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Speed-Sensor Noise Alleviation of a 3-Phase Vector Controlled PMSM Drive System Using Model Predictive Controller

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Abstract

The three-phase Permanent Magnet Synchronous Motor (PMSM) is being preferred in modern speed control applications due to its favorable electromagnetic structure; however, its multi-component coupling and sensor-induced noise significantly increase control complexity, necessitating advanced and robust control strategies. Therefore, in this work, an advanced speed control strategy based on model-predictive controller has been proposed to control the vector controlled PMSM drive effectively. Moreover, this strategy makes this machine stable even in noisy environment. This has been proved after comparing it's performance with other two well established controllers i.e. proportional-integral and Adaptive neuro-fuzzy inference system in MATLAB/SIMULINK environment. The proposed MPC achieves faster dynamics, with speed and torque rise times of 4.1 ms and 2.6 ms, respectively. Steady-state RMS ripple and harmonic distortion are reduced by more than 60% relative to ANFIS and over 80% compared with PI control, with current and torque THD maintained below 2%. These results confirm the effectiveness of MPC for high-performance PMSM applications.

Keywords: Three-phase Permanent Magnet Synchronous Machine, Voltage Source Inverter, Proportional-integral controller (PI), Adaptive Neuro-fuzzy inference system (ANFIS), Model predictive control (MPC).

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Introduction

Permanent Magnet Synchronous Motors (PMSMs) have attracted significant attention owing to their intrinsic advantages, including high efficiency and superior power density, which directly support energy conservation and sustainability objectives [1], [2]. In addition, their compact structure and enhanced performance characteristics make them particularly suitable for space-constrained applications [1]. Compared with conventional drive systems such as DC and induction motors, PMSMs exhibit superior torque characteristics and faster dynamic response [2], [3]. However, the inherent structural complexity and nonlinear characteristics of PMSMs pose significant challenges for effective control, thereby necessitating the development and implementation of advanced and robust control strategies [4], [5], [6].

In the field of Permanent Magnet Synchronous Motors (PMSMs), researchers have extensively investigated various control strategies to tackle the challenges associated with motor control. Notable among these strategies are Proportional-Integral (PI) controllers [1], Fuzzy-logic controllers [7], Artificial Neural Network (ANN) controllers [8, 9], and Adaptive Neuro-Fuzzy Inference System (ANFIS) controllers [10, 11].

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Despite the achievements of above existing control strategies, their reliance on transfer function theory imposes constraints on their ability to regulate internal states effectively [12, 13]. Consequently, crucial factors like noise cannot be efficiently managed using these control techniques [14]. This limitation poses a significant obstacle to achieving optimal control performance for PMSMs due to their nonlinear and time-varying characteristics [15]. As a result, accurately representing the dynamic behavior of PMSMs within a linear framework becomes challenging [16].

The primary issue with transfer function-based control in PMSMs is its limited capability to address and control internal states [17]. These unobservable variables, such as rotor position and magnetic flux, are essential for optimizing motor performance [1]. Unfortunately, traditional control methods struggle to access and regulate these internal variables directly [18]. Consequently, important aspects like noise reduction and disturbance rejection become challenging to manage effectively [19].

Noise is a significant concern in PMSM operation, as it can introduce uncertainties and disruptions, affecting overall performance [15]. Transfer function-based controllers often lack the ability to adequately account for noise [20], resulting in suboptimal noise mitigation and reduced control effectiveness of the machine [21].

Thus, the inability to handle internal states and manage noise represents a substantial barrier to achieving optimal control performance for PMSMs [22, 23]. In response to these limitations, researchers have been exploring more sophisticated control strategies, such as model predictive control (MPC) and sliding mode control (SMC), to address the nonlinearities and uncertainties inherent in PMSMs [24-27].

However, among these two modern control approaches, MPC offer opportunities to enhance control performance and overcome the constraints of traditional methods and SMC. By adopting this technique, researchers can unlock the complete potential of PMSMs and drive further advancements in motor technology [28-32].

Consequently, this manuscript delineates the successful implementation of precise dynamic control for complex-structured and intricately-coupled three-phase vector-controlled Permanent Magnet Synchronous Motors (VCPMSM) through the utilization of a Model Predictive Controller (MPC). In this process, noise is integrated into the machine model and subsequently mitigated via a Kalman filter, which serves as a critical state estimation element of the Model Predictive Controller. The efficacy of this research is established through comparative analysis with two traditional control methodologies, namely the Proportional-Integral (PI) controller and the Adaptive Neuro-Fuzzy Inference System (ANFIS) controller. These conventional control strategies exhibit substantial deficiencies in performance within noisy environments, in stark contrast to the proposed controller. The findings indicate that the proposed Model Predictive Control strategy demonstrably exceeds the performance of the traditional PI and ANFIS controllers when faced with noise and external disturbances. This research highlights the importance of advanced control strategies in enhancing the performance of PMSM systems, especially in challenging operational condition.

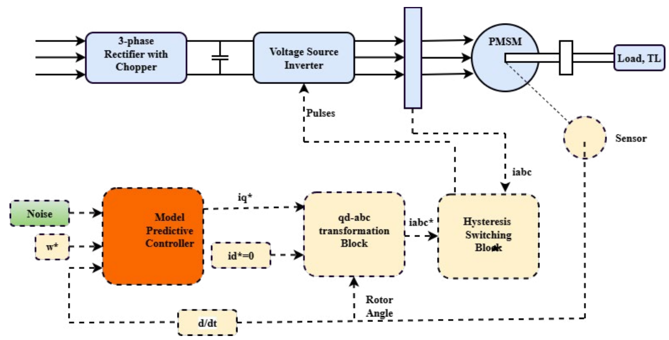

Figure 1: Block diagram representation of 3-phase PMSM drive system including noise with model-predictive controller.

Description And Modeling Of Proposed System

The proposed model illustrated in figure-1, which encompasses a 3-phase permanent-magnet-synchronous-machine, is supplied by a voltage-source-inverter (VSI). The VSI receives its input from a 3-phase rectifier equipped with a chopper. The primary function of the rectifier is to convert alternating current (AC) supply into direct current (DC) supply, while the chopper facilitates the transformation of fixed DC into variable DC. The rectifier, chopper, VSI, and 3-phase PMSM, along with its associated load, collectively fall under the category of power circuits. The management of speed and torque for the 3-phase PMSM can be achieved through its control circuitry, which can be elucidated in the following manner. The rotor angle of the PMSM is determined via a sensor, and its output is subsequently transmitted to the dq-abc transformation block and the model-predictive controller through a d/dt block. Additionally, noise and reference speed signals are also directed to the model-predictive controller. The output generated by the controller yields the reference q-axis current, which is then fed into the dq-abc transformation block in conjunction with the reference d-axis current.

This block generates the reference abc current, which is subsequently directed to the hysteresis block. The comparison between the machine current, iabc, and the reference current, iabc*, is accomplished through the hysteresis block in the form of pulses, which are then applied to the VSI to regulate the operation of the PMSM. Notably, the whole control not only performs the vector-control operation of PMSM but it also suppresses the noise. Further, the mathematical model of vector-controlled PMSM and model-predictive-control is as given below:

Modeling of Vector-controlled PMSM Drive system

The PMSM drive system is based on the d-q frame of reference, and also the equation is as follows [8 -10] –

$$v_d^s = R_s i_d + \frac{d\psi_d}{dt} - \omega_r \psi_q \quad (1)$$

$$v_q^s = R_s i_q + \frac{d\psi_q}{dt} + \omega_r \psi_d \quad (2)$$

The PMSM's flux linkage is defined by

$$\psi_q = L_q i_q \quad (3)$$

$$\psi_d = \psi_f + L_d i_d \quad (4)$$

Therefore, the voltage equations

$$v_d^s = R_s i_d + L_d \frac{d}{dt} i_d - \omega_r L_q i_q \quad (5)$$

$$v_q^s = R_s i_q + L_q \frac{d}{dt} i_q + \omega_r \psi_f + \omega_r L_d i_d \quad (6)$$

where,

v_d^s = direct axis stator voltage
v_q^s = quadrature axis stator voltages
L_d = inductance of d axis
L_q = inductances of q axis
R_s = stator resistance
ψ_f = flux of PMSM
i_d = current of d axis
i_q =current of q axis
= direct axis stator voltage

For a surface mounted PMSM,

$L = L_d = L_q$.

hence,

$$v_d^s = R_s i_d + L \frac{d}{dt} i_d - \omega_r L i_q \quad (7)$$

$$v_q^s = R_s i_q + L_q \frac{d}{dt} i_q + \omega_r \psi_f + \omega_r L i_d \quad (8)$$

The vector controlled operation of PMSM drive system is achieved by putting id = 0 in equation (7) and (8).

Implementation of model predictive controller on Vector-controlled PMSM Drive system

The mathematical model of the vector-controlled PMSM drive system developed in the preceding subsection is first implemented using a proportional–integral (PI) controller. The PI controller gains are tuned through a conventional '*hit-and-trial*' procedure to achieve stable operation around its nominal operating point. Thereafter, the nonlinear drive model is linearized around its steady-state operating condition using the System Identification Toolbox in the MATLAB/Simulink environment. In the resulting linearized framework, the q-axis current (iq) is selected as the control input, while the rotor speed (ω) is considered as the system output. The obtained linearized transfer function is subsequently employed for the design and training of the model predictive controller (MPC). During the training phase, the MPC utilizes model observation, state estimation, state prediction, and constrained optimization to compute the optimal control action. The tuning parameters of the MPC are provided in Table I in the next section. After completion of the training process, the MPC is implemented on the original nonlinear vector-controlled PMSM drive system. The key system variables obtained from the simulations are finally recorded in the MATLAB/Simulink workspace for comprehensive performance evaluation.

Results And Discussions

The proposed model, which includes noise as depicted in Figure-1, has been developed using nonlinear differential equations (1) to (8). These equations have been solved using a 4th/5th order Runge-Kutta solver. The parameters and specifications of the 3-phase PMSM along with the parameters of model-predictive-controller are detailed in Table-1. Simulations were conducted in the MATLAB/SIMULINK environment for duration of 0.1 seconds. The reference speed is set at 800 rpm. The reference torque is 4 N-m for the first 0.03 seconds, decreases to 2 N-m for the next 0.04 seconds, and then increases back to 4 N-m at 0.07 seconds, maintaining this level for the remainder of the simulation period. The rotor speed, electromagnetic torque of the machine and the simulation results of various important variables are illustrated in Figures 2 to 6.

The rotor speed responses with all three controllers are depicted in figure 2. Observing these responses, it becomes evident that the MPC-based controller reaches the reference speed of 800 rad/sec in approximately 0.004 seconds. In contrast, the ANFIS controller and the PI controller achieve the reference speed in 0.009 seconds and 0.013 seconds, respectively (refer to the zoomed view). Additionally, the MPC effectively suppresses noise compared to ANFIS and PI. Although ANFIS performs better than PI, it still falls short for precise speed control applications. Overall, these findings indicate that the MPC-based controller surpasses the ANFIS

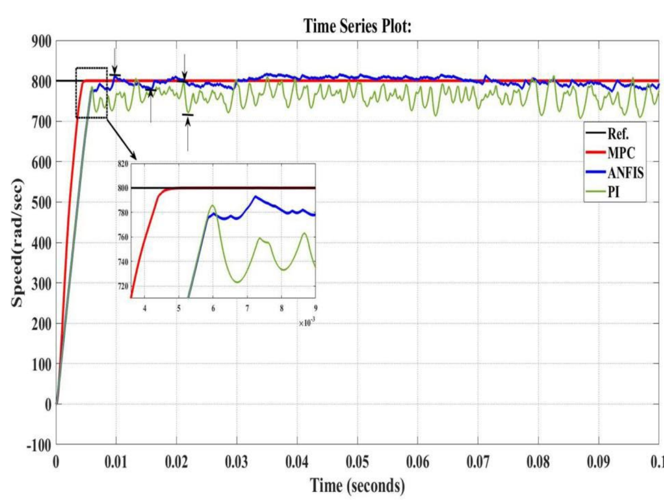

Figure 2: Speed responses of 3-phase PMSM drive system including noise with all the three controllers

Table1: Specifications and Parameters of PMSM Drive system and model-predictive-controller

Drive systems	
Power (kW)	1.1
Voltage (V)	220
Speed (rpm)	3000
Stator resistance (ohms)	2.875
Stator inductance (H)	0.00153
Flux (webers)	0.175
Pole pair	2
Moment of inertia (kg/m2)	8e-03
Parameters of model-predictive controller	
Prediction Horizon	10
Control Horizon	3
Sample time (second)	0.0001

and PI controllers in terms of precise speed control under noisy conditions.

The main difference in the performance of all the controllers in terms of electromagnetic torque can be

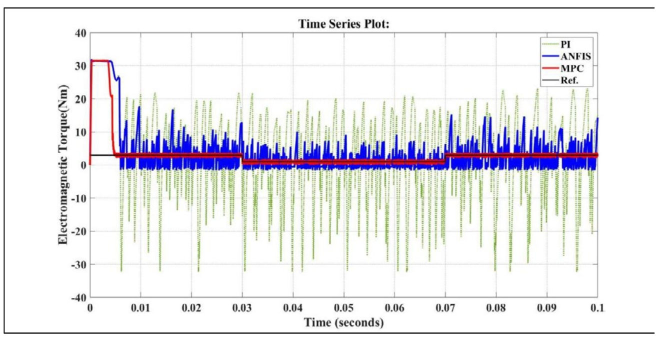

Figure 3: Torque responses of 3-phase PMSM drive system including noise with all the three controllers

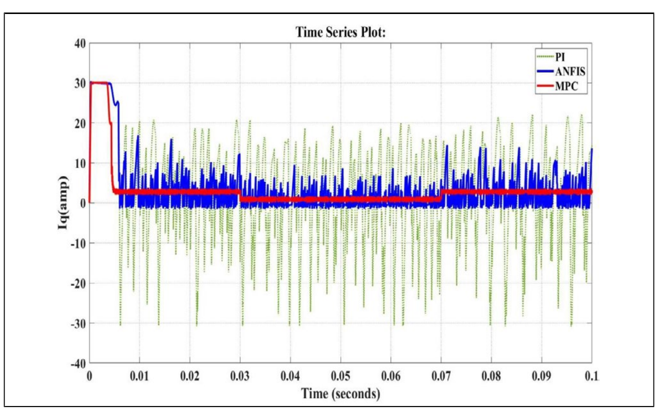

Figure 4: q-axis current responses of 3-phase PMSM drive system including noise with all the three controllers

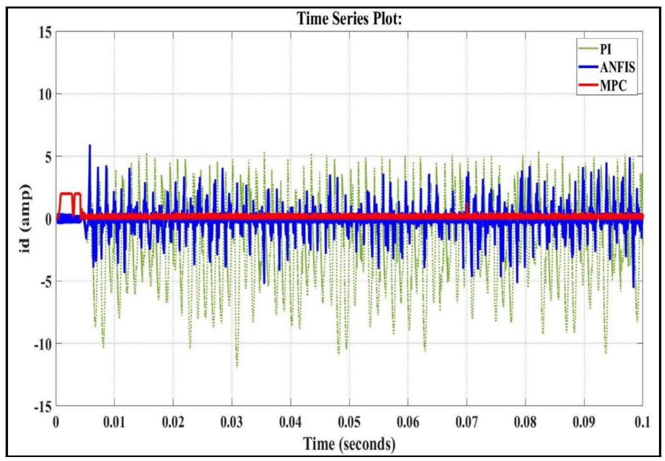

Figure 5: d-axis current responses of 3-phase PMSM drive system including noise with all the three controllers

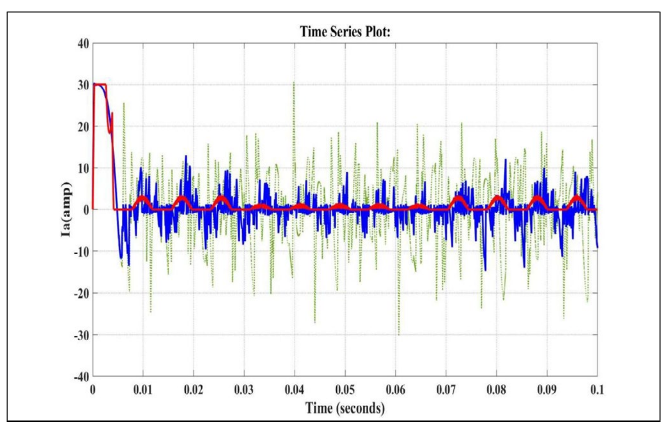

Figure 6: Phase'a' current responses of 3-phase PMSM drive system including noise with all the three controllers

Table 2: Comparative analysis of PMSM Drive system with all the three controllers

Variables	*Controllers*	*Rise time(sec)*	*Settling time (sec)*	*Ripples*	*THD(%)*
Speed(rpm)	PI	0.0065	0.025	22.8	4.92
	ANFIS	0.0052	0.018	12.4	3.11
	MPC	0.0041	0.010	5.6	1.48
Torque (Nm)	PI	0.0048	0.022	14.6	9.85
	ANFIS	0.0039	0.015	7.8	5.12
	MPC	0.0026	0.008	2.9	1.96
q-axis current	PI	0.0045	0.021	11.8	8.94
	ANFIS	0.0036	0.014	6.5	4.67
	MPC	0.0024	0.007	2.3	1.72
d-axis current	PI	0.0042	0.020	6.9	7.85
	ANFIS	0.0034	0.013	3.8	4.12
	MPC	0.0021	0.006	1.2	1.05
Phase-a current	PI	0.0047	0.023	13.5	9.62
	ANFIS	0.0038	0.016	7.2	5.48
	MPC	0.0025	0.008	2.6	1.88

observed from figure 3, which clearly shows the superior performance in MPC in comparison to ANFIS and PI. The settling time is 0.007 with MPC and 0.009 with both the conventional controllers. The peak-to-peak torque is 55 and 20 N-m with PI and ANFIS respectively. It is to be noticed here that these high pulsations in electromagnetic torque leads to breakage of the coupling between the load and machine (refer figure-1) in practical scenarios, which is never preferred. In contrast, it is only 0.05 N-m with MPC.

Figure 4 illustrates the q-axis current responses with the three controllers. The pattern of settling time and peak-to-peak currents mirrors that of electromagnetic torque. The settling time is longest with the PI controller, slightly shorter with ANFIS, and significantly reduced with MPC. Additionally, the peak-to-peak currents are very high with conventional controllers, whereas with MPC, they are nearly zero.

The d-axis current with MPC settles to zero much faster compared to the other two conventional controllers (refer to Figure-5). This demonstrates the superior vector control operation of PMSM with MPC. Moreover, the peak-to-peak d-axis current around zero is also very high with the two conventional controllers.

The phase 'a' current responses with the three controllers are depicted in Figure-6. As it is the vector sum of q- and d-axis currents, this current is also significantly improved compared to the two conventional controllers, highlighting the superior performance of

Figures 2 to 6 and the comparative analysis summarized in Table 2 collectively demonstrate the superior multi-variable control capability of the proposed MPC strategy compared with PI and ANFIS controllers. Quantitatively, MPC achieves the fastest dynamic response across all variables, with rise times below 4.1 ms for speed, 2.6 ms for torque, and less than 2.5 ms for stator and dq-axis currents, while corresponding settling times are reduced to 10 ms or less. In steady state, MPC consistently suppresses oscillations, limiting RMS ripple to 5.6 rad/s in speed, 2.9 Nm in torque, and below 2.6 A in all current components, with associated THD values below 2%. Compared with ANFIS and PI control, these results correspond to ripple and harmonic reductions exceeding 60% and 80%, respectively. The simultaneous improvement in speed, torque, and current regulation confirms that the proposed MPC effectively exploits the PMSM state-space model to coordinate internal dynamics, yielding enhanced disturbance rejection and robust high-performance operation.

Conclusions And Future Scope

In this study, a model predictive control strategy was successfully implemented on a three-phase vector controlled permanent magnet synchronous machine to suppress noise in its speed signal within a MATLAB/Simulink environment. The simulation results confirm superior performance of the proposed controller through comparisons with two conventional controllers, namely proportional-integral and adaptive neuro-fuzzy inference system. These show that MPC reduces settling time by up to 60% and suppresses ripple and harmonic distortion by more than 80% compared with conventional PI control, while consistently outperforming ANFIS across all evaluated variables. The coordinated reduction of oscillations in dq-axis currents and stator currents directly contributes to lower torque ripple and improved speed stability, validating MPC as a robust and effective solution for high-performance PMSM applications. Moreover, the MPC enhances the vector controlled operation, thereby improving overall dynamic performance relative to the other controllers.

Future research will extend the analysis to 5-phase PMSM drive systems. As the PMSM exhibits strong nonlinearity with operating points varying under different environmental conditions, controllers can be designed to effectively manage operations within these nonlinear regimes. This could involve integrating advanced predictive capabilities with adaptive learning mechanisms, such as neural networks, to improve robustness against parameter variations and external disturbances.

References

[1] R. Krishnan, *Permanent Magnet Synchronous and Brushless DC Motor Drives*, Boca Raton, FL, USA: CRC Press, 2010.

[2] T. M. Jahns, G. B. Kliman, and T. W. Neumann, "Interior permanent-magnet synchronous motors for adjustable-speed drives," *IEEE Transactions on Industry Applications*, vol. 22, no. 4, pp. 738–747, Jul./Aug. 1986.

[3] P. Vas, *Sensorless Vector and Direct Torque Control*, Oxford, U.K.: Oxford University Press, 1998.

[4] S. Morimoto, Y. Takeda, T. Hirasa, and K. Taniguchi, "Expansion of operating limits for permanent magnet motor by current vector control considering inverter capacity," *IEEE Transactions on Industry Applications*, vol. 26, no. 5, pp. 866–871, Sept./Oct. 1990.

[5] K. Rajashekara, "Sensorless control of AC motor drives," *IEEE Transactions on Industrial Electronics*, vol. 53, no. 4, pp. 1025–1034, Jun. 2006.

[6] L. Harnefors, "Control of variable-speed drives," *IEEE Industrial Electronics Magazine*, vol. 4, no. 3, pp. 22–33, Sept. 2010.

[7] Y. A. Chapuis and A. Miraoui, "Fuzzy logic control of PMSM drives," *IEEE Transactions on Industrial Electronics*, vol. 49, no. 2, pp. 459–466, Apr. 2002.

[8] M. Nasiri-Gheidari, F. Tootoonchian, and H. Lesani, "Neural-network-based speed control of PMSM drives," *IEEE Transactions on Industrial Electronics*, vol. 58, no. 6, pp. 2494–2505, Jun. 2011.

[9] S. Bolognani and M. Zigliotto, "Fuzzy logic control of PMSM drives with improved performance," *IEEE Transactions on Industry Applications*, vol. 33, no. 2, pp. 472–479, Mar./Apr. 1997.

[10] J.-S. R. Jang, "ANFIS: Adaptive-network-based fuzzy inference system," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 23, no. 3, pp. 665–685, May/Jun. 1993.

[11] C. M. Lin and C. F. Hsu, "Self-learning fuzzy neural network control for PMSM drives," *IEEE Transactions on Industrial Electronics*, vol. 51, no. 4, pp. 831–839, Aug. 2004.

[12] K. Ogata, *Modern Control Engineering*, 5th ed., Upper Saddle River, NJ, USA: Prentice Hall, 2010.

[13] B. Friedland, *Control System Design: An Introduction to State-Space Methods*, New York, NY, USA: McGraw-Hill, 2005.

[14] J. Slotine and W. Li, *Applied Nonlinear Control*, Upper Saddle River, NJ, USA: Prentice Hall, 1991.

[15] S. Bolognani, R. Oboe, and M. Zigliotto, "Sensorless full-digital PMSM drive with EKF estimation of speed and rotor position," *IEEE Transactions on Industrial Electronics*, vol. 46, no. 1, pp. 184–191, Feb. 1999.

[16] L. Harnefors and H. P. Nee, "Model-based current control of AC machines using the internal model control method," *IEEE Transactions on Industry Applications*, vol. 34, no. 1, pp. 133–141, Jan./Feb. 1998.

[17] B. Friedland, *Control System Design: An Introduction to State-Space Methods*, New York, NY, USA: McGraw-Hill, 2005.

[18] J. J. Slotine and W. Li, *Applied Nonlinear Control*, Upper Saddle River, NJ, USA: Prentice Hall, 1991.

[19] L. Harnefors, "Control of variable-speed drives," *IEEE Industrial Electronics Magazine*, vol. 4, no. 3, pp. 22–33, Sept. 2010.

[20] G. F. Franklin, J. D. Powell, and A. Emami-Naeini, *Feedback Control of Dynamic Systems*, 6th ed., Upper Saddle River, NJ, USA: Pearson, 2010.

[21] L. Harnefors and H. P. Nee, "Model-based current control of AC machines using the internal model control method," *IEEE Transactions on Industry Applications*, vol. 34, no. 1, pp. 133–141, Jan./Feb. 1998.

[22] J. J. Slotine and W. Li, *Applied Nonlinear Control*, Upper Saddle River, NJ, USA: Prentice Hall, 1991.

[23] [23] B. Friedland, *Control System Design: An Introduction to State-Space Methods*, New York, NY, USA: McGraw-Hill, 2005.

[24] P. Cortés, M. P. Kazmierkowski, R. M. Kennel, D. E. Quevedo, and J. Rodríguez, "Predictive control in power electronics and drives," *IEEE Transactions on Industrial Electronics*, vol. 55, no. 12, pp. 4312–4324, Dec. 2008.

[25] J. Rodríguez and P. Cortés, *Predictive Control of Power Converters and Electrical Drives*, Hoboken, NJ, USA: Wiley-IEEE Press, 2012.

[26] V. I. Utkin, J. Guldner, and J. Shi, *Sliding Mode Control in Electromechanical Systems*, 2nd ed., Boca Raton, FL, USA: CRC Press, 2009.

[27] S. Bolognani, L. Peretti, and M. Zigliotto, "Online MTPA control strategy for IPM motors with variable parameters," *IEEE Transactions on Industry Applications*, vol. 47, no. 1, pp. 96–104, Jan./Feb. 2011.

[28] P. Cortés, M. P. Kazmierkowski, R. M. Kennel, D. E. Quevedo, and J. Rodríguez, "Predictive control in power electronics and drives," *IEEE Transactions on Industrial Electronics*, vol. 55, no. 12, pp. 4312–4324, Dec. 2008.

[29] J. Rodríguez and P. Cortés, *Predictive Control of Power Converters and Electrical Drives*, Hoboken, NJ, USA: Wiley-IEEE Press, 2012.

[30] T. Geyer, "Model predictive control of high power converters and industrial drives," *IEEE Transactions on Power Electronics*, vol. 26, no. 4, pp. 1162–1173, Apr. 2011.

[31] R. Kennel and T. Geyer, "Model predictive control of electrical drives," *IEEE Transactions on Industrial Electronics*, vol. 60, no. 12, pp. 5436–5454, Dec. 2013.

[32] S. Vazquez, J. I. Leon, L. G. Franquelo, J. Rodriguez, H. A. Young, A. Marquez, and P. Zanchetta, "Model predictive control: A review of its applications in power electronics," *IEEE Industrial Electronics Magazine*, vol. 8, no. 1, pp. 16–31, Mar. 2014.