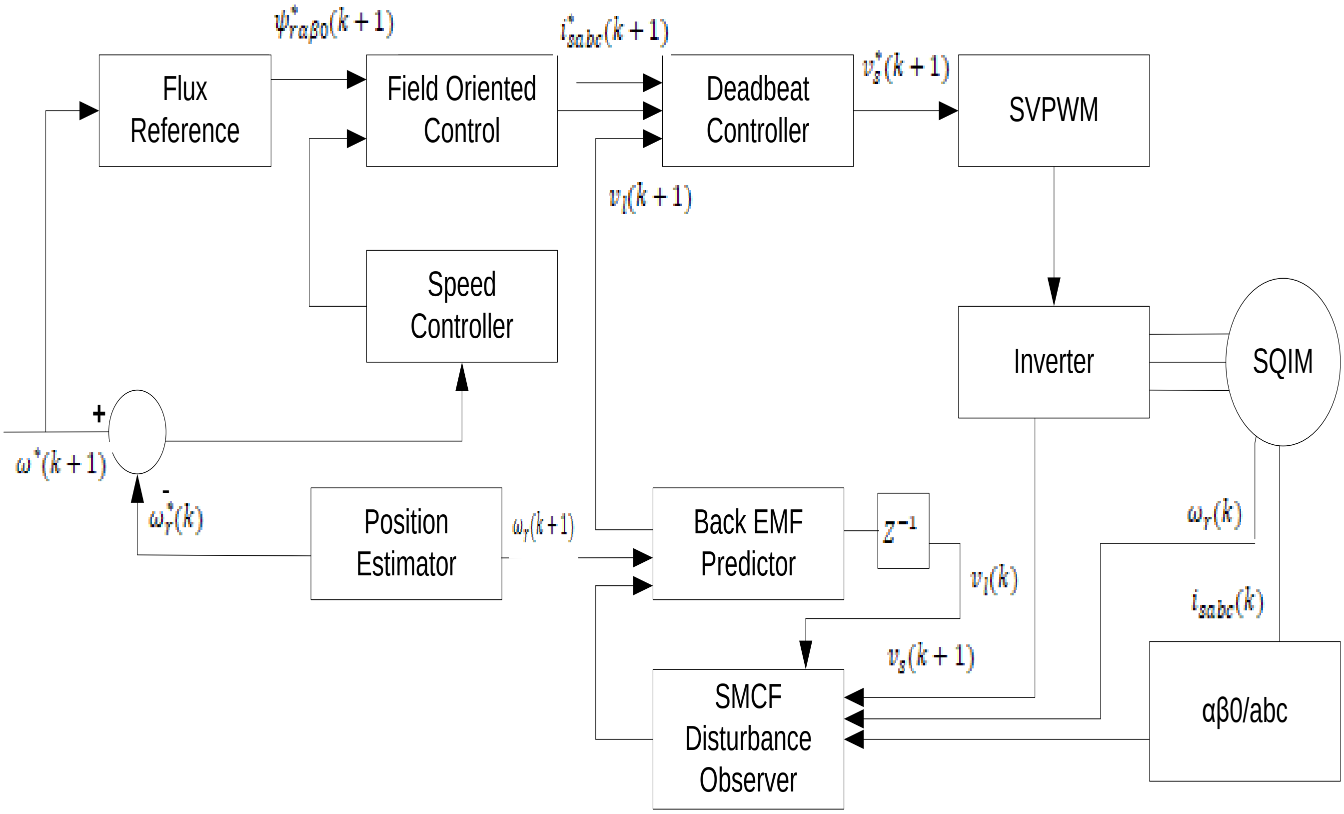

Fig. 1 Proposed vector control model for IM

Fig. 2 presents the DC voltage, which is almost linear and maintained at the 480V level. In Fig. 3 the current measured at the three phases are depicted. Observing the results it can be found that over the simulation period, varying the load and torque conditions, current does vary however maintained at least or negligible fluctuations. Noticeably, the simulation test has been done at the low-speed rotation (here we initialized with 55 (rad/s). Considering the fact that with high-speed rotation interference component increases that induce disturbances resembling noise component, we tested our model at relatively low-speed operation.

Noticeably, unlike Open-end wire IM (OEWIM) [29-31] where authors have applied multiple Inverters (dual inverter), which demands a significantly large number of switches to assist control, our proposed model applied a single 3-phase inverter. Thus, it can be computational more efficient as compared to doubly-feed (dual) inverter based SVPWM models. Fig. 4 presents the rotor speed, which can be found near stable even after a change in load and non-linear conditions. The torque generated over the simulation period is given in Fig. 5. The overall speed controllability feature of the proposed model can be visualized in Fig. 6.

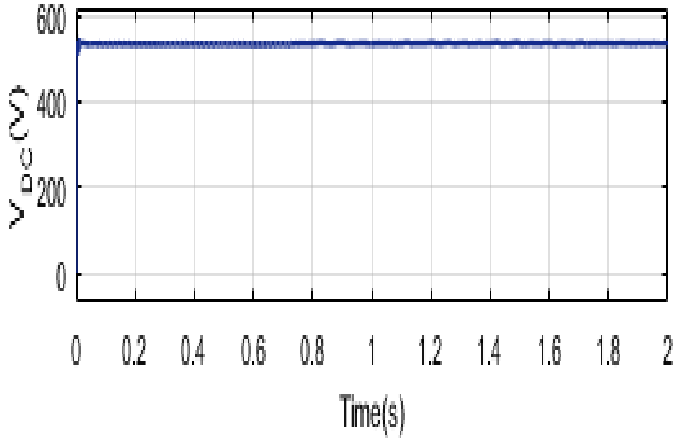

Fig. 2 V_{DC} maintained at 480 V

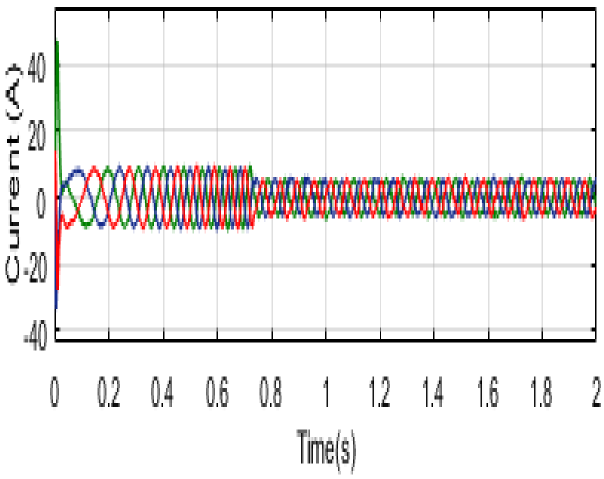

Fig. 3 $I_{abc}(A)$ current

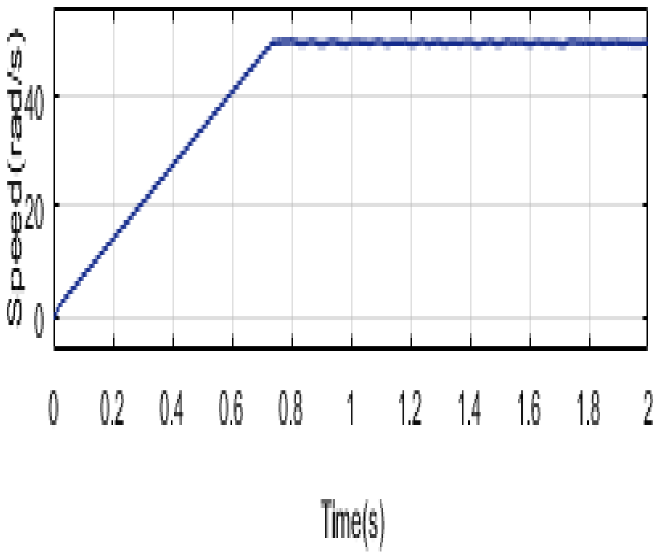

Fig. 4 Speed of the rotor (in rad/s)

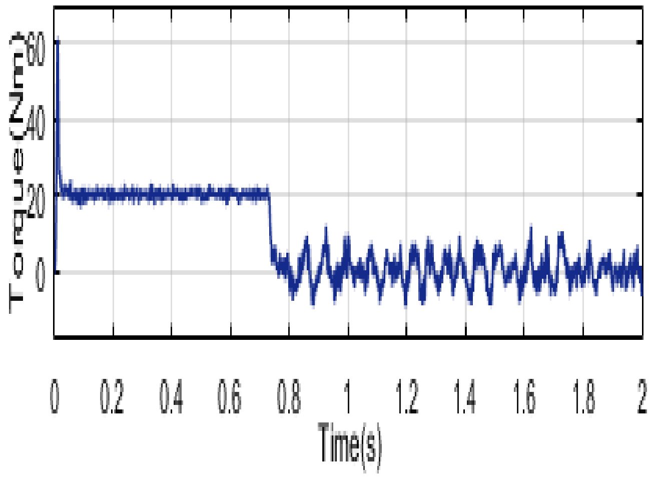

Fig. 5 Torque generated (Nm)

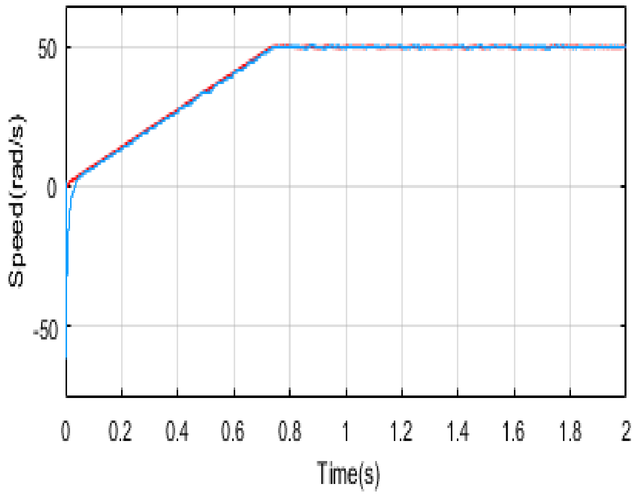

Fig. 6 Rotor Speed controllability (red-reference, blue-proposed)

Considering overall performance by the proposed model it can be stated that the inclusion of dynamic Observer unit and allied MPC concept could achieve satisfactory performance, especially to control the current, torque and speed of the IM. The results affirm that the proposed method can be efficient in better DC bus utilization and strong Zero-sequence current suppression along with swift Current/Torque response which is vital for major real-time drive applications. Observing the overall results and allied inferences, it can be found that the research questions, as framed in Section II affirms the acceptability of the proposed solution.

V. CONCLUSION

Realizing the significance of vector control in Induction motor, especially under noisy and interference conditions, this research focused on achieving a cumulative control approach. To achieve it, a multidimensional approach was formulated where at first motive was made on assuring optimal IM design parameter identification to be followed by Model Predictive Control implementation. Noticeably, the consideration of Prediction Error sensitive parameter identification helped to achieve optimal design for SQIM to be operated under noisy, interference environment in Sensorless set up.

The use of prediction error based IM parameter estimation strengthened the proposed model to ensure efficient motor design which further helped in alleviating parametric mismatch and errors. This way it achieved an error-resilient IM operating environment. Furthermore, exploiting the efficacy of MPC concept, this research employed Predictive Current Control followed by Toque control by employing a robust Observer model that dynamically estimates error in between the estimated and predicted flux-torque and current values, based on which it obtains the optimal voltage vector to be injected to the inverter for transient control. Noticeably, the proposed method considered dynamic parameters to make adaptive control decisions; it is suitable for non-linear IM applications. The used of SVPWM in conjunction with PI-based flux and current controller helped to achieve better and more efficient (transient controllability) while maintaining DC voltage consistent while torque-ripple suppression and current control. Unlike conventional efforts where efforts are made either to perform torque control or speed control, this research embodied both predictive current control as well as torque control in non-linear condition. It makes the proposed system novel and robust to meet contemporary IM control demands. In the proposed vector control model SVPWM was applied to control the signal patterns before feeding it to the inverter for transient controllability. The performance and allied inferences reveal that the proposed approach can be ready to implement for dynamic torque-current control of the IM used in applications like chassis dynamometers and engine dynamometers where IM is applied to provide load torque and imitate propulsion motors for electric vehicles.

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