A Review on Weighting Factor Design of Model Predictive Control Strategies for AC Electric Drives

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***Abstract*—Model predictive control (MPC) has been widely applied to AC electric drives over the last decade. Despite extreme efforts and proposed effective solutions, the researchers are still seeking to find more effective solutions for weighting factor (WF) design, parameter dependency, current/torque harmonics, variable switching frequency, and computational complexity. This paper presents a review of the WF design techniques of MPC strategies for AC electric drives. Thus, it aims to inform readers about the proposed techniques for WF design of MPC strategies and to accelerate their future research in this promising area.**

***Index Terms*—Electric drives, finite control set, model predictive control, power converters, weighting factor design.**

I. Introduction

TODAY, the electrification trend in transportation and the demand for renewable energy sources have increased attention to AC electric drives and accelerated the research in this field [1]–[5]. Even if AC electric drives are a mature technology, today, they combine all state-of-the-art methods in electric machines, control, power electronics, and microchip technology. The progress in one of these research areas has led to advances in others. The most significant multiplier in the design of more advanced control techniques and more optimized electric machines is undoubtedly the development of higher-capacity and lower-cost microprocessors [6]. Model predictive control (MPC) of AC electric drives is a good sample of this progress. Compared to mature control techniques, field-oriented control (FOC) and direct torque control (DTC), MPC has an easy concept with straightforward implementation and can manage system nonlinearities and multiple control objectives with ease [7]. These features are in accord with AC electric machines that have highly non-linear models with unknown load inputs and time-varying electrical and mechanical parameters. This is why MPC has been widely applied to AC electric drives in the last decade.

Despite the mentioned advantages of MPC, some challenges have been reported in the literature regarding weighting factor (WF) design, parameter dependency, current/torque harmonics, variable switching frequency, and computational complexity [8], [9]. Many effective solutions to these problems have been reported in the literature, but researchers are still seeking to find more effective solutions. Therefore, MPC applications for electric drives are still open to research. MPC strategies use discrete system models to predict the future behavior of electric drive systems. Time-varying changes in electrical (resistances, inductances, and flux linkage of permanent magnets) and mechanical (inertia and viscous friction) parameters are inevitable. To deal with the parameter dependency problem, incremental model-based MPCs [10]–[12], model-free MPCs [13]–[15], disturbance observer-based MPCs [16]–[18], and MPCs combined with parameter estimation [19] have been proposed. MPC strategies directly control the switching states of power converters but the availability of the switching combinations for a power converter is limited, resulting in high current/torque harmonics in electric drives. To suppress these harmonics, multi-vector-based MPCs [20], [21] and modulated MPCs [22], [23] have been reported. The modulated MPCs also help to prevent variable switching frequency problems. The computational complexity of MPC strategies, particularly in the presence of more power switches, is extremely high. To reduce the computational load, voltage vector elimination techniques, which allow for reducing the number of candidate voltage vectors, have been proposed [24]–[27].

As for the weight factor design problem, it directly affects the performance of MPCs and even causes stability problems. The conventional MPCs use the scalarization method, which consists of the weighted sum of the main and auxiliary control objectives, in generating the cost function. This flexible structure, the biggest advantage of MPC strategies, brings with it the problem of the WF selection, which is the main motivation of this paper. There is no systematic way of choosing weight factors. Therefore, researchers have proposed different effective ways to deal with this problem. These methods can be divided into two main groups as in Fig. 1: WF selection and WF elimination methods. The first group consists of classic approaches, numerical/algebraic methods, meta-heuristic optimization methods, and artificial intelligence (AI)-based methods, while the second group includes MPCs

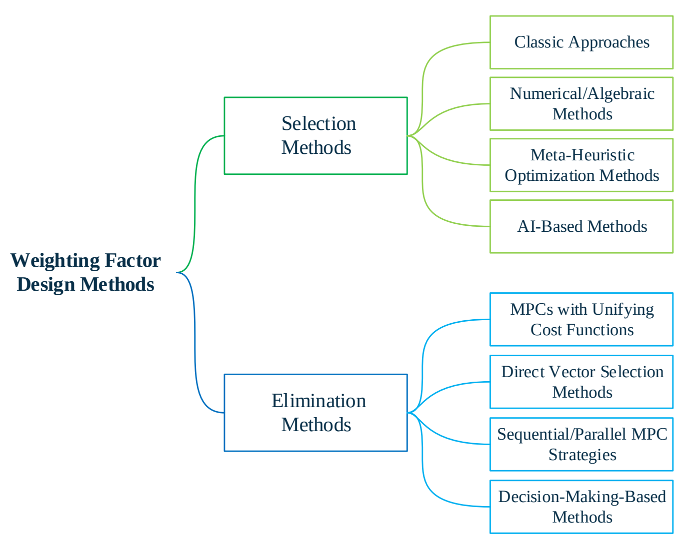


Fig. 1. Classification of WF design techniques for AC electric drives

with unifying cost functions, direct vector selection methods, sequential/parallel MPC strategies, and decision-making (DM)-based approaches.

Several valuable reviews on MPC applications of power converters and electric drives have already been covered [28]–[34]. But these papers introduce the concept, applications, challenges, solutions and latest trends, i.e. they address all these issues mentioned above. A recent study in [35] reduces the scope to WF selection techniques for MPC of power electronics and motor drives. Unlike [35], this paper focuses specifically on WF design techniques for AC electric drives and aims to accelerate readers' future research in this promising area.

II. CONVENTINAL FSC-MPC STRATEGIES FOR AC ELECTRIC DRIVES

There are three basic MPC strategies commonly applied to AC electric drives: model predictive current control (MPCC), model predictive torque control (MPTC), and model predictive direct speed control (MPDSC). MPCC and MPTC have a cascaded form: the inner control loop for current/torque control and the outer control loop for speed control. To overcome the limitations of the speed control loop caused by the linear controller, MPDSC provides a non-cascade form with a higher dynamic response. However, all these strategies suffer from the selection of WFs, and the selection process is significantly challenging when it comes to multiple WFs.

MPC strategies have been applied to the following four popular AC electrical machines: induction machines (IMs) [36], [37], permanent magnet synchronous machines (PMSMs) [38], [39], switched reluctance machines (SRMs) [40], [41], and synchronous reluctance machines (SynRMs) [42], [43]. Due to the popularity of PMSMs today, this section introduces MPC strategies over PMSM control.

Before introducing MPC strategies, giving the mathematical model of PMSM is useful. A PMSM model defined in the synchronously rotating reference ($dq-$) frame can be defined in the following form:

$$\dot{\mathbf{x}}_t = \mathbf{f}(\mathbf{x}_t, \mathbf{u}_t) + \mathbf{w}_t \tag{1a}$$
$$\mathbf{z}_t = \mathbf{h}(\mathbf{x}_t) + \mathbf{v}_t \tag{1b}$$

where $\mathbf{f}$ is the nonlinear system model, $\mathbf{h}$ is the measurement model, $\mathbf{x}_t$ is the state vector, $\mathbf{u}_t$ is the input vector, $\mathbf{z}_t$ is the output vector, $\mathbf{w}_t$ and $\mathbf{v}_t$ are the system and measurement noises that are independent, zero-mean, Gaussian noise processes of covariance matrices $\mathbf{Q}_t$ and $\mathbf{R}_t$, respectively. The vectors in (1) for the $dq-$frame are

$$\mathbf{x}_t = \begin{bmatrix} i_d \\ i_q \\ \omega_m \end{bmatrix}, \mathbf{u}_t = \begin{bmatrix} v_d \\ v_q \end{bmatrix}, \mathbf{h}(\mathbf{x}_t) = \begin{bmatrix} i_d \\ i_q \\ \omega_m \end{bmatrix},$$

and

$$\mathbf{f}(\mathbf{x}_t, \mathbf{u}_t) = \begin{bmatrix} \frac{1}{L_s} v_d - \frac{R_s}{L_s} i_d + p_p \omega_m i_q \\ \frac{1}{L_s} v_q - \frac{R_s}{L_s} i_q - p_p \omega_m i_d - \frac{p_p}{L_s} \omega_m \psi_{\text{pm}} \\ \frac{3}{2} \frac{p_p}{J_t} \psi_{\text{pm}} i_q - \frac{B_t}{J_t} \omega_m - \frac{\tau_l}{J_t} \end{bmatrix},$$

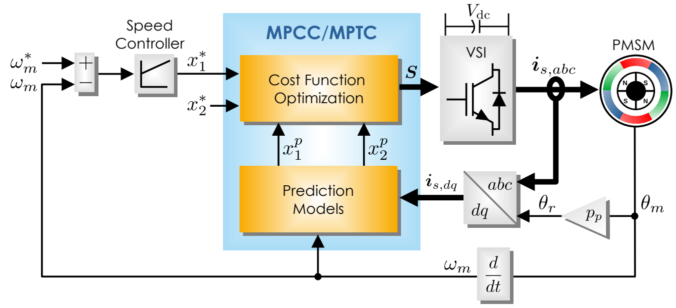


Fig. 2. Block diagram of MPCC and MPTC strategies ($x_1 = i_q,\ x_2 = i_d$ for MPCC; $x_1 = \tau_e,\ x_2 = \parallel \psi_s \parallel$ for MPTC)

where v_d, v_q, i_d, and i_q are the $dq-$axis components of stator voltages and currents, respectively, ω_m is the mechanical angular speed, R_s and L_s are the stator resistance and inductance, respectively, ψ_{pm} is the permanent magnet flux linkage, τ_l is the load torque, p_p is the pole-pairs, J_t and B_t are the inertia and viscous friction, respectively.

After applying the following first-order forward Euler approximation,

$$\dot{\mathbf{x}}_t \approx \frac{\mathbf{x}_{k+1} - \mathbf{x}_k}{T_s}, \tag{2}$$

the discrete PMSM model can be obtained as follows:

$$\mathbf{x}_{k+1} = \mathbf{I}_3 \cdot \mathbf{x}_k + T_s \cdot \mathbf{f}(\mathbf{x}_t, \mathbf{u}_t) \tag{3}$$

where T_s is the sampling time and $\mathbf{I}$ is the identity matrix.

A. Model Predictive Current Control

MPCC is certainly the most common MPC strategy as it is suitable for both power converters and electric drives. MPCC is reported to provide less current harmonics than MPTC [44]. It also has lower computational complexity compared to MPTC and MPDSC. It uses the following predicted stator currents obtained using the discrete PMSM model in (3):

$$i_{d,k+1}^p = \left(1 - \frac{R_s T_s}{L_s}\right) i_{d,k} + p_p T_s \omega_{m,k} i_{q,k} + \frac{T_s}{L_s} v_{q,k} \tag{4a}$$
$$i_{q,k+1}^p = \left(1 - \frac{R_s T_s}{L_s}\right) i_{q,k} - p_p T_s \omega_{m,k} i_{d,k} - \frac{T_s p_p}{L_s} \omega_{m,k} \psi_{\text{pm}} + \frac{T_s}{L_s} v_{q,k} \tag{4b}$$

The basic cost function used to evaluate voltage vectors in MPCC only includes current error terms and does not require any WFs since both terms are of the same unit. However, this flexible structure can be expanded by additional control objectives in different units, such as overcurrent protection term, switching frequency regulation term, input voltage balancing term, and so on. In this case, each additional control objective is included in the cost function with a WF as follows:

$$g = \left| i_d^* - i_{d,k+1}^p \right| + \left| i_q^* - i_{q,k+1}^p \right| + \lambda_j f_j \tag{5}$$

where f_j is the jth additional control objective, λ_j is the WF of the jth additional control objective, and $j \in \{1, 2, \ldots, n\}$. The block diagram of the MPCC can be found in Fig. 2.

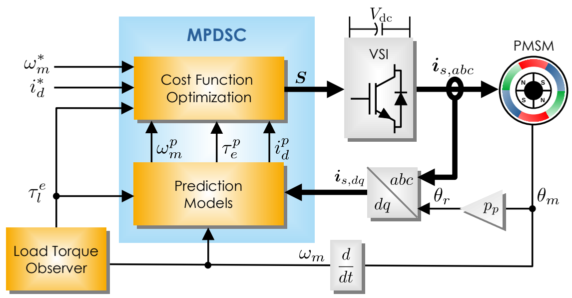


Fig. 3. Block diagram of MPDSC strategy

B. Model Predictive Torque Control

MPTC is one of the other popular MPC strategies with high dynamic response and lower torque ripples than MPCC. Unlike MPCC, which controls the current in the internal control loop, MPTC directly controls electromagnetic torque and flux. To predict the electromagnetic torque, it uses stator current predictions in (4) and stator flux predictions in (6). Finally, the predicted electromagnetic torque can be obtained as in (7).

$$\psi^p_{d,k+1} = L_d i^p_{d,k+1} + \psi_{\mathrm{pm}} \tag{6a}$$
$$\psi^p_{q,k+1} = L_q i^p_{q,k+1} \tag{6b}$$

$$\tau^p_{e,k+1} = 1.5 p_p \left(\psi^p_{d,k+1} i^p_{q,k+1} - \psi^p_{q,k+1} i^p_{d,k+1}\right) \tag{7}$$

The cost function of MPTC consists of errors of torque and flux, which are different units; therefore, even the simplest cost function needs a WF. Similarly to MPCC, it is possible to extend this cost function with additional control objectives as follows:

$$g = \left|\tau_e^* - \tau^p_{e,k+1}\right| + \lambda_\psi \left|\left|\boldsymbol{\psi}_s^*\right| - \left|\boldsymbol{\psi}^p_{s,k+1}\right|\right| + \lambda_j f_j \tag{8}$$

where λ_ψ is the WF of stator flux errors and $|\boldsymbol{\psi}_s|$ is the amplitude of stator flux vector. The block diagram of MPTC is shown in Fig. 2.

C. Model Predictive Direct Speed Control

MPDSC eliminates the outer control loop and provides a non-cascade form, providing better dynamic performance and the ability to reject disturbances [45]. It uses the equation of motion to predict the speed in addition to the stator current, stator flux, and electromagnetic torque predictions, as depicted in (9). However, speed prediction requires unknown load torque information, which is costly to measure. The well-accepted and cost-effective way to obtain the load torque is to estimate it with an estimator/observer [46], [47]. This obviously means MPDSC has higher computational complexity than MPCC and MPTC. But, it can be ignored in applications where higher control performance is required.

$$\omega^p_{m,k+1} = \frac{T_s}{J_t}\tau^p_{e,k+1} + \left(1 - \frac{T_s B_t}{J_t}\right)\omega_{m,k} - \frac{T_s}{J_t}\tau^e_{l,k} \tag{9}$$

The cost function of MPDSC consists of the sum of different quantities; therefore, it inherently needs WFs to balance their effects on the cost function.

$$g = \lambda_\omega \left(\omega_m^* - \omega^p_{m,k+1}\right)^2 + \lambda_\tau \left(\tau^p_{e,k+1} - \tau^e_{l,k+1}\right)^2 + \lambda_i \left(i_d^* - i^p_{d,k+1}\right)^2 + \lambda_j f_j \tag{10}$$

where λ_ω, λ_τ, and λ_i are the WFs of speed error, torque error, and current error, respectively. The block diagram of the MPDSC is presented in Fig. 3.

III. Weighting Factor Design Methods

As aforementioned in Section I, the proposed WF design methods can be divided into two main groups: WF selection methods and WF elimination methods. The following sections first introduce WF selection methods, followed by WF elimination methods.

A. Weighting Factor Selection Methods

WF selection methods can be considered in four main groups: classic approaches, numerical/algebraic methods, meta-heuristic optimization methods, and artificial intelligence (AI)-based methods.

1) Classic Approaches: The most common WF selection method is the trial-and-error method [48]. Besides its tedious and time-consuming nature, the electric drive is unlikely to determine the optimum voltage vectors under different operating conditions with this method. Another well-known method is to choose the WF as the ratio of the nominal values of the control objectives; for example, WF for MPTC is as follows [49], [50]:

$$\lambda_\psi = \frac{\tau_{eN}}{|\boldsymbol{\psi}_{sN}|} \tag{11}$$

where τ_{eN} and $\boldsymbol{\psi}_{sN}$ are the nominal values of electromagnetic torque and flux, respectively. In this method, both control objectives are of equal importance. However, this method fails in the presence of multiple WFs. To circumvent this limitation, each control objective can be normalized individually and then combined [51]:

$$g = \frac{\left|\tau_e^* - \tau^p_{e,k+1}\right|}{\tau_{eN}} + \lambda_\psi \frac{\left|\left|\boldsymbol{\psi}_s^*\right| - \left|\boldsymbol{\psi}^p_{s,k+1}\right|\right|}{\boldsymbol{\psi}_{sN}} + \lambda_j \frac{f_j}{f_{jN}} \tag{12}$$

When $\lambda_\psi = \lambda_j = 1$ in (12), all control objectives are of equal importance in the cost function. Similar to the previous method, the application of the normalization method is limited only by the presence of main (or primary) control objectives, such as current control in MPCC and torque and flux control in MPTC. If additional (or secondary) control objectives, such as common-mode voltage reduction and switching frequency regulation, are present, these terms will have equal weight with the main control objectives and will directly affect the voltage vector selection, resulting in poor control performance. Therefore, classic approaches are not effective solutions in the presence of secondary control objectives.

2) Numerical/Algebraic Methods: Various numerical and algebraic methods have been proposed to overcome the problems caused by fixed WFs in classical approaches [52]–[55]. In [52], a flux limit is set for the flux error and if the flux error term is less than this limit, the flux is set to a minimum value. Otherwise, WF is changed to a higher value to increase the effect of flux control in the cost function. The authors note that this simple approach improves steady-state torque and flux control in a variety of operating conditions without sacrificing dynamic performance. In [53], a variable WF based on speed variation is designed to reduce THDs of phase currents in steady states and improve dynamic control performance in transient states. In the proposed method, depending on the variation of the speed, the WF is increased linearly or quadratically to improve the THDs of the phase currents, and the WF is decreased linearly or quadratically to obtain a better transient control performance. That is, it prioritizes flux control in steady states and torque control in transient states. A variable WF for switching frequency regulation term is also proposed in [54]. The authors derived an expression between the current ripple and the magnitude and phase angle of the voltage reference. Based on this expression, they indicate that switching frequency reduction can lead to reference tracking failure or current spikes in some areas of the voltage space plane. To mitigate this adverse effect, the WF of the switching frequency regulation term is reduced in these areas over a newly designed cost function as follows:

$$g = C_v + kC_v n \tag{13}$$

where k is a constant for scaling, n indicates the number of commutations between two consecutive switching states, and C_v is voltage error defined according to the following equation

$$C_v = \left|v_\alpha^* - v_\alpha^p\right| + \left|v_\beta^* - v_\beta^p\right|. \tag{14}$$

This method still includes a parameter k to tune, and no analysis has been made on the effect of this parameter.

In [55], an algebraically WF design method has been proposed for the PDSC of PMSM. However, the WF of the speed error term requires accurate knowledge of J_t and ψ_{pm}, which are time-varying. The authors note that any inconsistencies in these parameters cause steady-state errors in speed and current controls. To overcome this difficulty, they incorporate integral terms into the cost function.

3) Meta-Heuristic Optimization Methods: Meta-heuristic optimization algorithms have been successfully applied to various engineering optimization problems. Unlike gradient-based optimization methods, they do not need a mathematical model between the system output and the parameters to be optimized [58]. This is why they are so popular in engineering applications. Various papers have also been reported on the optimization of WFs with meta-heuristic optimization algorithms such as genetic algorithms (GAs), particle swarm optimization (PSO), and simulated annealing (SA). These papers mainly focus on the WF design of MPTC strategy and can be divided into two groups in terms of different points of view: offline/online optimization studies and multi/single-objective optimization studies.

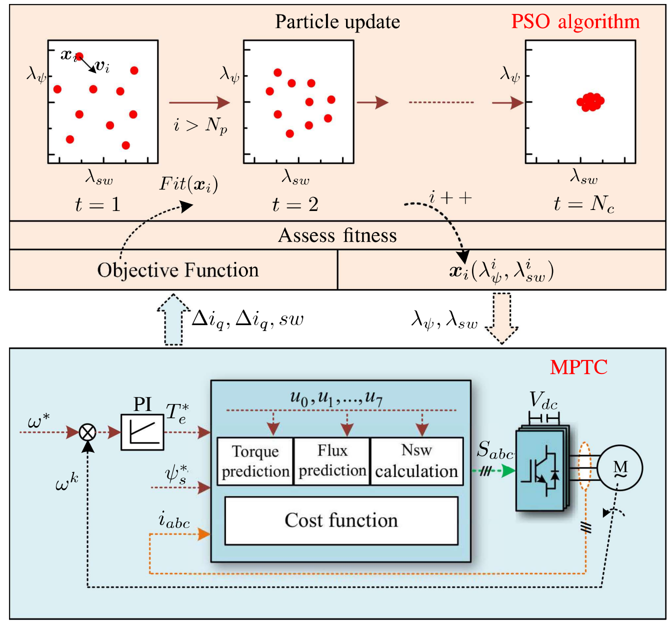


Fig. 4. Block diagram of WF design of MPTC based on meta-heuristic optimization [56].

Offline optimization studies can be regarded as multi-objective and single-objective optimization studies. The first group considers the WF optimization problem as a multi-objective optimization problem [59]–[61]. This approach yields a set of solutions, called the Pareto set, rather than a single solution; therefore, a final solution must be chosen from the Pareto set. This raises another tedious process. To overcome this difficulty, several papers choose a final solution by applying different DM methods to the Pareto set [60], [61]. In [59] and [60], the non-dominated sorting genetic algorithm-II (NSGA-II) is used to optimize WFs. While in [59] three parameters related to electromagnetic torque, flux, and average switching frequency are optimized, in [60] a similar approach is used to optimize the two parameters related to electromagnetic torque and flux. [60] also takes advantage of the TOPSIS DM method to easily get a final result. In [61], the WF of the flux error term is optimized by NSGA-II through electromagnetic torque and flux errors. To choose a better WF considering the overall performance, it compares the effect of TOPSIS-based, ranking-based, and Euclidean distance-based DM methods on the control performance. It is reported that TOPSIS and Eucledian distance-based DM methods mostly choose the same WF and ranking-based DM provides better control performance than the other methods. To throw off the multi-objective optimization and the resulting DM process, a few authors consider this problem to be single-objective and use speed errors to tune the WF associated with the flux term [61]. Despite good control performance, it can be difficult to correlate speed errors with additional control objectives when multiple WFs are involved.

In addition to offline WF optimizations, some researchers use these meta-heuristic optimization algorithms online [56], [62]. An SA is used in [62] to optimize the WF of the flux error term in MPTC while a PSO is used in [56], as shown in Fig. 4,

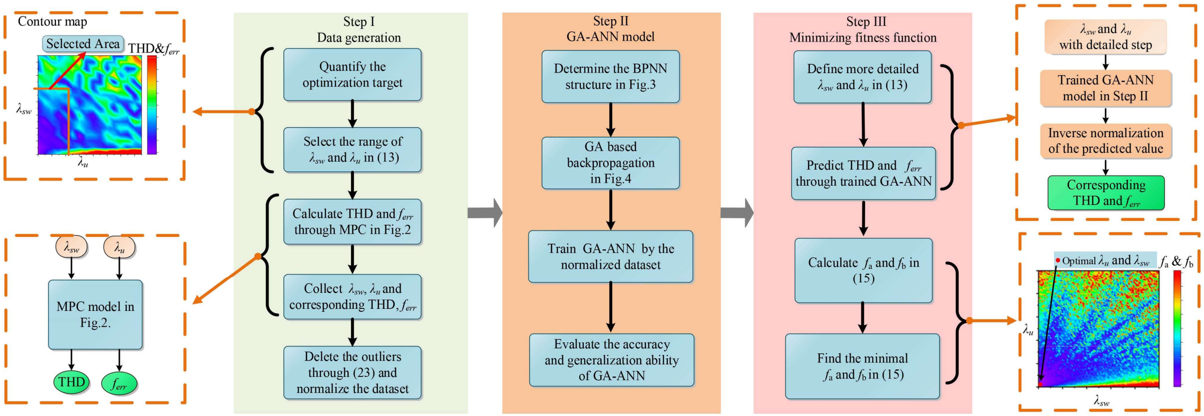


Fig. 5. Block diagram of GA-ANN-based WF design for MPCC of a PMSM drive fed by a three-level T-type inverter [57].

to optimize the WFs of both flux error and switching frequency regulation terms. Both optimization algorithms use cost functions that consist of the sum of different control objectives, such as MPC strategies. This raises a similar problem with the cost function of MPCs. However, metaheuristic algorithms are not suitable for use online due to their low convergence rates and excessively high computational loads. Although their simplified or micro versions have been proposed for online optimizations, they are unlikely to adapt to the rapid dynamic changes of electric drives due to their low convergence rate.

4) Artificial Intelligence-Based Methods: AI has spread to many engineering fields today and its influence is increasing day by day. As a result of this popularity, various AI-based applications have emerged in electric drive systems, and this trend can also be seen in the WF design of MPC strategies [57], [63], [64]. AI-based techniques can be divided into three groups: meta-heuristic optimization algorithms, fuzzy logic (FL), and artificial neural networks (ANN). Since meta-heuristic optimization algorithms were covered in the previous section, this section focuses on the remaining techniques.

The authors in [63] introduce an FL-based WF design for MPTC of IM drive fed by a three-level neutral-point clamped (3L-NPC) converter. The proposed method is capable of tuning online the WFs associated with the flux error term (λ_ψ) and neutral point voltage balance term (λ_u) through two sub-FL systems. Finally, better control performance is achieved than conventional MPTC.

The authors in [64] propose an ANN-based WF design for the MPTC of IM. The proposed ANN can update online the WFs of the flux error term (λ_ψ) and switching frequency regulation term (λ_{sw}) in addition to flux reference ($\boldsymbol{\psi}_s^*$), which is always considered fixed in the previous studies. The results show that it provides satisfactory control performance. An artificial neural network (ANN)-based WF design for MPCC of PMSM drive fed by a three-level T-type inverter is presented in [57]. The proposed method also uses a GA as the backpropagation algorithm to train the ANN; hence it is called GA-ANN by the authors. With the proposed GA-ANN, the WFs of switching frequency regulation (λ_{sw}) and neutral point voltage balance (λ_u) are tuned and finally improved control performance is achieved compared to conventional ANN. The entire block diagram can be found in Fig. 5.

B. Weighting Factor Elimination Methods

This section reviews the WF elimination techniques: model predictive flux/power control, direct vector selection methods, sequential/parallel MPC strategies, and decision-making-based approaches.

1) MPCs with Unifying Cost Functions: Model predictive flux control (MPFC) [65], [66], model predictive power control (MPPC) [67], [68], and model predictive active/reactive torque control (MPARTC) [69], [70] are designed to eliminate the WFs in MPTC. MPFC has been applied to electric drives in many studies, but there are a limited number of papers using MPPC in electric drives despite their popularity in power converters. MPARTC has been proposed as an alternative to MPPC in the control of electric drives.

As for the MPFC of PMSM, the amplitude of stator flux vector reference $|\psi_s^*|$ is taken equal to the reference value of stator flux amplitude $|\psi_s|^*$ in MPTC as given in (15) [65], [66].

$$|\psi_s^*| = \ |\psi_s|^* \tag{15}$$

Also, the angle of stator flux vector reference ψ_s^* needs to be determined. This can be calculated using electromagnetic torque definition in (16), where $\theta_{s,k+1}$ and $\theta_{r,k+1}$ are the electrical position of stator and rotor fluxes, respectively, $\delta_{sr} = \theta_{r,k+1} - \theta_{s,k+1}$ is the difference between the angles of stator and rotor fluxes.

$$\begin{aligned}\tau_{e,k+1} &= \frac{3}{2}\frac{p_p}{L_s}\boldsymbol{\psi}_{r,k+1} \times \boldsymbol{\psi}_{s,k+1} \\ &= \frac{3}{2}\frac{p_p}{L_s}\psi_{\text{pm}}e^{j\theta_{r,k+1}} \times \psi_{s,k+1}e^{j\theta_{s,k+1}} \\ &= \frac{3}{2}\frac{p_p}{L_s}|\psi_{\text{pm}}||\psi_{s,k+1}|\sin\delta_{sr}\end{aligned} \tag{16}$$

$$\theta_{r,k+1} = \theta_{r,k} + T_s p_p \omega_{m,k+1} \tag{17}$$

Using (16), the angle reference δ_{sr}^* between the rotor flux vector and stator flux vector can be calculated as follows:

$$\delta_{sr}^* = \arcsin\frac{2L_s\tau_e^*}{3p_p|\psi_{\text{pm}}||\psi_{s,k+1}|^*} \tag{18}$$

It is now possible to calculate the stator flux reference as follows:

$$\psi^*_{s,k+1} = |\psi_{s,k+1}|^* \, e^{\theta^*_{s,k+1}}, \tag{19}$$

where

$$\theta^*_{s,k+1} = \theta_{r,k} + T_s p_p \omega_{m,k+1} + \delta^*_{sr}. \tag{20}$$

Since the stator flux is the main control purpose in MPFC, the cost function is described as the difference between its reference and predicted values. Compared to (8), the cost function in (21) does not include a weighting factor.

$$g = \left|\psi^*_{s,k+1} - \psi^p_{s,k+1}\right| \tag{21}$$

Unlike MPTC, MPPC uses active and reactive powers instead of torque and flux, which have different units [67], [68]. Thus, both quantities used in the cost function have the same unit (power) and no longer need to use WF, similar to MPCC. The active and reactive power expressions can be calculated by the predicted stator currents in (4) and predicted stator fluxes in (6) as follows:

$$P^p_{k+1} = 1.5 p_p \omega_m \left(\psi^p_{d,k+1} i^p_{q,k+1} - \psi^p_{q,k+1} i^p_{d,k+1}\right) \tag{22a}$$

$$Q^p_{k+1} = 1.5 p_p \omega_m \left(\psi^p_{d,k+1} i^p_{d,k+1} + \psi^p_{q,k+1} i^p_{q,k+1}\right) \tag{22b}$$

Using the definitions in (22), the cost function can be defined given below.

$$g = \left|P^*_{k+1} - P^p_{k+1}\right| + \left|Q^*_{k+1} - Q^p_{k+1}\right| \tag{23}$$

where P^*_{k+1} and Q^*_{k+1} can be obtained by substituting (6) and (7) into (22) as follows:

$$P^*_{k+1} = \omega^*_m \tau^*_e \tag{24}$$

$$Q^*_{k+1} = \frac{L_s \omega^*_m (\tau^*_e)^2}{1.5 p_p (\psi_{\mathrm{pm}})^2} \tag{25}$$

As an alternative to MPPC in which active and reactive powers are used in the cost function, MPARTC makes use of active and reactive torques [69], [70]. Thus, the cost function consists of the same units, and the need for WF is eliminated. The expressions for the predicted active/reactive torques are as follows:

$$\tau^p_{ea,k+1} = 1.5 p_p \left(\psi^p_{d,k+1} i^p_{q,k+1} - \psi^p_{q,k+1} i^p_{d,k+1}\right) \tag{26a}$$

$$\tau^p_{er,k+1} = 1.5 p_p \left(\psi^p_{d,k+1} i^p_{d,k+1} + \psi^p_{q,k+1} i^p_{q,k+1}\right) \tag{26b}$$

The resulting cost function is

$$g = \left|\tau^*_{ea,k+1} - \tau^p_{ea,k+1}\right| + \left|\tau^*_{er,k+1} - \tau^p_{er,k+1}\right| \tag{27}$$

where

$$\tau^*_{er,k+1} = \frac{L_s (\tau^*_e)^2}{1.5 p_p (\psi_{\mathrm{pm}})^2}. \tag{28}$$

The authors in [69] note that control of active/reactive torques is equivalent to control of active/reactive powers, respectively. Therefore, there is no need to design a WF as in MPPC.

Despite the advantages of these three MPC strategies, they are all designed under the assumption that there are no additional control objectives. When it comes to additional control objectives, they require the use of WFs. Such an application is reported in [66].

2) Direct Vector Selection Methods: Traditional MPC strategies have the following two steps: 1) prediction step and 2) optimization step. In the prediction step, voltage vectors produced by the power converter are used to predict the values of control variables for $k+1$ time instant. Then, in the second step, it is tested whether the predicted values are close to the reference values. Direct vector selection (DVS) methods calculate the reference voltage vector directly, taking the values of control variables for $k+1$ time instant as reference values [71]. This significantly reduces the computational complexity as the prediction step is reduced to one, especially when using multi-level converter topologies. The reference voltage vector is then compared with the possible voltage vectors generated by the power converter over the cost function in (29). Similar to MPCC, MPFC, and MPPC, the cost function consists only of variables (voltage error terms) with the same unit, resulting in a cost function without WFs, and the use of WFs is unavoidable in the presence of additional control objectives [42], [72].

$$g = \left|v^*_d - v^p_d\right| + \left|v^*_q - v^p_q\right| \tag{29}$$

3) Sequential/Parallel MPC Strategies: Sequential and parallel MPC strategies are quite popular in controlling electric drives as they simply eliminate WFs in MPC strategies.

Sequential MPCs evaluate each control objective sequentially, as shown in Fig. 6, i.e. the first control objective is optimized first and some candidate voltage vectors are

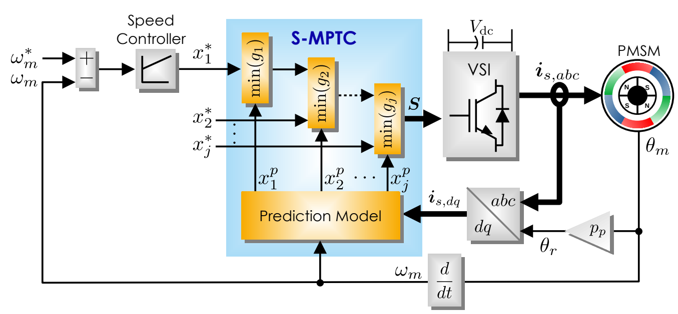


Fig. 6. Block diagram of S-MPTC strategy ($x_1 = \tau_e,\ x_2 = \parallel \psi_s \parallel$)

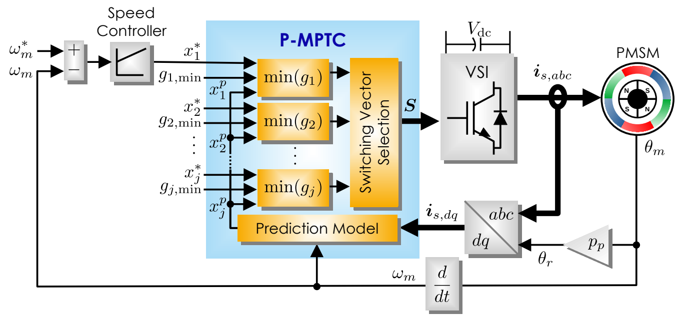


Fig. 7. Block diagram of P-MPTC strategy ($x_1 = \tau_e,\ x_2 = \parallel \psi_s \parallel$)

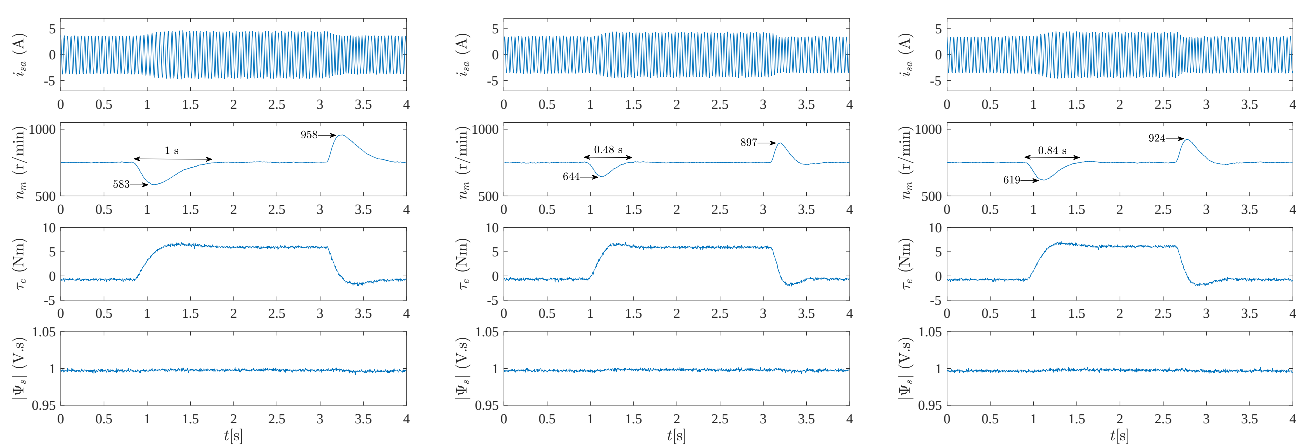
selected for subsequent steps [73]–[80]. These vectors are then sequentially evaluated for the second control objective and further. Although this simple mechanism has been applied to the MPTC strategy successfully, it is reported that this technique is inappropriate in the presence of equal importance control objectives, such as MPCC, MPFC, and MPPC [74]. The same authors also state that torque control should be the first control objective for MPTC, otherwise, stability issues arise. This may result in non-optimal control of flux. To deal with this problem, they have proposed a sequential MPTC (S-MPTC) with an interchangeable order, called generalized S-MPTC. Also, the number of selected candidate voltage vectors is increased in this method from two to three compared to conventional S-MPTC. To tackle the priority selection problem in conventional S-MPTC, another approach, called even-handed S-MPTC, is proposed in [75] with the voltage vector selection based on a modified form of the sequential method. This method solves the priority selection of control objectives in a simple way, but its computational complexity is quite high due to the need to sort the cost values. A comparison between conventional MPTC, S-MPTC, and even-handed S-MPTC can be found in [81]. To further improve control performance, the lexicographic method with tolerance values is adapted to S-MPTC in [76]. Although a better control performance is obtained than conventional and generalized S-MPTCs, it is a disadvantage that it needs some tuning parameters. In [77], the objective function of MPTC with dual T-type converter is split into main (torque and flux) and additional (capacitor voltage balancing) control objectives. The proposed method first optimizes main control objectives and then four candidate voltage vectors minimizing the main cost function are evaluated for additional control objectives. Finally, it selects a voltage vector minimizing the additional cost function. Thus, it eliminates the WF of additional control objective but it still contains a WF in the main cost function.

Parallel MPCs evaluate control objectives simultaneously and restrict the error term of each control objective within the predetermined boundaries. Although this technique was originally proposed for the MPTC strategy with the block diagram in Fig. 7 [82]–[85], it has also been successfully applied to the MPDSC strategy [86]. The conventional parallel MPTC (P-MPTC) in [82] includes some parameters (threshold values for flux and torque) to tune. To deal with this problem, the authors in [85] demonstrate the importance of proper threshold selection and propose an improved P-MPTC by eliminating tuning parameters and updating the voltage selection mechanism. However, similar to the conventional S-MPTC, torque is assigned as the primary control objective, which may result in the selection of non-suboptimal voltage vectors under some operating conditions.

Both methods improve control performance over conventional ones, but their designs are complicated when additional control objectives are involved. Therefore, all past studies ignore additional control objectives. Because all cases should be kept in mind at the voltage vector selection phase and determine the state-machine clearly. It is possible to see the design process that started to become complicated in [86].

4) Decision-Making-Based Approaches: Various DM methods have been proposed for eliminating WFs of MPC strategies, particularly MPTC, over the last decade [87]–[103]. These techniques consider the optimization problem in MPC in a multi-objective way and each voltage vector is evaluated for each control objective separately. Next, a voltage vector selection technique, which is the key point of decision-making methods, is applied to choose an optimal voltage vector considering all control objectives.

The ranking-based DM, proposed in [87] for MPTC of IM, assesses each voltage vector separately for both control objectives, i.e. torque and flux control objectives, and then assigns them a ranking value from smallest to largest of cost values. Finally, it chooses the voltage vector with the minimum average ranking value. However, it suffers from computational complexity and issues with the inclusion of additional control objectives. The necessity of a sorting algorithm to determine sorting values of voltage vectors raises computational complexity excessively considering the increasing number of voltage vectors and additional control objectives. To this end,



(a) (b) (c)

Fig. 8. Experimental results of three DM-based MPC strategies under load changes of 6 Nm at 750 r/min (a) TOPSIS-MPTC in [93], (b) EDS-MPTC in [100], (c) ADS-MPTC in [100].

TABLE I
OVERVIEW OF WF DESIGN METHODS

	Control Performance	Flexibility	Design Complexity	Computational Complexity
Classic Approaches	✗✗	✓✓	✗✗	✓✓
Numerical/Algebraic Methods	✗	✗	✗	✓
Meta-Heuristic Optimization Methods	✗	✓✓	✗✗	✓✓
AI-Based Methods	✓✓	✗	✗✗	✗
MPCs with Unifying Cost Functions	✓	✗✗	✓✓	✓
Direct Vector Selection Methods	✓	✗✗	✓✓	✓✓
Sequential/Parallel MPC Strategies	✓✓	✓	✗	✗
Decision-Making-Based Methods	✓✓	✓	✓	✗

a novel hybrid sorting algorithm has been introduced in [88] to reduce the computational burden. It also assumes that each control objective is of equal importance in the selection of the voltage vector. This leads to a balance issue between main control objectives and additional control objectives, leading to poor control performance and even stability issues. The reported issue is clearly visible in [89], which uses the same technique. Even though the authors add a switching frequency regulation term to the cost function of MPTC, they only manage to eliminate the WF associated with the flux error term while manually tuning the WF of the switching frequency regulation term. Another approach, called the top-three voltage vector approach, has been proposed in [90]. Differently, it selects the first three candidate voltage vectors for each control objective, which minimizes the corresponding control objective, and then decides on one common voltage vector. But this paper ignores the case that the intersection set is null. To address these problems, the VIKOR-based DM method in [91], multi-objective fuzzy DM method in [92], TOPSIS-based DM method in [93], [94], coefficient of variation-based DM method in [95], grey relational analysis-based DM method in [96], [97], and weighted sum-based DM [98], [99] have been proposed. While these solutions are strong candidates for addressing these issues, they introduce additional tuning parameters to weight the importance of each control objective. In [100], two DM methods based on Euclidean and absolute distances are proposed and compared with TOPSIS DM-based MPTC. Both proposed DM methods provide a higher dynamic response with lower computational complexity than the TOPSIS DM method as shown in Fig. 8. In [101], an equivalent weighting factor method is proposed to achieve the optimal weighting factor online. The proposed DM method achieves lower torque and flux fluctuations than the ranking-based DM with less computational complexity. However, the DM methods in [100] and [101] have similar issues related to the inclusion of additional control objectives. An ensemble regulation-based DM has been proposed in [102], which assigns priorities to control objectives in terms of core control objectives, system demands, and physical constraints. With this method, the priorities of the MPTC strategy are ranked as in Fig. 9. The results show that it improves the control performance at the expense of computational complexity. In addition, when the candidate voltage vector cannot be determined, it is not discussed how the proposed method works when the voltage vector cannot be found considering the priorities of the control objectives. In [103], a cooperative DM method, which considers control objectives as master problems and sub-problems, allows the inclusion of additional control objectives without any tuning parameters. Although this method provides better control performance with the reduced computational burden compared to generalized S-MPTC in [74] and effective MPTC in [90], it needs a sorting algorithm like the ranking-based DM method. This complicates its applicability for multilevel inverter topologies due to increased computational load. However, it is a state-of-the-art method.

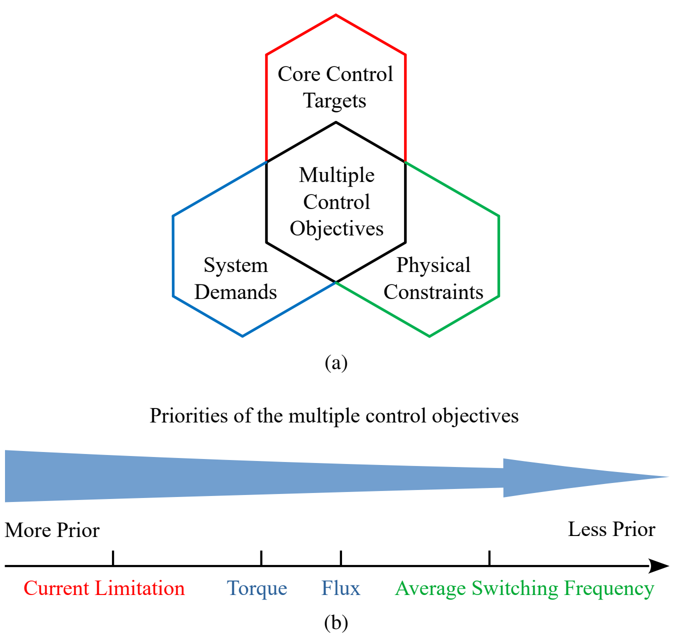


Fig. 9. Multiobjective problem definition in [102] (a) Description of multiple control objectives (b) Prioritization of control objectives for the FCS-MPC scheme proposed by [102].

IV. CHALLENGES AND TRENDS

Various WF design techniques have been reported so far in this paper, and Table I presents an overview of the main characteristics of WF design techniques in terms of control performance, flexibility in including additional control objectives, design complexity, and computational complexity.

The main challenges of WF selection methods are that they need an offline training process or a cumbersome empirical tuning phase. The empirical tuning phase may be very tedious, especially when multiple additional control targets exist. In addition, their control performance is limited under changing operating conditions of electric drives as almost all provide constant WFs. As for the online WF selection methods, they either have extremely high computational complexity and/or require expert knowledge to design.

WF elimination techniques have better control performance but the inclusion of additional control objectives is still problematic for direct vector selection methods, DM-based MPCs, and MPCs with unifying cost functions. Although sequential/parallel MPCs are more flexible in the inclusion of additional control objectives, their design complexities significantly increase with the number of additional control objectives. Direct vector selection methods allow reducing computational complexity remarkably in the optimization stage. DM-based methods provide satisfactory control performance against changing operating conditions of electric drives but their computational complexities also go up with the number of additional control objectives.

Recent studies show that the trend is toward WF elimination techniques. The efforts are intended for easily incorporating additional control objectives in direct vector selection methods and DM-based MPCs, reducing the design complexity of sequential/parallel MPCs, and lessening the computational complexity of DM-based MPCs.

Consequently, expectations from forthcoming WF design techniques can be listed as follows:

1) Advanced control performance under changing operating conditions of electric drives,
2) Flexible design in the inclusion of additional control objectives,
3) Simplified design for multiple additional control objectives and multi-level power converter applications,
4) Acceptable computational complexity for multiple additional control objectives and multi-level power converter applications.

V. Conclusion

MPC strategies for AC electric drives have been very popular over the past decade, and the literature indicates that this popularity will continue to grow in the next decade. To contribute to researchers in their new research and spotlight some state-of-the-art methods, this paper has focused on WF design techniques, one of the main challenges in MPC design, especially in AC electric drive applications. Although effective solutions have been proposed for specific applications, it is obvious that researchers are looking for more general WF design techniques with improved control performance, greater flexibility, and less design and computational complexity.

Considering the existing WF design techniques, AI-based and DM-based methods stand out. It is obvious that AI will dominate in many engineering fields in the near future as many disciplines. New neural networks with lower computational complexity and open-source design tools will encourage researchers to apply them to the WF design of MPC. On the other hand, designing DM-based methods with lower computational complexity and greater flexibility stimulates researchers in this field.

Finally, the WF design problem of MPC strategies is still open to research and awaits researchers to come up with new promising solutions.

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