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REVIEW

Model predictive control for energy efficient AC motor drives: An overview

Muhammad Bilal Shahid[1,2] | Weidong Jin[1,3] | Muhammad Abbas Abbasi[2,4] | Abdul Rashid Bin Husain[4] | Hafiz Mudassir Munir[5] | Mannan Hassan[6,7] | Aymen Flah[8,9,10,11] | Ahmed Saad Eddine Souissi[12] | Thamer A. H. Alghamdi[13,14]

[1]School of Electrical Engineering, Southwest Jiaotong University(SWJTU), Chengdu, China

[2]Department of Electronic Engineering, Faculty of Engineering, The Islamia University of Bahawalpur, Bahawalpur, Pakistan

[3]China-ASEAN International Joint Laboratory of Integrated Transportation, Nanning University, Nanning, China

[4]School of Electrical Engineering, Universiti Teknologi Malaysia, Johor Bahru, Malaysia

[5]Department of Electrical Engineering, Sukkur IBA University, Sukkur, Sindh, Pakistan

[6]College of Information Science and Electronic Engineering, Zhejiang University, Hangzhou, China

[7]School of Information Science and Engineering, NingboTech University, Ningbo, China

[8]Processes, Energy, Environment, and Electrical Systems, National Engineering School of Gabès, University of Gabès, Gabès, Tunisia

[9]Centre for Research Impact & Outcome, Chitkara University Institute of Engineering and Technology, Chitkara University, Rajpura, Punjab, India

[10]Applied Science Research Center, Applied Science Private University, Amman, Jordan

[11]Chitkara Centre for Research and Development, Chitkara University, Baddi, Himachal Pradesh, India

[12]Department of Industrial Engineering, College of Engineering, Northern Border University, Arar, Saudi Arabia

[13]Wolfson Centre for Magnetics, School of Engineering, Cardiff University, Cardiff, UK

[14]Electrical Engineering Department, Faculty of Engineering, Al-Baha University, Al-Baha, Saudi Arabia

Correspondence

Muhammad Bilal Shahid, Hafiz Mudassir Munir and Thamer A. H. Alghamdi.
Email: bilal.shahid@iub.edu.pk, mudassir.munir@iba-suk.edu.pk and Alghamdit1@cardiff.ac.uk

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Abstract

State-of-the-art model-based predictive control techniques for AC motor drives are reviewed in this paper. A plethora of MPC algorithms with vast number of complex ideas has emerged in the last decade and this work makes an attempt to present those concepts in an intuitive, comprehensive and hierarchical manner. More emphasis is laid on finite control set model predictive control (FCS-MPC) methods, especially predictive torque control (PTC) and predictive current control (PCC) because of their emergence as the prime focus of ongoing research in energy efficient drive control. The main focus of this review is to analyse the most recent work, signpost the future research directions, identify the core challenges and consolidate the ideas into a coherent and concise reference. A comprehensive classification based on actuation signals is presented and reviewed in detail. Then, the important challenges in MPC implementation, such as computational complexity reduction and delay compensation, weighting factor selection for multi-objective cost functions, steady state performance and ripple reduction, parameter variations/model mismatching and achieving extended prediction horizons, are surveyed and

Abbreviations: CARIMA, controlled auto-regressive integrated moving average; CCS, continuous control set; DSC, direct speed control; DTC, direct torque control; EKF, extended Kalman filter; FCS, finite control set; FMCC, forced machine current control; FOC, field oriented control; FPGAs, field programmable gate arrays; FW, field weakening; GPC, generalised predictive control; IPMSM, interior permanent magnet synchronous motor; MPC, model predictive control; MPDCC, model predictive direct current control; MPDTC, model predictive direct torque control; MTPA, maximum torque per ampere; MV, medium voltage; NPC, neutral point clamped; PCC, predictive current control; PMSM, permanent magnet sychronous motor; PSC, predictive speed control; PTC, predictive torque control; SVM, space vector modulation; THD, total harmoic distortion; UIO, unknown input observer; UPS, uninterruptable power supplies; VSI, voltage source inverter; VVs, voltage vectors.

most relevant solutions are reviewed. A detailed analysis of the last five years related work is given at the end and it is concluded that the future course seems to be diverting towards voltage vector selection with optimised phase, magnitude and duty ratios. Computational burden is still one of the main hurdle towards MPC proliferation and adaptation in AC drive control at the industrial level. However, with advent of high speed and cheaper signal processors and development of efficient algorithms, MPC is rapidly becoming the control method of choice for energy-efficient drive control.

KEYWORDS
electric machines, electric power generation, harmonics, machine control

1 | INTRODUCTION

More than 70% of the equipment used by end users is motorised in the majority of industrialised and emerging countries [1]. Motor-driven systems account for 65% of energy consumption in the European Union [2]. Given their extensive use across several sectors, optimising the efficiency of motors is crucial for enhancing the overall efficiency of end-user applications. Implementing efficient control methods may enhance motor performance, leading to a remarkable reduction in energy losses by up to 70% [3]. Additionally, it can substantially lower energy consumption and the production of harmful greenhouse gases by up to 30% [4]. Over 85% of motors utilised in industrial applications are AC motors, which encompass both induction and synchronous motors [5]. Therefore, enhancing the efficiency of AC motors will significantly influence energy consumption, the environment, and the fulfilment of future energy requirements. Consequently, there has been a surge in interest in this field of study to create efficient control methods and variable speed control techniques.

Due to the continuous advancement and reduction in the size of semiconductor technology, current DSP processors have become affordable and efficient, computing systems with high-speed capabilities. Because of this, the focus of control research in power electronics has shifted from traditional approaches to more sophisticated control methods, such as model predictive control (MPC). This has made it possible to redirect emphasis away from conventional procedures. Despite the increased computing cost, MPC presents several benefits, including its straightforward and systematic approach to managing constraints, system non-linearities, and multivariable systems [6]. Integrating these characteristics into traditional control methods like direct torque control (DTC) and field-oriented control (FOC) not only adds complexity to the controller but also decreases the effective bandwidth. An anti-windup mechanism is employed in conventional cascaded control systems to enforce limitations and mitigate overshoots by saturating the output of the controller. In cascaded systems, the outer loop exhibits a much greater time constant compared to the inner control loop, and it also varies in terms of saturation limits. The combination of these loops results in a decrease in the total bandwidth of the controller.

MPC was classically used for slow varying process control applications [7]; however, with the availability of faster DSP processors, it is being applied to power electronics with larger sampling frequencies. It has been successfully employed for uninterruptable power supplies (UPS), power converters/rectifiers and energy efficient AC drives [8, 9]. In fact, MPC research has exponentially increased in the last decade as shown in Figure 1 [10–12].

Many good reviews on the applications of MPC to electrical drives have been done in the past five years. In [13], MPC strategies that achieve longer prediction horizons for medium voltage (MV) applications are reviewed. Special attention is given to extrapolation and event-based horizon methods for achieving longer prediction horizons to ensure MPC controller stability and better steady state performance. A performance comparison of model predictive direct torque control (MPDTC) and model predictive direct current control (MPDCC) to forced machine current control (FMCC) in terms of torque and current distortions in MV drives is presented in [14] and it is concluded that MPC methods outperform FMCC for extended switching horizons. In [15, 16], four areas of MPC application in power electronics are identified, namely grid connected converters, motor drives, and inverters with the LC filter and RL load. The authors in [17] describe in detail how MPC has played an important role in the evolution of

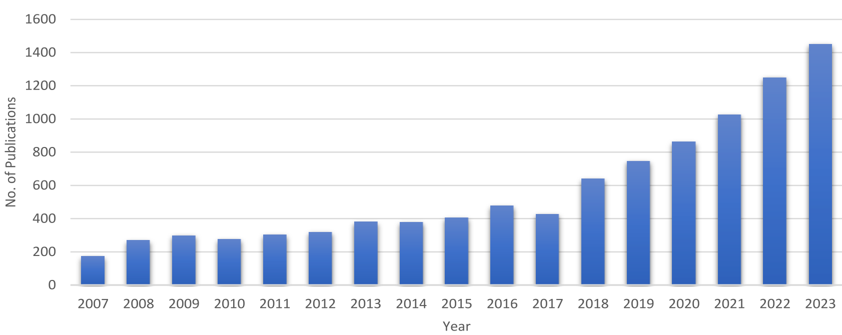


FIGURE 1 Research trends on MPC for motor drive control: number of publications by year.

power electronics in terms of better control performance. In [18], fundamental principles and formulations MPC are covered. The most recent review of FCS-MPC for electrical drives is presented in [19].

The key research areas in MPC for electric drives can be classified into the following categories: (1) improving MPC steady state performance and reduction of torque and current ripple, (2) reducing computational burden by developing efficient optimisation algorithms, (3) formulating and solving MPC problems for multi-level converter topologies used in industrial drives, (4) sensorless operation and dynamic MPC with the observer, and (5) handling model mismatch and parameter variations.

This paper is organised as follows: Section II describes in detail how the MPC algorithms can be classified in different ways. Section III discusses the most important control and performance challenges and their solutions associated with MPC. Section IV identifies current and future research hot spots and directions of MPC. Finally, the paper is concluded in section V.

2 | CLASSIFICATION OF MPC ALGORITHMS

The theory of model predictive control as an application of optimal control was developed in the 1960s and later in the 1970s. It was used in the process industry, where time constants are long enough to perform all the calculations within the sampling interval. The early ideas of its use in power electronics were developed in the 1980s for applications, where switching frequencies were very low and there was ample time available to compute the control signals. It could not be used for high-frequency applications because of the unavailability of fast microprocessors at the time. However, with the advent in microprocessor technology and DSP processors, the interest in MPC has increased in recent decades.

2.1 | MPC for electrical drives

Model predictive control incorporates a range of controller types used in power electronics systems. The commonalities among these controllers are as follows: (1) a system model is used to predict the controlled variables future behaviour up to a certain time window called the 'prediction horizon'; (2) a cost function is employed to obtain an optimal control signal for a certain time window called the 'control horizon'; and (3) the first element of this control signal is applied. The procedure is iterated for equivalent durations of time intervals and is referred to as the 'receding horizon' policy. The controller's model is derived from the physical system by determining the parameters through various experiments. Stator and rotor resistances as well as inductances are parameters of AC motors that are ascertained through no-load and blocked rotor tests. It is necessary to have an understanding of mechanical properties such as inertia and viscous friction. Given that MPC is a model-dependent control approach, the precision of these parameters and their fluctuations during operation significantly impact the steady-state performance and stability. The discrete state space form of the system model can be expressed as follows:

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k) \\ y(k) &= Cx(k) + Du(k) \end{aligned} \tag{1}$$

where $A, B \in \Re$. In its most generic form, the cost function may be expressed and includes references, future inputs, and system states as follows:

$$J = f\left(x^{*}(k), x(k), x(k+1), \cdots x\left(k+N_p\right), u(k), u(k+1), \cdots u(k+N_c)\right) \tag{2}$$

In (2), both the prediction horizon (NP) and the control horizon (NC) are often set to one in power electronics applications due to the low computing requirements. The optimal control signal can be defined as follows:

$$u(k) = [1 \quad 0 \quad 0 \quad \cdots \quad 0]\arg(\min_u J) \tag{3}$$

To reduce errors, the entire optimisation procedure is repeated once the system has received the ideal control signal. The outputs are then measured and compared with the references. Figure 2 graphically illustrates the operational concept of MPC.

Figure 3 shows the standard MPC block diagram used in electrical motors. It has a power converter that can produce voltages to the stator windings with variable amplitude and frequency. The control objective, dependent on the control method, determines how these voltages, called voltage vectors (VVs), are generated. A rectifier, not included in the image for brevity, is typically used to connect the line voltage supply to a constant DC voltage source, which supplies the converter. Metal Oxide Semiconductor Field Effect Transistors (MOSFETs) and Insulated Gate Bipolar Transistors (IGBTs) are used in the power converters. It is possible to regulate the stator voltages that minimise the inaccuracy between the references $r^{*}(k)$ and controlled variables like torque, speed, or currents by adjusting the ON/OFF position and/or duty ratios of these switches. The MPC controller applies the switching signals, denoted as S, directly or indirectly through a modulator. Figure 4 also includes a list of other power converters frequently used to control AC motors.

The following is a concise description of the drive's operation: (1) Measurements: the current sensor and the speed encoder, respectively, are used to determine the motor's speed and current simultaneously. (2) Approximation: While fluxes are not directly measurable, these values are estimated from the measurements. Measurements are also used to determine speed in sensorless operation. (3) Predictions: A mathematical model of the motor is used to account for all potential future inputs and to forecast how the controllable variables (such as torque, flux, currents, etc.) will behave. Based on the control algorithms, these inputs could be a limited number of switch

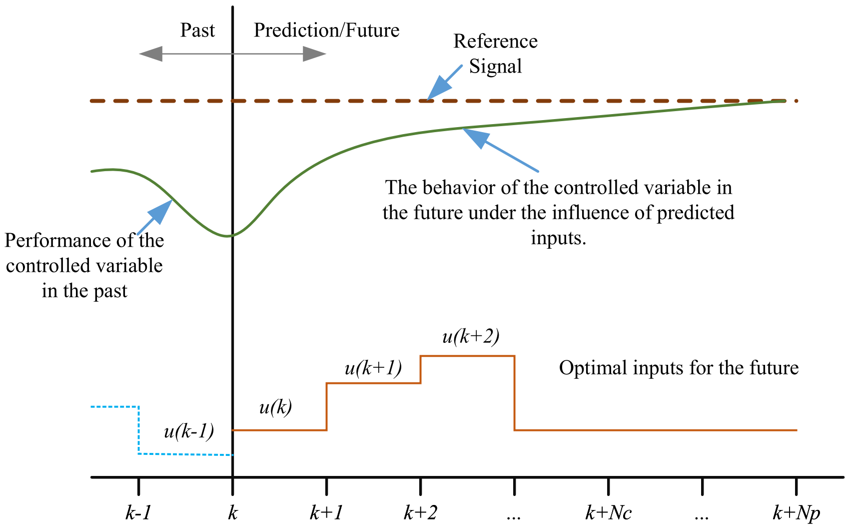


FIGURE 2 The general operating concept of the MPC.

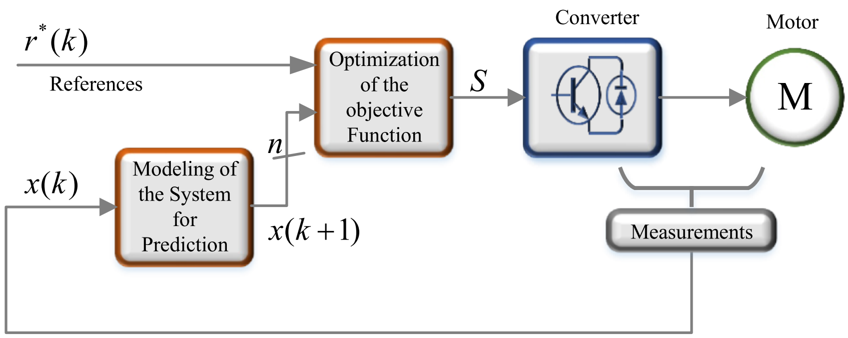


FIGURE 3 A comprehensive MPC setup for electric motor drives.

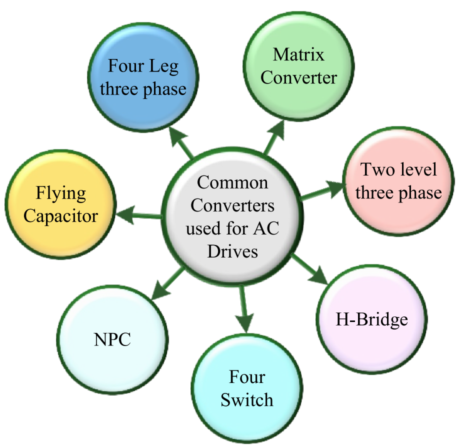


FIGURE 4 Commonly used power converters with ac motor drives.

actuations or an unlimited number of duty ratios. (4) Optimisation: In the following sample period, the optimal input is applied based on the comparison between the reference and forecast values of the controlled variables, which were used to determine which future input would provide the smallest cost function [20].

In [15], the authors identify four key areas of MPC applications in power electronics: (1) power quality control utilising various converters, (2) electric drives, (3) power converters connected to the grid, and (4) adjustable power supplies. These are the four areas that are discussed in A. The converter/inverter topologies that are utilised in these applications are distinct from one another, and the MPC controllers are developed specifically for each situation. These are some of the areas in which MPC has received a great deal of favourable reviews [20, 21].

2.2 | CCS versus FCS MPC

Continuous control set (CCS) and finite control set (FCS) MPC are the two primary types of motor control MPC algorithms, which are based on the controller's signal application to the motor drive. By adjusting duty ratios during a sample period in order to activate switches, CCS-MPC creates control or gating signals using a modulation strategy like Pulse Width Modulation (PWM) or Space Vector Modulation (SVM). In contrast to CCS, FCS-MPC applies switching states continuously throughout the sample time. In CCS, the best control signal is found by making the cost function's partial derivative equal to zero; in FCS, testing all control vectors is typically done by enumeration. Finding the best answer in very short sample periods is a computationally demanding problem since CCS synthesises actuation signals using a modulator. Due to its elimination of modulation and cheap computing effort for short horizons, FCS is chosen over CCS in this regard, even though CCS provides fixed-frequency operation and relatively a low steady-state error.

Consider the simplified motor drive circuit depicted in Figure 5 in order to acquire a deeper comprehension of the distinction between CCS-MPC and FCS-MPC, as well as the idea behind the control set that is being discussed. The circuit includes a two-level, three-phase inverter, a DC source Vdc, and a controller (not illustrated) that controls the inverter's operation by generating gating signals. To prevent 'shoot-through' failures, which could cause a DC source terminal short circuit, the switches are controlled in a complimentary manner. For a control period that is equal to sampling time T_s, is shown in Figure 6, that is an example control signal for switch S_a. During the control interval, the switch S_a stays ON for t_a seconds and OFF for the remaining duration $(T_s - t_a)$ between T_s and t_a seconds. Figure 6 shows that the lower switch bar S_a functions in the opposite way; the total effect of these two switches complimentary operations is to apply a voltage to the first stator phase of the motor, which is called V_{an} voltage.

It is possible to determine the average v_{aN} voltage as follows:

$$\overline{v}_{aN} = \frac{1}{T_s}\int_0^{t_a} V_{dc}dt = \frac{t_a}{T_s}V_{dc} = d_a V_{dc} \tag{4}$$

The duty ratio of switch S_a is defined by the term d_a. Likewise, the voltages at point b and c may be expressed as follows:

$$\overline{v}_{bN} = d_b V_{dc} \tag{5}$$

$$\overline{v}_{cN} = d_c V_{dc} \tag{6}$$

The voltage space vector can be expressed as follows:

$$v = \frac{2}{3}\left(\overline{v}_{aN} + \overline{v}_{bN}e^{j\frac{2\pi}{3}} + \overline{v}_{cN}e^{j\frac{4\pi}{3}}\right)$$

$$= \frac{2}{3}V_{dc}\left(d_a + d_b e^{j\frac{2\pi}{3}} + d_c e^{j\frac{4\pi}{3}}\right) \tag{7}$$

In equation (7), the duty ratios determine the magnitude and angle of the complex quantity. During the control period, the switches in FCS-MPC are either turned ON or OFF; hence, duty ratios can only be 1 or 0. When the duty ratios are limited to 1 and 0 (FCS), this inverter design has eight potential voltage vectors. These vectors can be presented in Figure 7.

If all the upper inverter switches are set to the ON $v_7(111)$ state or the OFF $v_0(000)$ state, the resultant voltages in the stator will be zero. The vectors referred to as 'null vectors' have identical effects; hence, just a single null vector is utilised in the optimisation process. The remaining voltage vectors are referred to as 'active vectors', and they constitute a 'finite control set' in conjunction with a single null vector.

A control space is referred to as a 'continuous control set (CCS) ', when duty ratios can take on continuous values instead of being limited to discrete values of 1 and 0. Figure 8 illustrates a voltage vector with $d_a = 0.1, d_b = 0.45, d_c = 0.8$. The magnitude of this vector is 0.404 times the value of Vdc, and this vector has an angle of 26.5^o degrees. However, including a modulator is essential for generating these voltage vectors, leading to an increased cost. Moreover, identifying the optimal voltage vector for CCS (duty ratios) is challenging because of the many possible voltage vectors. In contrast, FCS entails

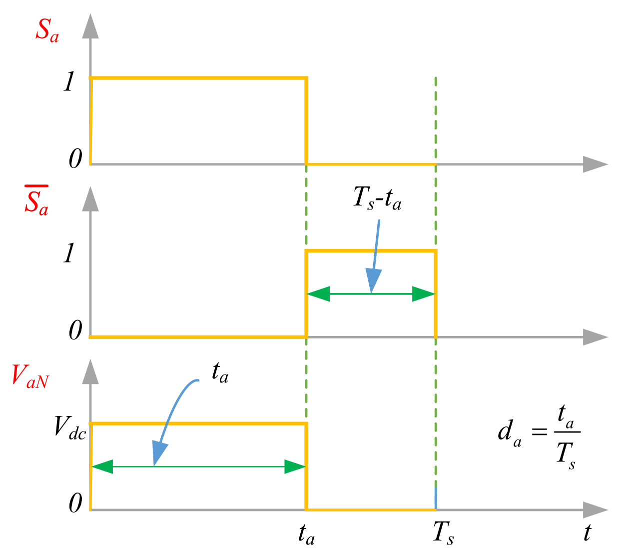


FIGURE 6 An example control signal for a given switch and resulting output voltage at point 'a'.

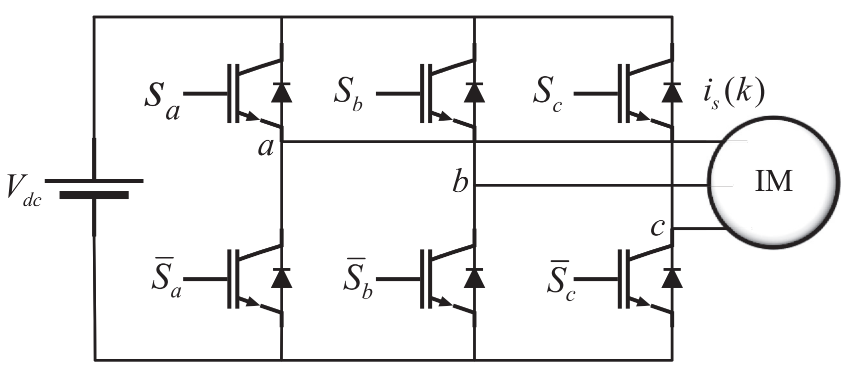


FIGURE 5 Two-level three-phase inverter.

conducting tests on a restricted range of voltage vectors with pre-determined magnitude and angle (enumeration) to get the minimum cost function value. Table 1 briefly describes the essential attributes of CCS and FCS [22, 23].

Generalised Predictive Control (GPC) is the most often used version of CCS in drive applications. GPC utilises a transfer function model of the machine known as the Controlled Auto-Regressive Integrated Moving Average (CARIMA) model [24]. GPC employs long horizons for predicting and is a more computationally demanding technique. Consequently, it is deemed undesirable in several applications [25]. Additional CCS-MPC techniques encompass deadbeat MPC as well as functional MPC methods such as Laguerre-based and functionally weighted predictive control [26]. These methods employ a linearised model of the machine, ignoring the non-linear nature of the system and posing higher computational demands on the hardware. The dynamical response of the drives must be accelerated by a sampling time that is adequately short in CCS-MPC. Nevertheless, the model prediction accuracy decreases as the sampling time increases, which leads to a decrease in control performance and increases the current and torque ripples [10, 27]. In the same way, the continuous control signal generated in the CCS-MPC system must be converted to discrete switching signals by the modulator. In order to accurately represent the continuous control signals and prevent excessive THD, the modulator frequency must be adequately high. The drive's control performance is considerably compromised by the discretisation error caused by the small modulator frequency. In [28, 29], hybrid CCS-MPC schemes with predictive switching sequence optimisation techniques and additional modulators were proposed.

Exploring the potential of using non-linear models in electric motor systems within the context of CCS-MPC presents a compelling research opportunity. The non-linear motor models in electric drive systems, such as induction motors or PMSM, display non-linear behaviour as a result of complicated electromagnetic processes, saturation effects, and rotor dynamics. Linear models may lack the capacity to incorporate all non-linear elements necessary for achieving optimal control performance. However, the inclusion of non-linearities adds further intricacy and makes the optimisation process more computationally demanding. This difficulty can be addressed by (i) enhancing the non-linear model formulations and optimisation methods to improve efficiency and (ii) establishing a hybrid strategy that integrates CCS-MPC with other control techniques such as gain scheduling or adaptive control. Utilising non-linear models in CCS-MPC offers several advantages, including enhanced control performance, effective tracking of reference signals, expanded operating conditions, greater efficiency resulting in reduced harmonics and

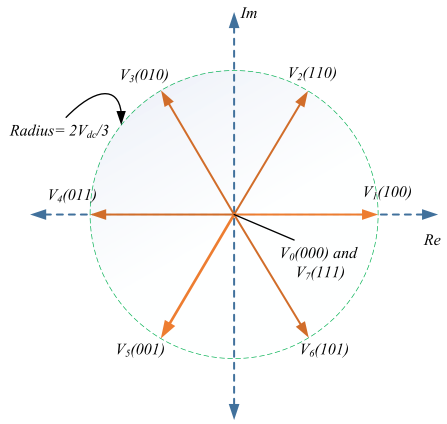


FIGURE 7 Two-level three-phase converter voltage space vectors for FCS-MPC.

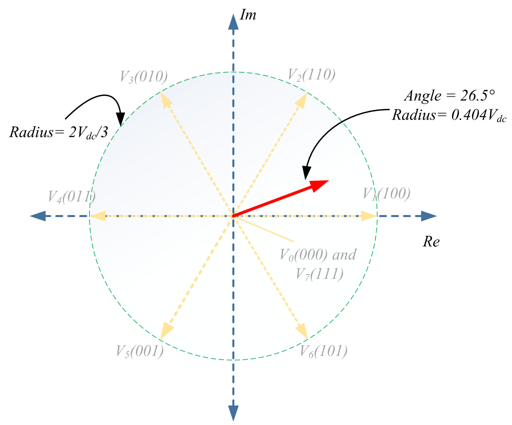


FIGURE 8 An example voltage vector for CCS.

TABLE 1 Key characteristics of CCS and FCS MPC.

Feature	CCS-MPC	FCS-MPC
Model of the machine	Linear	Non-linear
Modulation	Yes	No
Actuation	Indirect	Direct
Optimal solution technique	Analytical (Unconstrained) quadratic programming (constrained)	Enumeration (Unconstrained) non-linear programming (constrained)
Examples	Generalised predictive control (GPC), deadbeat MPC, functional MPC	Predictive torque control (PTC), predictive current control (CCS)
Prediction horizons	Longer	Short: Normally 1 or 2
Switching frequency	Fixed	Variable

disturbances [30]. Consequently, FCS has gained significant popularity in recent times.

2.3 | PTC and PCC

Figures 9 and 10 illustrate two commonly employed FCS-MPC techniques for induction motors: predictive torque control (PTC) [31] and predictive current control (PCC) [32]. The images illustrate the presence of two control loops in both schemes: an outside speed control loop and an inner torque control loop, also known as a current control loop. The symbols depicted in the picture are as follows: i_s, v_s, ψ_s, and ψ_r correspond to stator current, stator voltage, stator flux, and rotor flux space vectors, respectively. Additionally, ω^* represents the reference rotor speed, while the measured rotor speed is denoted as ω. In the context of torque, the symbol p with a superscript represents the predicted value at time instant k. θ refers to the rotor flux angle, while i_α and i_β represent the stator currents in a stationary reference frame. Stator current and stator or rotor flux are commonly selected as state variables in both PTC and PCC. The dynamic model of an induction motor can consist of [14]

$$\frac{d}{dt}\begin{bmatrix} i_s \\ \psi_r \end{bmatrix} = \begin{bmatrix} -\dfrac{1}{\tau_\sigma} & \dfrac{k_r}{R_\sigma \tau_\sigma}\left(\dfrac{1}{\tau_r} - j\omega\right) \\ \dfrac{L_m}{\tau_r} & -\left(\dfrac{1}{\tau_r} - j\omega\right) \end{bmatrix} \begin{bmatrix} i_s \\ \psi_r \end{bmatrix} + \begin{bmatrix} \dfrac{1}{R_\sigma \tau_\sigma} \\ 0 \end{bmatrix} v_s \tag{8}$$

where R_s and R_r are stator and rotor resistances, L_s, L_r and L_m are stator, rotor and mutual inductances; $\tau_\sigma = \frac{L_s L_r - L_m^2}{L_r\left(R_s + R_r k_r^2\right)}$ represents the time constant of the stator transient, $\tau_r = \frac{L_r}{R_r}$ represents the time constant of the rotor, and $k_r = \frac{L_m}{L_r}$ represents the coupling factor of the rotor. In order to employ (8) in MPC, it is necessary to have a discretised version of the model, often produced by utilising Euler's technique.

$$x(k+1) = x(k) + T_s(Ax(k) + Bu(k)) \tag{9}$$

The variable T_s represents the sampling time, typically expressed in microseconds. The selection is also with regards to the computational delay that it will infer.

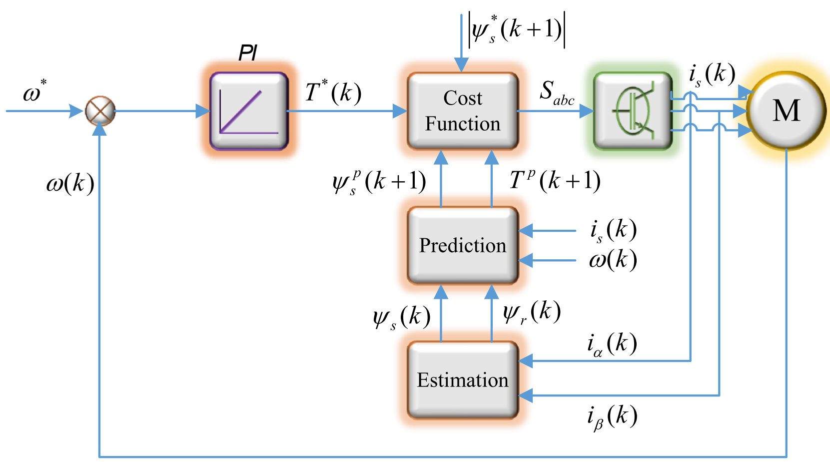


FIGURE 9 Block diagram of predictive torque control (PTC) for the induction motor.

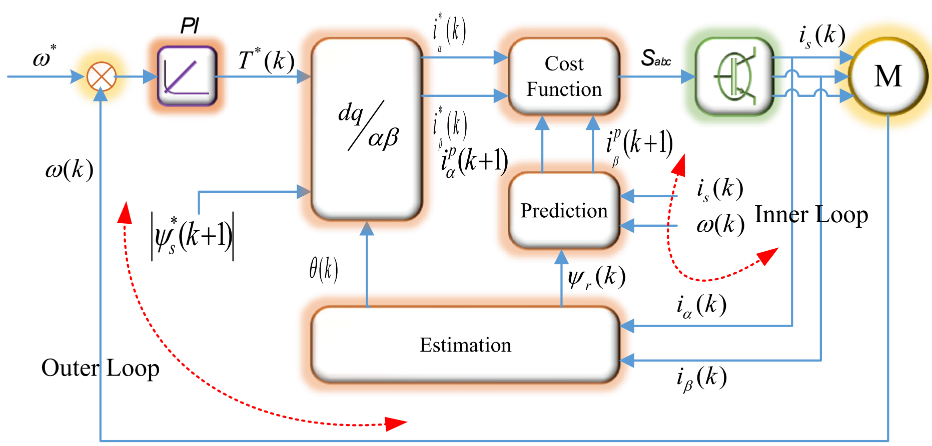


FIGURE 10 Block diagram of predictive current control (PCC) for the induction motor.

Both PCC and PTC employ the induction motor's discretised state space model for the estimate, prediction, and optimisation phases. The following is a description of these equations:

$$\hat{\psi}_s(k+1) = \psi_s(k) + T_s v_s(k) - T_s R_s i_s(k) \tag{10}$$

$$\hat{T}(k+1) = 1.5p\Im\mathfrak{m}\left(\hat{\psi}_s(k+1)^* \hat{i}_s(k+1)\right) \tag{11}$$

$$g = |T^*(k) - T^p(k+1)| + \lambda\left|\psi_s^*(k) - \psi_s^p(k+1)\right| \tag{12}$$

$\hat{\psi}_s$, $\hat{T}$, and $\hat{i}_s$ are terms used to denote estimates of stator flux, torque, and current, respectively. The objective function is represented by the symbol g. Similarly, in the case of PCC,

$$\hat{i}_s(k+1) = \left(1 - \frac{T_s}{\tau_\sigma}\right) i_s(k) + \frac{T_s}{R_\sigma \tau_\sigma}\left(k_r\left(\frac{1}{\tau_r} - j\omega(k)\psi_r(k) + v_s(k)\right)\right) \tag{13}$$

$$i_d^*(k) = \frac{|\psi_r(k)|^*}{L_m} \tag{14}$$

$$i_q^*(k) = \frac{2L_r T^*(k)}{3L_m |\psi_r(k)|^*} \tag{15}$$

$$g = \left|i_\alpha^*(k) - i_\alpha^p(k+1)\right| + \left|i_\beta^*(k) - i_\beta^p(k+1)\right| \tag{16}$$

These techniques use a PI controller and dq transformations (in PCC only) to produce the inner-loop torque or current references from the outer speed loop, whether it has an encoder or not. The characteristics of the inner and outer loops vary in terms of bandwidths and time constants. The time constant of the outer speed loop exceeds that of the inner-loop, resulting in a slower production of torque reference. There have been several attempts to eliminate the outer loop in order to prevent this variations in dynamic performance [20]. During the implementation phase, the fluxes, speeds, and angles are estimated (sensorless operation). Then, potential voltage vectors are forecasted for future currents, torques, and fluxes using dynamical machine models. The difference (error) between these predictions and references is then computed. The errors are ultimately evaluated using a cost function (optimisation) in order to identify the voltage vector that yields the lowest value. The computational load increases in direct proportion to the number of FCS voltage vectors that need to be verified, and this number is influenced by the system's architecture. PTC is more complex but more robust, responsive, and energy-efficient than PCC, while PCC is simpler and more accurate at low speeds and torques but less responsive and robust than PTC. The choice between PTC and PCC depends on the specific requirements of the application and the available computational resources.

3 | CHALLENGES IN MPC

Although MPC has many advantages over traditional control techniques, it still has some performance problems. These problems include steady state error, computational burden, variable switching frequency disturbance reduction and stability. Currently, MPC is in the evolving stage for high frequency power electronics applications and faces certain challenges. These challenges and most recent proposed solutions are discussed below.

3.1 | Modelling challenges

In most of the MPC algorithms, a linearised discrete state space model $x(k+1) = Ax(k) + Bu(k)$ of the ac motor is used for the prediction and estimation of flux, current and torque. In this model, motor parameters such as inductances and resistances are assumed to remain constant during the operation. In reality, however, these parameters do change with changes in motor temperature. The actual model parameters can be represented as time-dependent quantities marked $c(t)$ in Figure 11. Therefore, due to the model mismatching, the values estimated and predicted by the MPC controller do not represent the actual values. This might lead to an erroneous response by the controller and must be tackled carefully. This difference can also occur due to the modelling error during inaccurate machine tests conducted to determine machine parameters.

Different machine models are used in different MPC algorithms; for example, GPC uses linear transfer function model (CARIMA) for predicting the response [33]. Linear and non-linear state space models are also employed in CCS-MPC and FCS-MPC. In [34], the discrete space model of an induction machine is suggested for implementing non-linear direct model predictive torque control. The authors in [35] also use non-linear state space models of PMSM to enhance the dynamic performance of model predictive torque control in low-speed and high-speed regions using Maximum Torque per Ampere (MTPA) and Field Weakening (FW) concepts. However, the stator voltage model of the machine is mostly used for predictions [36, 37].

AC machines are complex non-linear systems and the modelling error also occurs when these models are linearised. Most of the indirect MPC controllers use linearised models,

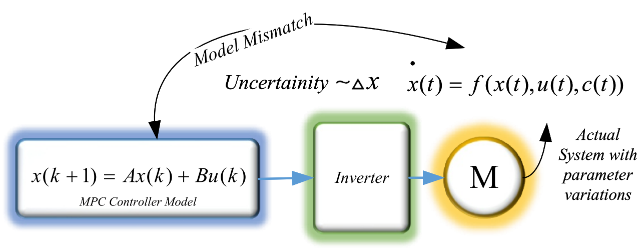


FIGURE 11 Importance of the accurate model for MPC operation.

while direct MPC is based on non-linear models. Since MPC is implemented on modern high-speed DSP processors, therefore, these models are discretised before they can be used for prediction. Different discretisation methods are available to convert differential equations of the machine to difference equations such as the Euler method. However, in low sampling frequency applications such as MV and HV, Euler approximation does not give good results and higher order approximation methods (e.g. Tustin approximation) should be used [38]. Other methods are also used for better accuracy; these include Bilinear Transformation or Tustin method [39], second order Euler approximation [40], exact discretisation [41] and Runge–Kutta method [42]. Discretisation is achieved with constant sampling frequency; however, variable sampling for discretisation is also reported in [43] to produce better results. The concept of oversampling is introduced in [44] to increase the performance of direct MPC. These methods tend to improve the drawbacks of MPC. However, they also increase the complexity and order of the prediction model, resulting in high computational demands which is the main reason for using simple and low order approximation methods such as the Euler forward rule.

3.2 | Parameter variations and estimation

The system can still be efficiently controlled by MPC even when there are small changes to the parameters or a model mismatch $\left(\dot{x}_{act} - \dot{x}_{model} \approx \Delta x\right)$ [45]. Dynamic performance, however, degrades significantly for large errors. Other variables, such as the drive's operating point, the objective function optimisation, and the delay compensation system, influence this degradation. There is no guarantee that the controller will remain stable when faced with extreme parameter fluctuations. When trying to estimate the stator flux for use in torque control applications, the impact of resistance change is very important. A machine's stator flux may be approximated using either its voltage or the current model. Using the existing model might lead to inaccurate flux estimates since it is vulnerable to changes in rotor resistance at higher switching frequencies. The voltage model is also quite sensitive to low-frequency fluctuations in stator resistance [46].

Parameter accuracy is crucial for robust MPC functioning, as previously mentioned. The impact on PTC and PCC operations of varying mutual inductance L_m and stator resistance R_s is addressed in [47]. Even if L_m is altered 20 times the initial value, the controller remains stable, and changes in L_m do not significantly affect PTC. Nevertheless, a 10% change in inductance might cause the controller to become unstable since PCC is extremely sensitive to variations in L_m. Compared to the mutual inductance effect, the effect of stator resistance R_s on PTC and PCC is the inverse. PCC maintains its stability regardless of changes in R_s, but PTC starts to destabilise once R_s is altered by more than 2.5 times its initial value.

The problem of parameter variation can be addressed by including an online parameter estimation strategy into the control algorithm. It is the machine model that determines how the parameter estimator is designed. Low operating frequency stator flux estimations are unsatisfactory when using a voltage model for predictive torque control (PTC) because the model is sensitive to variations in stator resistance. In [48], a simulation based research is provided that aims to create a resistance estimator using optimum vector selection-based flux estimations. The rotor's resistance fluctuates significantly during operation because of the heat it generates. The change in resistance greatly impacts the performance of the MPC, as the rotor time constant also varies. The Unknown Input Observer (UIO) is employed in [49] to forecast the load torque and induction motor rotor resistance solely from the input and output measurements.

The observer's most significant advantage is the ability to estimate the system's states and parameters all at once. So far, only research based on simulations has been carried out because of the computing challenges associated with the real-time implementation of the suggested observer. To get over the problems caused by parameter volatility and model mismatch, the author in [50] use Sliding Mode Observer to estimate R_s, R_r and rotor flux concurrently. Model-free predictive control is advised for the Interior Permanent Magnet Synchronous Motor (IPMSM) in ref. [51]. This is done to remove MPC's reliance on the system model and, therefore, on the parameters. This method relies on the fact that there are current variations in the intervals between samples. Various other research have also addressed the issue of model mismatch and parameter fluctuations [52, 53].

In [54], parameter mismatch and prediction error correction has been proposed by decoupling between the flux observer and speed estimation using dual reference frame-based. Another solution to compensate lumped disturbance and parameter mismatch has been proposed by disturbance feed-forward compensation technique in [55, 56]. A Luenberger observer-based parameter estimation has been designed to increase the robustness of the predictive control; however, the effect of computational burden has not been considered in [57]. Reference model-based stator resistance estimation has been proposed in [58] for the six-phase induction motor. The stator flux estimation and stator resistance mismatch have been analysed in [59] using the current model observer.

Algorithmic-level concerns and challenges have an impact on the performance of MPC controllers for AC drives. Recently, numerous significant methods have evolved to enhance energy efficiency, mitigate dynamic losses, minimise steady state error, and decrease computing complexity.

3.3 | Cost function

Cost function is an essential part of MPC and usually represents the main objective of the controller. Since most of the

TABLE 2 Motor parameters.

Parameter	Value	Parameter	Value
Rated Torque, T_{nom}	9 $N.m.$	Stator resistance, R_s	3 Ω
Rated stator flux, ψ_{s-nom}	0.954 Wb	Rotor resistance, R_r	4.1 Ω
Rated voltage, v_{s-rat}	160 V	Stator inductance, L_s	342 mH
Base speed, ω_{base}	60 $rad/$sec	Rotor inductance, L_r	351 mH
Inverter DC source, V_{dc}	240 V	Mutual inductance, L_m	324 mH
Total number of pole pairs, p	2	Total inertia, J	0.0031 $kg-m^2$
Sampling time, T_s	40 μs	Total viscous friction, B	0.0019 $N.m.s$

MPC formulations are reference tracking problems, therefore the cost function will represent some norm of error between the reference value of the controlled signal and its predicted values up to the instant that defines prediction horizon. The general form of the cost function can be represented as follows:

$$g=\sum_{i=1}^{N_p}\lambda_j\left\|y_j^*(k+i)-y_j^p(k+i)\right\|_n \quad for\, j=1,2,\cdots q \tag{17}$$

where $y_j^*(k+i)$ represents the reference value of the j^{th} output at i^{th} instant into the future; $y_j^p(k+i)$ is the predicted value of the j^{th} output at i^{th} instant into the future and the prediction is made at current instant k; N_p is prediction horizon; q is the total number of outputs to be tracked; n represents the norm which might be absolute, infinity or quadratic norm; λ_j is the relative weighting factor of j^{th} output.

Reference generation is also an important aspect of MPC. In most AC drive applications, reference is generated by the outer speed loop which employs conventional PI controllers. This reference is usually torque (flux reference is considered constant) which can be transformed to corresponding current references in PCC. Prediction horizon is normally taken equal to one in high frequency power electronics applications due to computational requirements, and variables are predicted using the discrete model of the system. Weighting factors decide the relative importance of the controlled variables. The selection of weighting factors becomes challenging if the variables in the cost function have different units of measurement, for example, torque and flux in PTC. Cost functions and their characteristics are summarised in Table 2 for PTC, PCC and predictive speed control (PSC).

The cost function can capture many control objectives in a single equation but the challenge of the weighting factor selection becomes a major hurdle for satisfactory controller performance. Other than the objectives used in PTC and PCC, these might include speed control [60], DC balancing in the NPC converter in industrial drives [61, 62], reactive power control in matrix converter drives [63, 64], load current spectrum shaping [65], switching frequency reduction [66], and most recently switching instant optimisation [44].

Constraints define bounds on various system variables and constitute an important part of the cost function to ensure safe operation of the drives. In traditional PI controllers, constraints are implemented through the anti-windup mechanism. Since cascaded loops have different time constants, therefore anti-windup controllers need to be tuned individually, which becomes a challenging task because individual tuning does not always guarantee the good performance of the overall cascaded structure. One of the most important feature of MPC is easier handling of constraints. In general, constraints can be implemented on four variables, namely system input variable, output variable, state variables and differential inputs [20, 67]. In AC machines, these constraints could relate to currents, voltages, torque, flux, duty ratio, switching states and dynamic losses. However, implementing constraints also increases the complexity of the optimisation problem and finding a feasible solution becomes more challenging especially in the FCS-MPC case since the formulation translates to a constrained non-linear programming problem.

Constraints can be hard or soft, meaning they cannot be violated in any case or can be violated within certain bounds. Constraints can also be constant, variable and stochastic. Constraints in AC machines can be implemented as simple magnitude limits, restricted within offline MPC or online optimisation. Magnitude limits are defined in the cost function to constrain the motor starting currents and applied voltages [68]. A logical operator is used to trigger the limit. As an example, consider the following amplitude limiting the cost function:

$$g=\left|i_s^*-i_s(k+2)\right|+\eta(|\omega|>\omega_{\lim}) \tag{18}$$

It implements a constraint on the rotor speed ω and the restricting value is defined as $\omega_{\lim}$ and the constant η is taken as a large value. If the rotor speed is within the safe limits, that is, the logic condition $|\omega|>\omega_{\lim}$ is 'false', the cost function only involves the stator current error for optimisation, that is, $g=\left|i_s^*-i_s(k+2)\right|$. Whenever the rotor speed crosses that limit, the logic condition $|\omega|>\omega_{\lim}$ becomes 'true' and the cost function takes the form $g=\left|i_s^*-i_s(k+2)\right|+\eta$ which puts almost negligible emphasis on the current error due to the presence of a large constant, and the inputs which caused this condition to occur are effectively excluded from the feasible set. The controller selects inputs which try to avoid this condition and the speed is brought back to its safe limits.

3.4 | Weighting factors

The selection of weighting factors for MPC is still seen as an unresolved topic despite several attempts to find a solution. The performance is directly affected by the weighting factor's suitable selection since it allocates relative priority to the numerous control objectives in a single objective function. Look at PTC for induction motor drives as an illustration of how weighting factor selection affects MPC performance. There is a description of the PTC cost function in Table 2, and the motor parameters are provided in Table 2.

Figures 12 and 13 illustrate the impact of the weighting factor selection on stator currents, flux, and torque for an induction motor with no load and a step change in rotor speed from 80 rad/sec to −80 rad/sec at time $t = 1$ sec. Flux regulation takes precedence over torque reference tracking when the weighting factor's value is raised. Stator flux is maintained at 0.954 Wb for a weighting factor of 100 regardless of the speed reversal state, and the present THD is quite low at 0.08. However, more ripples are seen with larger λ values since torque is less important here. A poor flux response and greater THD in stator currents are found with a drop in λ, which also lessens the emphasis on flux management. Additionally, at smaller amounts of λ, torque reference tracking becomes more important, reducing torque ripples. The importance of choosing a weighting factor for achieving appropriate torque and flux management as well as high-quality current in PTC is clearly demonstrated by this example.

Some general guidelines are given in [69, 70] for the weighting factor selection in PTC, but no simple solution or analytical method is defined for its adaptation in other applications. In recent literature, two methods to deal with it have evolved; MPC without the weighing factor and the online adaptation of the weighting factor.

A proposed strategy for multi-objective optimisation involves the use of a ranking system to eliminate the need for a weighting element [71, 72]. While the process is effective for situations involving the selection of a single weighting factor, it becomes intricate and computationally burdensome for cases involving the selection of numerous weighting factors. Implementing the fuzzy-based multi-objective technique in [73] is computationally demanding and presents challenges for real-time execution when dealing with cost functions that involve many weighting elements. The authors in [74, 75] have recently provided an alternative approach that converts the torque reference into an equivalent flux reference, thereby eliminating the torque error from the cost function. The resultant cost function exclusively encompasses the discrepancy in flux and is called Predictive Flux Control (PFC). However, this technology is designed explicitly for PTC and cannot be used for other applications with varying control requirements. An equal torque effect approach is also recommended in [76, 77] to remove the weighting element from PTC.

Two separate cost functions have been developed sequentially in [78, 79], first torque based voltage vectors selected then from minimum torque vectors applied to flux-based cost function and minimum voltage vector chosen. This technique removes the need of the weighting factor. However, the flux response is distorted because of the restriction of the voltage vector available for flux prediction. Similar technique with slight modification is used in [80, 81]. In [72, 82], the multi-objective sorting technique is proposed to remove the need of the weighting factor. The lowest ranked voltage vector is selected for the inverter. In [83, 84], torque and flux control objectives are considered as separate cost functions and evaluated with seven vectors. Among these seven vector, optimal is selected for minimising both torque and flux ripples.

An alternative method for addressing the tuning of weighting factors is through online adaptation. The authors in [85] propose the use of Multi-Criteria Decision Making (MCDM) methods, such as VIKOR and Simple Adaptive Weighting (SAW). Although they have a tendency to improve the computational complexity of MPC. An alternative method involves dynamically adjusting the weighting factor in real time by utilising torque or current ripples [86]. This technique relies on the system parameters, which have the potential to fluctuate throughout the operation. Hence, the solution requires the inclusion of a parameter estimation method, hence increasing its complexity [87]. In [88], the tuning of the weighting factor is obtained by comparing torque and flux errors with the minimum error; however, the selection of the minimum error is needed to be determined and this method will not work properly when using more than two control objectives. Three control objectives have been tuned by the multi-objective genetic-based algorithm in [89, 90]; however, this has become computationally heavy. In [91, 92], NSGA-II with TOPSIS decision-making criteria is used to tune the weighting factor. However, this method required mathematical analysis and drive performance still depends on index values that make the controller computationally inefficient. Tuning of the weighting factor based on the principle of variation has been proposed in [93, 94] by making different cost functions. The process of variation applied to each cost function is time-consuming and therefore computationally heavy. The weighting factor has been tuned based on state normalisation and variable sensitivity balance in [95]; however, the range of the weighting factor and their values were not discuss according to the dynamic and transient response of the system. Figure 14 [96–103] summarises various methods reported in the literature.

3.5 | Optimisation

Once the cost function is formulated under certain system constraints, the next step is to find an optimal and admissible system input which minimises the value of the cost function. This step is called optimisation which is repeated every sampling time after receiving feedback. The optimal input signal is calculated for a certain number of sampling steps (prediction horizon). However, only the first element of this array is applied to the system and the process is repeated at every sampling time and is known as receding horizon policy. In

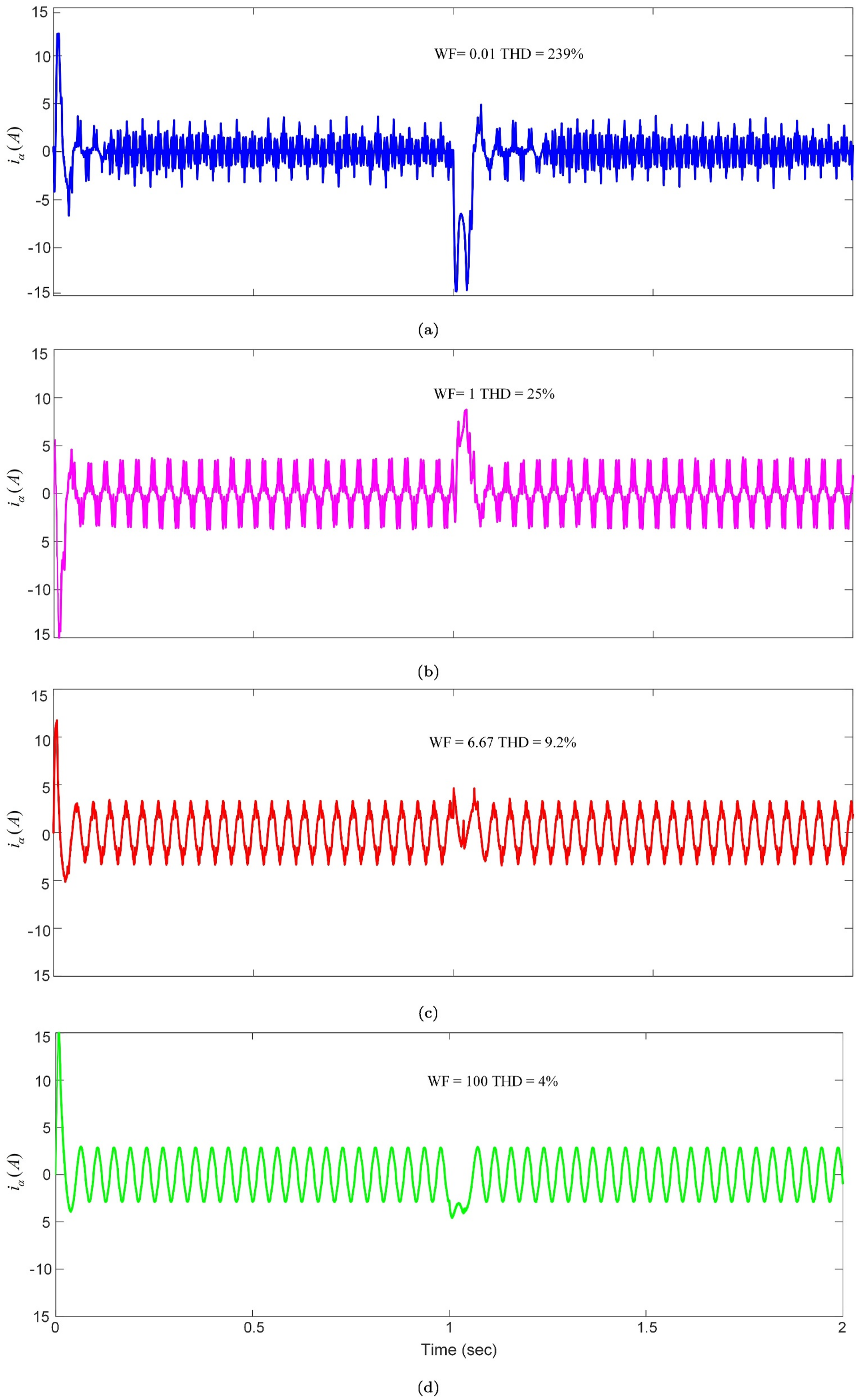


FIGURE 12 Effect of the weighting factor on stator current (phase-a).

most of the power electronics applications, the prediction horizon is kept to one to avoid computational complexities. The scale of the optimisation problem increases exponentially as the prediction horizon increases, resulting in increased computational requirements and processing time. Power electronics applications pose a significant challenge due to the need

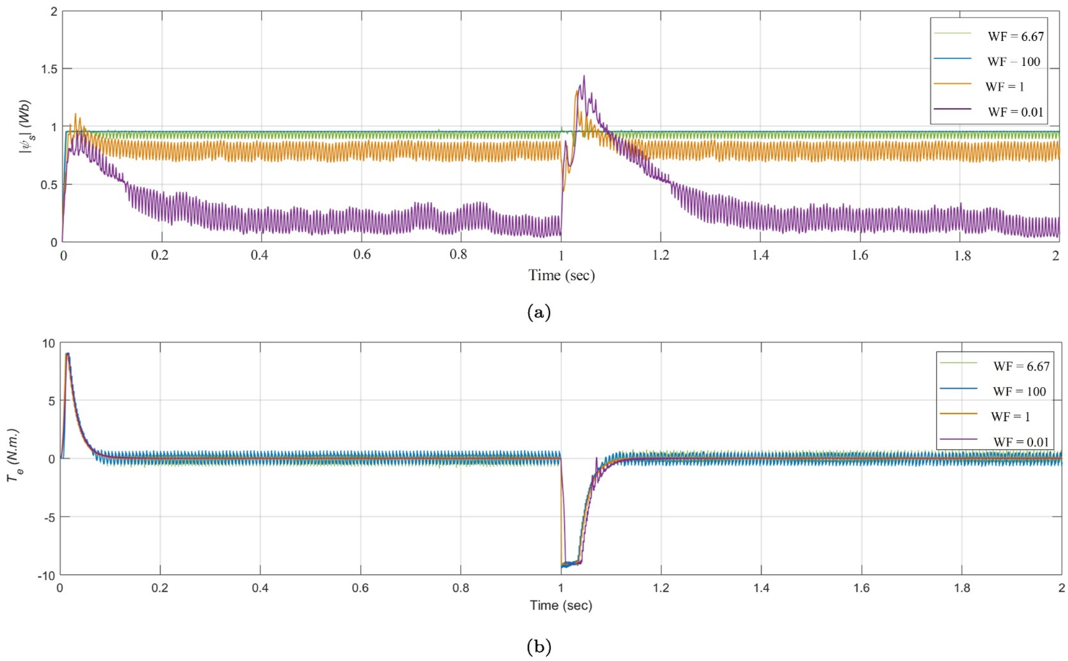


FIGURE 13 Effect of the weighting factor on the stator flux and torque response for the step change in speed at 1 s from 80 rad/sec to −80 rad/sec and no load condition.

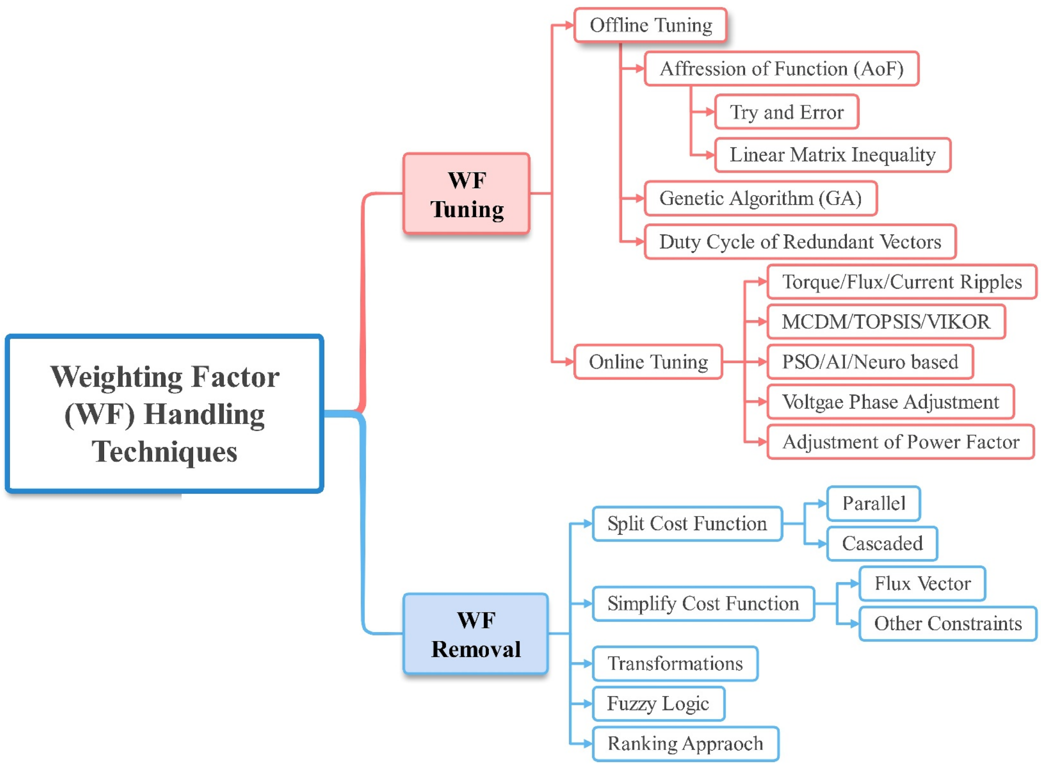


FIGURE 14 Various weighting factor selection techniques.

for rapid control updates to ensure system stability and performance. Optimisation complexity and computational requirements depend upon the converter topology, cost function, prediction horizon and type of MPC (FCS or CCS). In CCS, the optimised control signal is continuous in nature and is applied in conjunction with some modulation scheme.

A longer prediction horizon can be utilised more efficiently in CCS-MPC due to two reasons. Firstly, CCS-MPC operates directly with continuous control inputs such as voltage or current references rather than discrete switching states. Secondly, the formation of CCS can decrease the number of decision variables in the optimisation problem compared to traditional FCS-MPC [104]. Utilising specific optimisation methods like quadratic programming or warm start strategies allows CCS-MPC to make better advantage of the longer prediction horizon. Hence, these advancements in optimisation strategies assist in diminishing the computational load caused by the prolonged forecast timeframes and complex system dynamics [105]. However, in FCS, the discrete nature of converter switches is manipulated and calculated optimal signals are directly applied. But in some cases, the time to apply the optimal state is also calculated, which greatly increases the complexity of the algorithm. As a rule of thumb, computational burden in FCS exponentially increases with prediction horizon as the power of the total number of available voltage vectors [106]. The number of voltage vectors depends upon the converter topology. For example, in the two-level three-phase voltage source inverter, there are 6 active voltage vectors and two null or zero vectors. If the prediction horizon is 1, we have seven voltage vectors, which are tested one by one in the cost function and the voltage vector that produces the minimum value of the cost function is chosen as the next switching state. If the prediction horizon is increased to 2, the computational effort will exponentially increase due to the increased number of 49 voltage vectors, which need to be tested for determining optimal inputs. The computational complexity is further heightened in multi-phase and multi-level systems due to the presence of greater available voltage vectors (AVV) in comparison to traditional 2L-3P systems. The computational complexity of FCS-MPC increases as the number of voltage levels and phases increases [105, 107]. As an example, a 3-phase inverter operates at a voltage of 27 VV, while a 5-level, 3-phase inverter operates at a voltage of 125 VVs. Despite the computational load, FCS-MPC offers substantial advantages in multi-level and multi-phase systems compared to conventional control methods like PWM, which can be difficult to implement and need advanced modulation techniques [108]. Several methods have been suggested in literature to address the computational complexity, including shortening the prediction horizon, employing advanced optimisation algorithms, and utilising parallel computing techniques [109, 110].

To explain how the optimised voltage vectors can be applied to the converter, consider Figure 15 where three different ways are depicted for applying selected VVs for three time instants, that is, k, $k+1$ and $k+2$. For simplicity, it has been assumed that computational burden is negligible and there are no delays associated with it. Figure 15a shows the simple case of FCS-MPC, where optimal voltage vector V_u is selected at time instant k and is directly applied to the converter for the entire sampling interval. Similarly, V_v and V_w are the optimal selected VVs at time instants $k+1$, $k+2$ and applied for the complete sampling interval. Applying an optimal VV for the entire sampling time forces the torque and flux to keep changing in the same direction for a longer time which may result in undesired ripples.

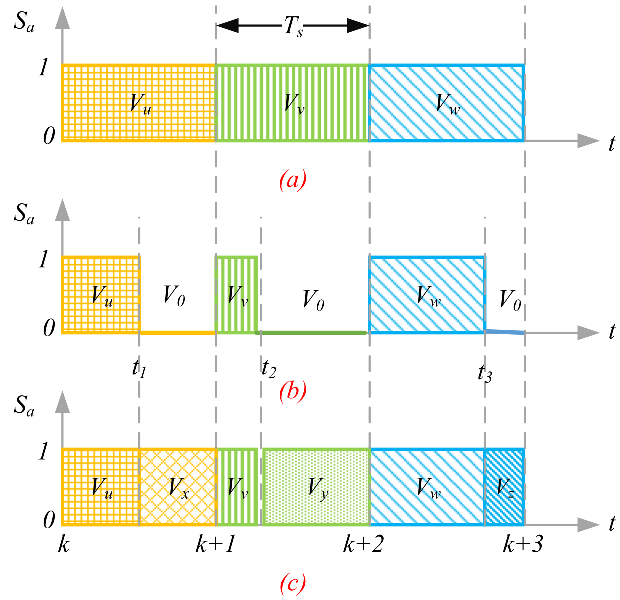


FIGURE 15 Multiple voltage vector-based MPCs (a) FCS-MPC (b) Two vector based with zero vector padding (c) two vectors based with the non-zero second vector.

The variable switching frequency or the sampling period is used to overcome the limitations of using the optimal voltage vector for the whole sampling period. The optimal voltage vector (VV) is implemented by utilising a fraction of the sample frequency and adjusting the sampling period accordingly. This enables more frequent updates of the controlled variables and helps to minimise fluctuations. This technique enhanced the dynamic response and offered greater control flexibility over the manipulated variable [111]. But it also leads to concerns about robustness and stability and increases complexity. Moreover, achieving precise tracking of the controlled variables at a greater sample rate may need the use of additional sensors, resulting in increased costs and system complexity [19, 112]. In summary, the use of variable sample periods in FCS-MPC enhances the system's performance and efficiency [113]. However, it necessitates a careful evaluation of trade-offs and handling of implementation issues. To overcome this problem, the concept of VV application time or duty ratio has been introduced [114] and is shown in Figure 15b.

First the appropriate vector V_u is selected at time instant k through the normal FCS enumeration method and then certain criterion, such as the minimisation of torque ripple, is used to determine the suitable time to apply the selected voltage vector [115] which is marked as t_1 on the figure. A null vector V_0 is padded along with this active vector for the remaining time of the sampling interval $T_s - t_1$. Similarly, at the start of the next sampling interval $k+1$, another optimal VV V_v along with optimal duty ratio $\frac{t_2}{T_s}$ is selected and applied for t_2 seconds. For the remaining time, a null vector is selected as before. In [116], it is argued that the second padded vector needs not to be a zero vector; it could be another active vector. This concept gives rise to multiple vector selection [117]-based FCS-MPC in which not only two, but three or more vectors can be selected along with their durations.

The idea of a double VV selection along with duty ratio optimisation is shown in Figure 15c. At time instant k, two voltage vectors V_u and V_x are selected and applied for t_1 and $T_s - t_1$ which represent their optimal duty ratios. Similarly, in the next sampling interval, two optimal voltage vectors V_v and V_y are selected along with their optimal duty ratios t_2 and $T_s - t_2$. In this way, the prediction horizon is effectively extended to two by applying two optimal vectors in a single sampling interval. A double voltage vector selection technique with direct flux control is discussed in [76]. In some research works, dynamic programming has also been recommended. See [94] for more details. The efficiency of electric drives utilising MPC can be enhanced by implementing virtual vectors and multi-vector-based methodologies, which have garnered considerable attention among researchers. Enhanced control can be attained by utilising virtual vectors that represent the switching states of the power converters. The multi-vector technique can be employed to simultaneously enhance the THD, torque, and flux ripples of the drive by utilising numerous virtual vectors. The achievement of high-performance control of the drive is facilitated by the utilisation of virtual vectors, as demonstrated in [118, 119]. The highest level of performance was attained by creating a virtual vector-based MPC for PMSM drive [120]. While multi-vector approaches enhance drive performance compared to single-vector techniques, they do not reduce the sampling frequency. The majority of multi-vector approaches are computationally burdensome because of the intricate vector selection and duty cycle algorithm. Furthermore, the multi-vector-based technique often organises the four segment switching frequencies using zero vectors, which do not effectively reduce the THD. The limitations of the multi-vector technique have been resolved through the implementation of virtual vector-based techniques, as documented in [121]. In [122], the vector is discretised and divided into several components to create virtual vectors. Similarly, the authors in [123, 124] partition the vector amplitude into many components after the appropriate vector is chosen. In [125], an increased number of virtual vectors have been generated by utilising both vector direction and vector amplitude. The virtual vector-based MPC techniques not only achieve optimum control performance comparable to multi-vector-based techniques but also simultaneously reduce the sampling frequency [126, 127].

3.6 | Extended prediction

Longer prediction horizons are essential for guaranteeing the closed loop stability of MPC. However, increasing the prediction horizon exponentially increases the computational effort. In AC drive applications, where sampling times are already in micro-seconds, achieving longer prediction horizons becomes more challenging. In most of the research work to date, the prediction horizon of one has been considered; though some efforts have been made to achieve longer prediction horizons, but it is still considered an open research area.

A prediction horizon of two with the weighting factor table is constructed on the basis of torque ripple in [128]. Sampling time is divided into two sub-intervals. Time for applying active voltage vector and time for applying null voltage vector effectively increase prediction horizon to 2 without increasing the computational effort.

The simulation study of enumeration-based non-linear FCS-MPC for the linear induction motor is considered in [129]. The controller is formulated for speed tracking and longer prediction horizons of up to 10 are analysed for ripple reduction. A distinction is made on feasible and non-feasible switching states to reduce the computational effort and redundant states are removed from enumeration.

Exponentially weighted functional model predictive control based on Laguerre coefficient is studied with the help of simulations for longer prediction and control horizon in [130]. Extended prediction is considered in other related works as well [13].

In MV and HV drive applications, sampling frequency is much lower, and longer predictions are easier to achieve as compared to higher sampling frequency applications. Three dominant techniques are used for extended predictions in MV and HV: move blocking strategy, extrapolation and event-based horizon [131]. In the move blocking strategy, prediction horizon is divided into two sub-horizons; first one with smaller sampling time steps and second one with multiples of sampling time without any considerable increase in the computational effort. In extrapolation, controlled variables with hysteresis bounds are considered and prediction horizon is divided into so-called switching horizon and prediction horizon. This technique is mostly used with FCS-MPC. A detailed review on these techniques is given in [13]. Recent works on the extended prediction for MV are included in [130].

3.7 | Computational burden & delays

Managing the computational demands of MPC is a significant challenge in the implementation and expansion of MPC in industrial power electronics applications. Although current hardware for real-time MPC implementation has significantly advanced and become quicker, it remains challenging to handle sophisticated algorithms such as MPC within a control interval of microseconds. A significant amount of the sample interval is dedicated to the computation of the ideal signal, resulting in delays. These delays are referred to as computational delays, which have an adverse impact on the performance of Model Predictive Control (MPC) and result in disturbances.

A significant portion of the computational workload in FCS-MPC is dedicated to the optimisation and selection of the voltage vector. If the number of possible voltage vectors is greater, this operation gets more complicated. In a basic two-level, three-phase inverter, there are a total of 7 voltage vectors (which includes the combination of two null vectors into one) as shown in Figure 16. However, in a Neutral Point Clamped (NPC) inverter, there are a total of 27 possible voltage vectors. The computational load is also influenced by prediction horizon.

Many other efforts have also been made to reduce the computational burden; the most important of them is listed in Figure 17.

The branch and bound algorithm is used in [132] to achieve longer prediction horizons for better steady state performance of MV drives. Natural switching constraints (Bounds) are taken into account in NPC to divide the admissible states into sub-optimal regions (Branch). Depending upon the current state, certain branches are tested for optimisation under the switching bounds. This method effectively reduces the computational burden and only certain sets of VV are tested. Normally, a bound on change in switch position (Δx) is forced which can be expressed as follows:

$$\max|\Delta x| \leq 1 \tag{19}$$

This method can reduce the computational burden by an order of magnitude. It is dependent upon the converter topology and is mostly used for MV drives. Some efforts have been made to use it for smaller sampling times [133, 134].

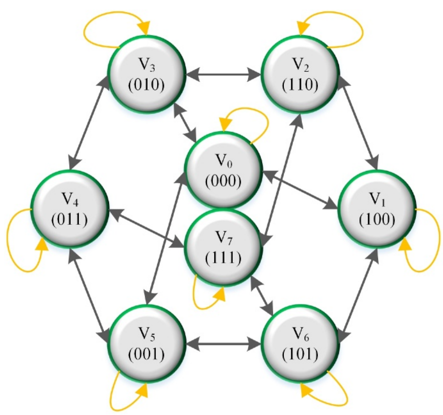


FIGURE 16 Restricting the next switching state by allowing only one switch position change.

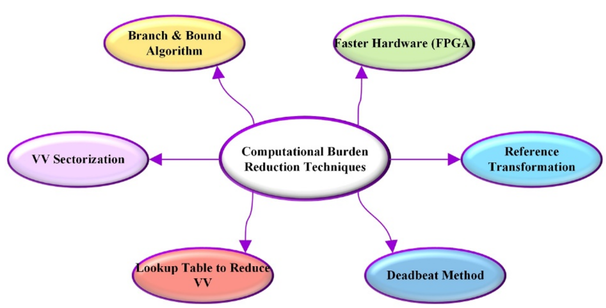


FIGURE 17 Techniques to reduce the computational effort.

Graph algorithm can be considered a type of branch and bound algorithm.

Another approach to alleviate the computational demands is to employ the notion of 'sectorisation'. The vector space is partitioned into tiny sectors, often six in number, known as DTC sectors, within the stationary $\alpha - \beta$ reference frame. Every sector comprises 'candidate vectors' represented as a lookup table. The assignment of these candidate voltage vectors to a certain sector is determined by the location of the stator flux $\theta_{\psi s}$, the stator flux error $|\psi_s^* - \psi_s|$, and the torque error $|T^* - T|$. In order to optimise the voltage vectors, the first step is to estimate the sector based on Equation (10) for estimating the stator flux.

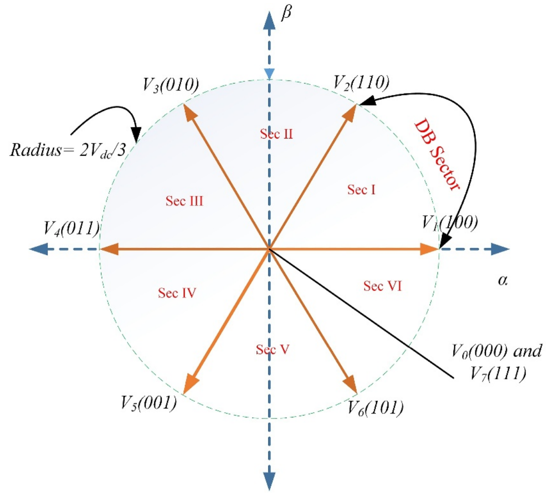
$$\theta_{\psi s} = \arctan\left(\frac{\Im\mathfrak{m}(\psi_s(k+1))}{\Re\mathfrak{e}(\psi_s(k+1))}\right) \tag{20}$$

$$(2S-3)\frac{\theta_{\sec}}{2} \leq \theta(S) \leq (2S-1)\frac{\theta_{\sec}}{2} \tag{21}$$

where N sectors of the plane are represented by $S = 1, 2, \cdots N$ and $\theta_{\sec}$ is the angular length of a single sector. If the plane is partitioned into six sectors, denoted as $N = 6$, $\theta_{\sec} = \frac{\pi}{3}$ the number of candidate vectors allocated to each sector is decreased to three from a total of seven vectors in a two-level, three-phase converter. Sectorisation involves additional calculations for determining flux location and sector selection, but it ultimately reduces the computing load as compared to conventional FCS-MPC methods. Recent studies, ref. [135], have reported that implementing sectorisation instead of the traditional enumeration approach in FCS-MPC leads to an average decrease of 25% in computing time.

The combination of MPC and the deadbeat method for PMSM drive reduces voltage vectors to two in [136]. A computational effort reduction of 48.3% is observed for a prediction horizon of two. The non-functioning candidate's proposed voltage vectors and sectors are illustrated in Figure 18 along with the corresponding table. In [137], a concept called lookup table-based model MPC is developed for PMSM and induction motor drives. The study reports a decrease of 40% and 20% in the overall calculation time for PMSM and induction motor drives, respectively. The Lyapunov function is employed in [138] to directly represent the cost function in relation to voltage vectors rather than the current error. This eliminates the need for intermediary computations and enables the attainment of closed-loop stability. The computational load in [139, 140] has been alleviated by reducing the number of voltage vectors in conjunction with utilising the Kalman filter estimate method.

Aside from algorithmic advancements aimed at minimising computing workload, field programmable gate arrays (FPGAs) offer a hardware-level option to attain the same outcome. FPGAs have a parallel architecture that enables accelerated processing. In [141–143], the utilisation of FPGAs to mitigate computational workload.



θ_DB	DB Sector	VV to be tested
[0, π/3]	I	V0, V1, V2
[π/3, 2π/3]	II	V0, V2, V3
[2π/3, π]	III	V0, V3, V4
[π, 4π/3]	IV	V0, V4, V5
[4π/3, 5π/3]	V	V0, V5, V6
[5π/3, 2π]	VI	V0, V6, V1

FIGURE 18 MPC combined with the DB method to reduce the number of voltage vectors.

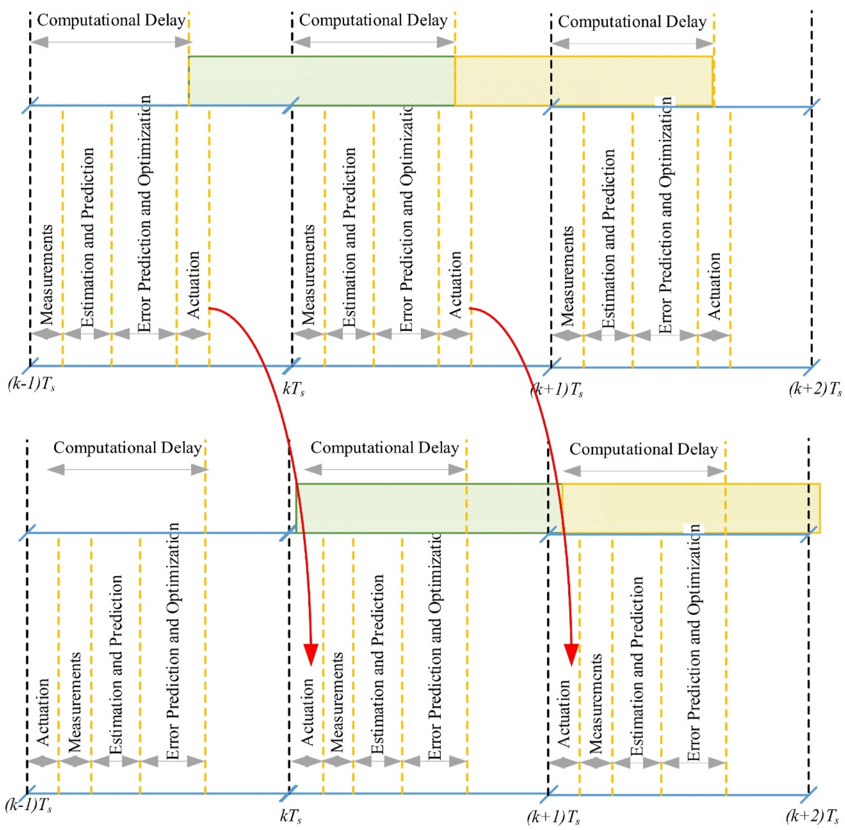


FIGURE 19 Computational delay compensation.

The main effect of the substantial computing cost of the MPC is a notable delay in the time it takes for measurements to be processed and for the converter switches to be activated. It is required to offset this delay in order to prevent undesired behaviour of the output, such as steady state errors.

Figure 19 illustrates the step-by-step procedure utilised in the execution of MPC in most motor driving applications. At the beginning of the sample period, load variables, primarily currents are monitored. The values of the controllable variables (torque, flux, or currents) are predicted at the next sampling moment $k+1$ in the subsequent step. After making the predictions, optimisation is done to evaluate the available voltage vectors, and the resulting error is measured at $k+1$ instant. This stage also requires choosing the most suitable voltage vector and favourable switching moment (duty ratio in CCS). Ultimately, the switching state selected is implemented. Ideally, these computations should be instantaneous, and the chosen switching state is applied at the start of the following sample period, denoted as $k+1$. However, in practical terms, it necessitates a specific duration dependent upon the sampling frequency and the processing velocity of the hardware.

A large ripple will result from the load variable rising to an undesirable level during this period due to the prior switching state continuing to be applied. A practical approach to mitigate computational delay is using a two-step ahead algorithm. This approach suggests that the actuation step be performed immediately after measurement and the prediction model be adjusted one step ahead to compensate for delays. For a comprehensive understanding of this approach is in [144]. Additional comparable methodologies are examined in [145, 146]. The paper [147] provides a detailed discussion of delay compensation approaches for multi-variable systems with low sampling frequency. It focuses on two compensation techniques: Initial State Projection and 'Admissible Switching Sequence Acceleration'. Most of the existing research uses a two-step ahead algorithm as the conventional way for delay compensation. This method often decreases the total harmonic distortion (THD) of the load variable by up to 5%.

In [148], the PTC-DSVM-based technique is proposed to reduce sampling frequency and hence computational burden; however, it required parameter-dependent equation and rotary coordinate transformation that reduces the robustness and simplicity of the overall system. Another computational burden reduction scheme based on discrete space vector modulation is proposed in [149] however, the estimation of appropriate reference voltage is a challenging task that is mandatory in space vector modulation. A passivity-based computational burden reduction technique is proposed in [150]; however, it uses a neutral point clamp converter that has a neutral voltage balance problem.

3.8 | Sensorless MPC

As explained earlier, MPC algorithms in AC drives need different feedback signals for prediction and optimisation. These signals include currents, voltages, speed, position, flux and torque. Speed, currents and voltages can easily be measured and other quantities like electromagnetic torque, rotor flux and stator flux are usually estimated from those measurements. To reduce the complexity and cost of the drive, sensorless operation is preferred. Various solutions have been proposed in conjunction with MPC to remove mechanical speed encoder/sensor for AC drives. Advantages of sensorless operation include lower complexity and cost of the drive, easier maintenance due to less hardware and cables, and rigid environment operation. Figure 20 shows the block diagram of the generalised sensorless operation of MPC. Measured currents and voltages are used in an estimator/observer to obtain the values of different signals. The design and mathematical equations used in the observer/estimator depend on various factors. These factors may include the range of operating speed and controlled variables or type of MPC (PTC or PCC).

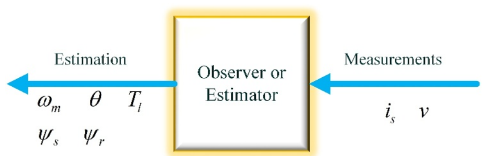


FIGURE 20 Sensorless MPC.

Sensorless techniques can be divided into three categories depending upon the speed of operation: Low speed, medium or high speed and all speed. Recently, more emphasis has been put on the design of the sensorless algorithm which can work in broader ranges of speed. In [151], for example, sensorless predictive current control (PCC) of the induction motor is studied. An Extended Kalman Filter (EKF) is used to achieve broader speed operation to estimate load torque, speed, position and rotor flux [53, 152]. Similarly, the authors in [153] also consider EKF for estimating noise-free stator currents, speed and fluxes for predictive torque control (PTC). An analytical estimation algorithm is introduced in [46] for IPMSM based on PCC-FOC with PWM to achieve a fixed frequency operation of the drive. Many good review papers are available for sensorless operation for direct control methods of AC drives; see refs. [54, 154, 155] for further details. It is worth noting, however, that adding sensorless feature to MPC controllers significantly increases the computational burden, and different techniques are considered to reduce this additional effort [144].

3.9 | Cascade-free MPC

Most of the MPC algorithms are implemented in a cascaded structure as shown in the block diagrams of PCC and PTC in Figures 9 and 10, respectively. This structure consists of an outer speed loop and inner current or torque loop. The outer speed loop, which generates torque and current references for the inner loop using simple PI controller, has larger time constant than the inner loop's time constant. Cascaded control structures always result in lower bandwidths or slower dynamic response due to their decoupled nature. Moreover, speed measurement noise will directly result in incorrect reference torque which will severely affect the performance of the drive. Most of the work in MPC is focused on inner control loops and is dependent upon the dynamics of the reference generated by the outer speed loop.

Many proposals have been put forward for cascade-free MPC implementation. In [156], the idea of Direct Speed Control (DSC) is introduced in an FCS-MPC framework for SMPM drives. Predictions are made for speed and currents, and optimal output states are selected on the basis of the minimum speed error. Low-speed operation is also considered to enhance the capabilities of the proposed algorithm to a wider range of operating speeds. In [157], a double integrator dynamic model is considered to form a combined optimisation problem for cascade-free speed control. Similar work is done in [158], which is to control the speed of PMSM using a matrix converter. However, due to multiple loop combinations, cascade-free formulations of MPC involve multiple control objectives and multiple weighting factors, which makes it difficult to achieve satisfactory performance. Tuning of multiple weighting factors and increased computational burden make cascade-free MPC less attractive.

3.10 | MPC for different speed regions

In most of the applications, MPC controllers are designed for normal medium range speeds and balanced voltages. However, there are certain problems associated with lower and higher operating speeds, starting a free running motor [159] to a new speed and considering the operation under unbalanced voltages [160]. Flux estimation can be obtained either from the current model or the voltage model. As mentioned previously, the current model is sensitive to rotor resistance variations at higher speeds, while the voltage model is sensitive to stator resistance variations at lower speeds. In [161, 162], the concept of Maximum Torque per Ampere (MTPA) is used with FCS-MPC to extend the controller stability and reduce ripple in lower speed operation. Similarly at higher speeds, the so called Field Weakening operation is considered with MPC in [163, 164].

Parameter identification is an essential component of ensuring the reliable and effective performance of the system in FCS-MPC during online adaptation. Precise system models have significance for control systems to achieve optimal performance [112]. Various methodologies have been utilised to calculate and update model parameters in real-time conditions, including recursive least squares, Kalman filtering, and machine learning-based systems. System model adaptation is a crucial aspect in accurately capturing the dynamic response of the drive [165]. This entails modifying the state-space model, cost function, and constraints in accordance with the observed system response in order to enhance the overall efficiency of the system. The rejection of disturbances in online adaptation follows. FCS-MPC can be built to mitigate disturbances by using advanced techniques such as online disturbance estimates and compensation methods like extended state observers, disturbance observers, and adaptive control techniques [166, 167]. Ensuring the ability of FCS-MPC to handle faults is an essential consideration to consider while implementing online adaptation. The control method can be modified by integrating real-time detection and identification of sensor failure or malfunctions in FCS-MPC [146]. Machine learning methods are currently being extensively studied for their ability to adapt to changing conditions and variations in system parameters in online adaptation.

3.11 | Miscellaneous MPC challenges

One of the problems associated with direct control techniques is variable switching frequency, which results in the spread spectrum of the controlled variables. Spread spectrum generates undesired harmonics, noise, current and voltage ripples and increases THD. To shape the frequency contents of load currents, the idea of 'frequency weighting' is coined in [168]. The cost function is formulated with the frequency domain weighting factor. The gain of this factor can be tuned to achieve a filter like operation. However, this method is not much effective to achieve fixed frequency operation. FCS-MPC can be combined with traditional PWM techniques and the FOC method to achieve a concentrated spectrum with a constant frequency. Most recent works on fixed frequency operation are [42, 169, 170]. Miscellaneous issues related to improving MPC performance include disturbance rejection [46, 171], increasing controller bandwidth [20], stability issues and robustness [172, 173] and frequency reduction for loss minimisation [174, 175]. Irrespective of all the challenges discussed so far, MPC has played an important role in improving the energy efficiency of the ac motor drives by providing an intuitive and optimised control mechanism. The most important contributions towards energy efficiency improvement are summarised in Table 3 as compared to some of the well-established control methods.

3.12 | Model free predictive control (MFPC)

The previous section clearly demonstrates that the performance of the MPC algorithm is significantly influenced by the understanding of the system model. Nevertheless, the parameters of the system typically undergo changes over time. Thus, an effective model should be subject to change throughout time. Nevertheless, acquiring such a model is unattainable due

TABLE 3 MPC comparison for energy efficiency.

MPC method	Compared with	Performance improvement
MP-DTC for MV drive with NPC inverter	Standard DTC	MP-DTC with N = 1 reduces switching frequency by an average of 16.5% while maintaining the same quality of controlled variables at a sampling frequency of 350 Hz [176]
MP-DCC for PMSM drive prototype	Linear control (PI) with PWM	MP-DCC with N = 1 reduces switching frequency up to 70% at a sampling frequency between 30 and 50 KHz [177]
MP-DTC for MV	Forced machine current control (FMCC)	MP-DTC with longer horizon gives 25% and 50% less current and torque ripples [178]
FCS-PCC	CCS-PCC	Current ripple and THD increase linearly with the modulation index in CCS, while it remains fairly constant in FCS. FCS also effectively handles delays [179]
PTC	PFC	PFC outperforms PTC by achieving 3 times less THD of load currents. PFC also removes tuning of the weighting factor [180]

to the huge computing load it entails, making it impractical for the actual implementation of the control system. In addition, the challenge of accurately identifying the beginning parameters of an unknown plant is also a significant concern. An inconsistency between the parameters of the model and the controller can result in a decline in performance and, in certain instances, the instability of the control [181, 182]. A different strategy involves employing an on-demand model to manage predictions [183]. The fundamental concept involves storing the performance data of the system in a database and utilising it to forecast the behaviour of the system rather than relying on a fixed model. Instead of estimating a huge global model covering the full operating range, a local model of the system is predicted using input–output information from a small neighbourhood at the current operating point. Some MFPC techniques substitute a lookup table with the control system's input and output data for this data-driven model [184]. Throughout the course of each sample, the data-driven model/lookup table is continuously updated. Subsequently, the data is transformed into a linear form and employed to forecast the behaviour of the system [185]. Figure 21 displays a comprehensive block schematic of the control system. Recently, there has been a growing use of MFPC approaches in power electronics and drives. The MFPC technique has several advantages compared to the typical MPC technique, such as the absence of model identification, the capacity to handle model uncertainty, adaptability to changes, and applicability to complex systems [186, 187]. Nevertheless, MFPC still faces several research challenges such as the need for a substantial amount of input–output data, ensuring stability and addressing convergence issues, the absence of interpretability, and dealing with computational complexity [188]. Research into MFPCs is expanding, particularly in the realm of electric drives and power converters [189, 190].

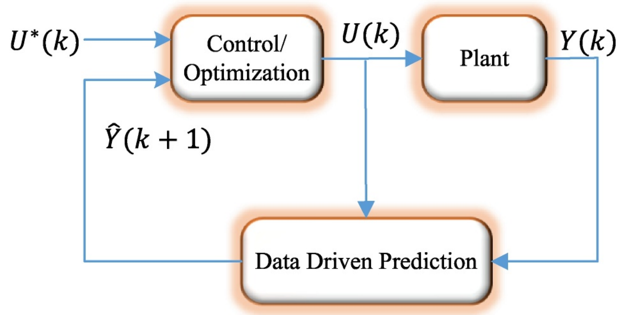


FIGURE 21 Block diagram of general model free predictive control.

4 | RESEARCH TRENDS

After analysing more than 250 publications of the past five years related to MPC for electric drives, seven key areas were identified as the main focus of ongoing research. These areas are summarised in Table 4. This classification is purely for discussion purposes as one area cannot be entirely separated from the other without having effective overlapping. For example, reducing the computational effort will affect steady state performance (ripple), changes in the optimisation algorithms and it also will impact the switching frequency. Similarly, while suggesting some structural changes such as cascade-free operation, it will greatly change the computational effort, dynamic performance of the controller and computational delays. Therefore, these areas should be considered as interdependent and affecting each other in complex manners.

Figure 22 shows the percentage distribution of the research publications among these loosely divided areas. The major focus of the work has been towards improving steady state performance and reducing ripples in the torque and currents. At the same time, almost equal attention was given in suggesting structural changes in the controller. These changes include sensorless operation, Maximum Torque per Ampere (MTPA) operation for low-speed region and Field Weakening operation. The weighting factor has also been a major interest under investigation. Different algorithms and methods were suggested to its online adaptation, removal and tuning. Almost equal importance was given to comparing the performance of MPC with other control methods such as DTC and FOC. A significant effort was also put in reducing computational

TABLE 4 Key research areas in MPC for electrical drives.

Area code	Area	Related subtopics
A	Steady state performance	Ripple reduction, steady state error, delay compensation, extended prediction
B	Computational burden	Branch & bound, graph algorithms, FPGA implementation, sectorisation, voltage vector reduction
C	Optimisation	Cost function formulation, weighting factor removal, tuning and online adaptation, dynamic programming
D	Switching behaviour	Fixed frequency operation, duty ratio control, loss minimisation, sampling effects on switching frequency
E	Structural improvements	Sensorless/encoderless operation, low-speed and high-speed operation, observer design and estimation, cascade-free operation,
F	Machine models	Parameter variations, model mismatch and uncertainties
G	Comparative study	Hybridisation of MPC with other techniques, benchmark study of MPC

burden and tackling parameter variations during drive operation. Generally, good mathematical models are available in power electronics, so this area is the one with minimum focus in research. The overlapping work in these areas is indicated in the column bar graph, as shown in Figure 23. As the chart shows, most of the work has been in improving steady state performance of MPC by suggesting changes at the optimisation level such as weighting factor selection and removal. The other combinations in improving steady state performance or reducing ripples include structural improvements (E), controlling switching behaviour or duty ratio and reducing computational effort. In fact, more emphasis in the past five years seems to be concentrated on suggesting new MPC algorithms for different converter topologies for AC drives such as the matrix converter and multilevel converters (NPC), sensorless operation with reduced voltage vectors, duty ratio optimisation and controlling switching frequency for dynamic loss minimisation. In the near future, more complex MPC algorithms with extended predictions for servo drives at higher sampling frequencies are expected to emerge. The reduction of the computational burden without sacrificing the steady state performance will also remain the main focus of interest. Better voltage vector selection algorithms are also anticipated to improve the duty ratio optimisation with minimum efforts. There is still enough work to be done in solving weighting factor selection, achieving extended prediction horizons and reducing the computational effort. Consequently, there have been compromises between the effectiveness of various performance indicators [191]. Therefore, the Pareto front in control system design represents the collection of optimal solutions, where enhancing one control aim necessitates compromising performance in another. Hence, it is worth considering the exploration of optimal solutions on the Pareto front using techniques like multi-objective optimisation methods or preference-based approaches.

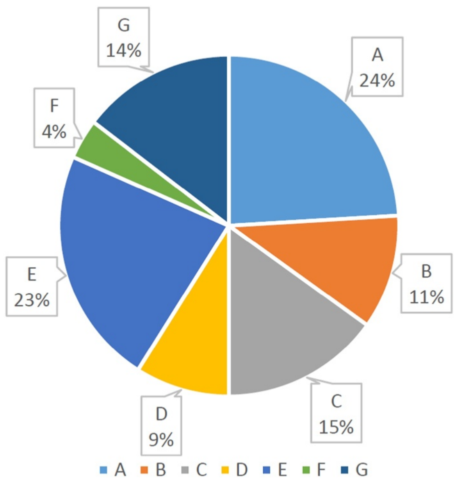


FIGURE 22 Key research areas in MPC for electrical AC drives (2012–2023).

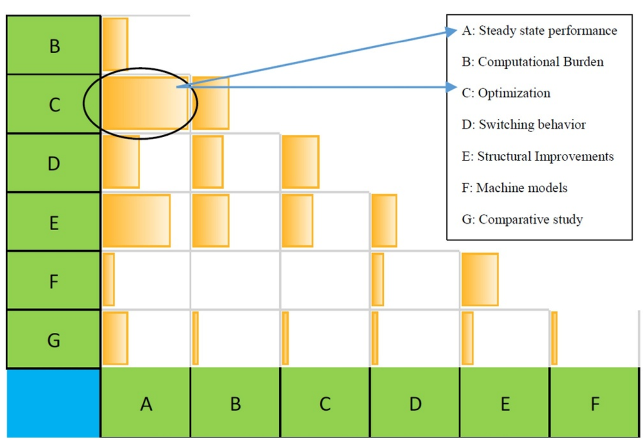


FIGURE 23 Research work combining different areas.

5 | CONCLUSION

This paper presents a comprehensive analysis of the latest research on model-based predictive control for AC electrical motor drives and highlights the main obstacles that need to be addressed. This text provides a thorough categorisation of CCS-MPC and FCS-MPC algorithms based on several criteria. It specifically focuses on two often utilised FCS-MPC approaches, namely PTC and PCC, and provides a detailed review of both. Predictive direct torque control (PDTC) and direct current control (PDCC) algorithms are increasingly preferred for medium- and high-voltage drives due to their various benefits compared to older control approaches. When compared to direct torque control (DTC), these improvements result in a 70% reduction in switching losses and the capability to achieve up to a 50% drop in ripples. These benefits apply not just to low-frequency drive applications but also to high-frequency servo drives. The concept of voltage vector optimisation in terms of magnitude, phase and optimised switching instant is explained. Parameter variations and model mismatching effects on MPC performance and recent solutions are described. Factors having a significant impact on improving the steady state performance of MPC are discussed at the algorithmic and structural level. Sensorless techniques, flux estimation, observer design and its effects on computational cost and ripples and different optimisation solutions are also presented in detail. A survey of relevant and most important solutions on improving steady state performance, reducing computational burden and modifying spread spectrum associated with FCS-MPC shows that the selection of weighting factor in PTC algorithms is still open research challenge. Similary obtaining optimised voltage vector with minimum effort and mathematical complexity for duty ratio control and achieving longer prediction horizons for lower ripples, continus to dominate the research in MPC for energy efficiency in motor drives. Although 70% reduction in switching losses has already been reported.

AUTHOR CONTRIBUTIONS

Muhammad Bilal Shahid: Writing – original draft. **Weidong Jin**: Supervision. **Muhammad Abbas Abbasi**: Investigation; Writing - review & editing. **Abdul Rashid Bin Husain**: Project administration. **Hafiz Mudassir Munir**: Writing – review & editing. **Mannan Hassan**: Methodology; Software. **Aymen Flah**: Project administration; Visualisation. **Ahmed Saad Eddine Souissi**: Validation; Writing – review & editing. **Thamer A. H. Alghamdi**: Funding acquisition; Resources; Supervision; Writing – review & editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Data are available on request from the authors. The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Muhammad Bilal Shahid https://orcid.org/0000-0002-0864-6135
Hafiz Mudassir Munir https://orcid.org/0000-0001-9345-4762
Mannan Hassan https://orcid.org/0000-0001-8256-8449

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