Latest Advances of Model Predictive Control in Electrical Drives—Part I: Basic Concepts and Advanced Strategies

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***Abstract*—The application of model predictive control in electrical drives has been studied extensively in the past decade. This article presents what the authors consider the most relevant contributions published in the last years, mainly focusing on three relevant issues: weighting factor calculation when multiple objectives are utilized in the cost function, current/torque harmonic distortion optimization when the power converter switching frequency is reduced, and robustness improvement under parameters uncertainties. Therefore, this article aims to enable readers to have a more precise overview while facilitating their future research work in this exciting area.**

***Index Terms*—Electrical machine, model predictive control (MPC), variable speed drives, weighting factors.**

I. Introduction

Electromobility is one of the most relevant actions to fight against global warming. Starting in 2030s, several countries will only approve new cars that do not use fossil fuels [1], [2]. Although the control of motor drive applications has been one of the most classic electrical engineering challenges, today, with the development of electric vehicles, it has become a very relevant and timely research subject [3]. The development of microprocessors has motivated the exploration of more sophisticated strategies to control electrical machines using power semiconductors. Model predictive control (MPC) is one of these control techniques [4]–[9]. The interest in using this technique in electrical drives is based on two essential facts: 1) in electrical and mechanical engineering, some outstanding mathematical models allow the prediction of the future behavior of the system

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with high accuracy, and 2) modern microprocessors allow to do a very high number of real-time calculations at an affordable cost. Besides, MPC is easy to understand, easy to implement, can deal with nonlinearities, and can handle several variables simultaneously [10], [11]–[13].

The main challenges that should be solved when using MPC strategies in motor drive applications are as follows.

1) The quality improvement of the load current/torque when the power converter switching frequency is reduced.
2) The weighting factor calculation in the cost function to control more than one variable simultaneously.
3) The dependency of MPC strategy from the quality of the models and the parameter mismatches.

Consequently, this article presents the most relevant contributions recently reported in the literature to overcome these challenges. In this regard, the machine currents' quality has been significantly improved using a finite control-set MPC (FCS-MPC) strategy with multiple prediction steps [14]–[20]. Furthermore, a very attractive solution has been developed for three-level neutral-point (NP) clamped converters in medium voltage [21]–[24]. Here, optimized pulse patterns are embedded with an MPC strategy to improve performance while reducing the converter losses notably. The weighting factor calculation in the cost function, running simulations, or using some iterative solutions is not particularly appreciated by the community because it does not guarantee the operation in an optimal point [25]. The use of artificial neural networks (ANN) for the calculation of the weighting factors emerges as a very powerful solution that integrates power electronics with techniques of artificial intelligence (AI) [26]. Another interesting solution is to avoid the need for weighting factors, using what is known as sequential MPC, obtaining very promising results [27]. The parameter dependency is addressed by a new strategy known as model-free MPC. Here, the prediction is performed using estimated variables, improving significantly the robustness of the MPC technique [28]. The next pages will explain the most relevant features of these strategies, including also additional references.

II. Classical MPC Approaches in Drives

As is well-known, there are two main control strategies for electrical drives: field-oriented control (FOC) and direct torque control (DTC) [29]–[32]. These approaches achieve closed-loop control of the stator currents with high dynamic performance. The first one relies on an inner PI-based current control loop and, the second one uses a predefined lookup table that relates the position of the stator flux and the sign of the torque and flux error. Starting from these two basic strategies, MPC has been applied in electrical drives to control the internal stator current [model predictive current control (MPCC)] and also to directly control the machine's torque and flux [model predictive torque control (MPTC)] [33]–[40].

The analysis here presented is based on the control of an induction machine (IM). Thus, the five classic electrical and mechanical equations in stationary reference frame are described as [10], [41]

$$\boldsymbol{v}_s = \boldsymbol{i}_s R_s + \frac{\mathrm{d}\boldsymbol{\psi}_s}{\mathrm{d}t} \tag{1}$$

$$0 = \boldsymbol{i}_r R_r + \frac{\mathrm{d}\boldsymbol{\psi}_r}{\mathrm{d}t} - j\omega\boldsymbol{\psi}_r \tag{2}$$

$$\boldsymbol{\psi}_s = L_s\boldsymbol{i}_s + L_m\boldsymbol{i}_r \tag{3}$$

$$\boldsymbol{\psi}_r = L_r\boldsymbol{i}_r + L_m\boldsymbol{i}_s \tag{4}$$

$$T_e = \frac{3}{2}p\,\mathrm{Im}\{\overline{\boldsymbol{\psi}}_s\,\boldsymbol{i}_s\} \tag{5}$$

where $\boldsymbol{v}_s$ is the stator voltage vector, $\boldsymbol{\psi}_s$ and $\boldsymbol{\psi}_r$ are the stator and rotor flux, $\boldsymbol{i}_s$ and $\boldsymbol{i}_r$ are the stator and rotor currents, T_e is the electromagnetic torque, and ω is the speed. The parameters R_s and R_r are the stator and rotor resistances, L_s, L_r, and L_m represent the stator, rotor, and mutual inductances, respectively. In (5), $\overline{\boldsymbol{\psi}}_s$ stands for the complex conjugate of $\boldsymbol{\psi}_s$ and $\mathrm{Im}\{\cdot\}$ operator denotes the imaginary part.

A. Model Predictive Current Control

Based on the IM model described above, the dynamic model for the stator current can be expressed as [10], [41], [42]

$$\frac{\mathrm{d}\boldsymbol{i}_s}{\mathrm{d}t} = -\frac{R_\sigma}{\sigma L_s}\boldsymbol{i}_s + \frac{k_r}{\sigma L_s}\left(\frac{1}{\tau_r} - j\omega\right)\boldsymbol{\psi}_r + \frac{1}{\sigma L_s}\boldsymbol{v}_s \tag{6}$$

where $\sigma = 1 - k_r k_s$ is the total leakage coefficient, $k_r = \frac{L_m}{L_r}$ and $k_s = \frac{L_m}{L_s}$ are the magnetic coupling factors, and $R_\sigma = R_s + k_r^2 R_r$.

Several discretisation methods have been proposed to obtain the predictions of the stator currents from (6) [10]. The most utilized method is the forward Euler discretization, which leads to the following discrete-time prediction model for the stator currents

$$\boldsymbol{i}_s^{k+1} = \left(1 - \frac{T_s R_\sigma}{\sigma L_s}\right)\boldsymbol{i}_s^k + \frac{T_s k_r}{\sigma L_s}\left(\frac{1}{\tau_r} - j\omega^k\right)\boldsymbol{\psi}_r^k + \frac{T_s}{\sigma L_s}\boldsymbol{v}_s^k \tag{7}$$

where T_s is the sampling period.

For the MPCC strategy, usually, the rotor flux reference is considered constant during the sampling period. Consequently, to control the motor, the expression (7) is continuously evaluated to predict the stator current selecting the proper voltage vector. The cost function is characterized by its high flexibility and the possibility to add systems constraints and, it is expressed as

$$g = \left(i_{s\alpha}^* - i_{s\alpha}^{k+1}\right)^2 + \left(i_{s\beta}^* - i_{s\beta}^{k+1}\right)^2. \tag{8}$$

Finally, the classical control scheme for MPCC is depicted in Fig. 1, which shows the inner control loop performing the predictive current control, and the outer loop handling speed and torque control [4], [10], [43].

B. Model Predictive Torque Control

Similarly to MPCC, several reports demonstrate the advantages of MPTC, highlighting its very fast response under torque steps maintaining the stator flux amplitude constant. Besides,

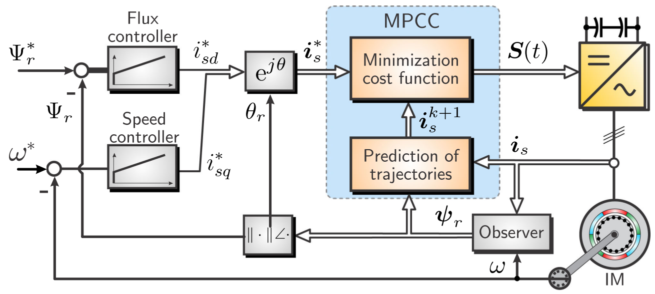

Fig. 1. Cascaded FOC structure with speed and flux outer control loop and the MPCC inner control loop.

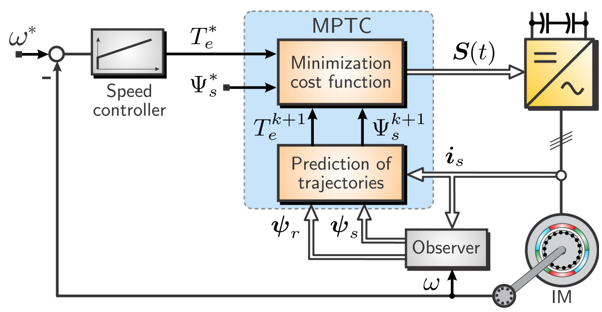

Fig. 2. Control diagram of the MPDTC strategy.

note that in comparison with MPCC no current controller is implemented in MPTC. To control the electromagnetic torque predictions of the stator current $\boldsymbol{i}_s^{k+1}$ and stator flux ψ_s^{k+1} must be evaluated for the seven possible voltage vectors of the 2L-VSI inverter. Expressions for future torque and flux are [10], [26], [38]

$$\boldsymbol{\psi}_s^{k+1} = \boldsymbol{\psi}_s^k + T_s \boldsymbol{v}_s^k - R_s T_s \boldsymbol{i}_s^k \tag{9}$$

$$T_e^{k+1} = \frac{3}{2} p \operatorname{Im}\{\overline{\boldsymbol{\psi}}_s^{k+1} \boldsymbol{i}_s^{k+1}\}. \tag{10}$$

The cost function is defined as a linear combination of torque and flux errors, as described in the following equation:

$$g = \left(T_e^* - T_e^{k+1}\right)^2 + \lambda_\Psi \left(\Psi_s^* - \Psi_s^{k+1}\right)^2 \tag{11}$$

where $\Psi_s = \|\boldsymbol{\psi}_s\|$ is the amplitude of the stator flux vector and λ_ψ is the weighing factor. The classical control diagram of this method is illustrated in Fig. 2. In this figure, the torque reference is obtained from a speed loop controller and the stator flux magnitude is usually set as a constant. Finally, as is detailed in Fig. 2, the torque and flux variables are estimated by measuring the speed and the stator currents.

An important problem in (11) is the calculation of the weighting factor λ_ψ, which has a critical influence on the overall performance of the drive.

C. Model Predictive Speed Control

In addition to torque and machine current control, MPC is also often considered to implement the speed control loop of a drive. In fact, MPC can provide benefits in this specific application, such as robustness to parameter variation and easy inclusion of flux weakening constraints. In [44], a linear implementation of MPC is proposed for the speed control loop of a servo permanent magnet synchronous machine (PMSM) drive, showing good results, superior to the one obtained with classical PI control. However, being the MPC solution obtained analytically considering a linear plant, external constraints cannot be added to the controller. In [45] and [46], the case of MPC speed control for synchronous motor drive is studied. Also in this case, an unconstrained implementation of MPC, with the addition of integral terms in the cost function to compensate bias errors and external disturbances is considered. Results show improved performance with respect to classical PI speed control and excellent robustness to mechanical model mismatches and electrical parameters uncertainties. Finally, in [47], a sensorless MPC speed loop for a PMSM drive is designed, where the speed MPC is combined with the position estimation in the current loop. Since the estimated rotor position cannot be as reliable as the real position sensor information, the MPC reference speed is adjusted according to the position estimation reliability. This method prevents system instability and achieve achieving superior steady state and dynamic response. In [44]–[47], the MPC speed loop is always cascaded with an external torque control, which can be implemented using MPC or in a classical fashion. However, taking advantage of the MPC flexibility, it is possible to combine the speed and torque control in a single control loop. An effort in this direction has been taken in [48]–[50], where combined speed and torque MPC has been applied to IM [48], PMSM [49], and IPM synchronous motor drive [50], respectively. Results shows that, despite the more complex implementation and the additional calculation required by the control, the computational burden can be contained and performances, in terms of load variation recovery time and, in general, dynamic performances. Moreover, in this case, a nonlinear constrained implementation of MPC is considered allowing a better response to the drive nonlinearities and improving robustness to system parameters variation.

III. Weighting Factor Calculation

Optimization of the weighting factors can be a very challenging task for cost functions with multiple objectives that are in conflict or can not be unified. Several solutions have been proposed to solve this optimization problem. Weightless MPTC cost functions can be obtained by unifying the dimensions of the control objectives [51], or splitting the control problem into two cost functions [52]–[54]. However, the use of weighting factors can not always be avoided due to too many objectives that can not be unified. To calculate the weighting factors, methods that use ANNs [26], [55], [56], fuzzy optimization [57], or multiobjective genetic algorithms [58] were proposed. It needs to be mentioned that the methods using online weighting factor calculation like in [55]–[57] can add additional computation burden to the control algorithm. On the other hand, the method introduced in [26] uses an offline calculation procedure of both the weighting factors and the flux reference providing a fast drive start and good performance during different loading conditions. The design process is straightforward and applicable to different cost functions [59]. Nevertheless, the price that has to be paid

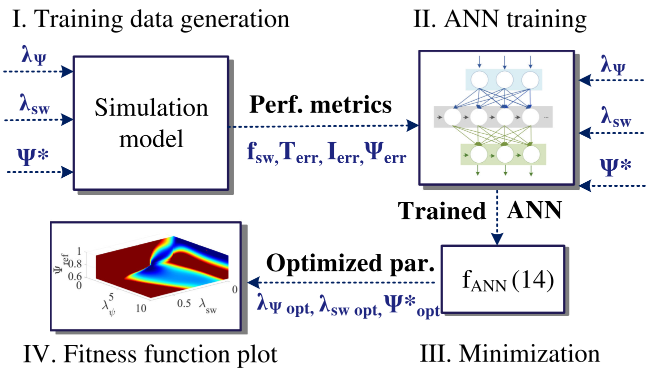

Fig. 3. Cost function parameter calculation workflow using the ANN.

for the offline calculation is the additional memory to store the calculated weighting factors. In addition, the study cases are limited and interpolations techniques have to be implemented to cover all the online operation points.

A. Training the ANN and Fitness Function Design

The function of the ANN in the weighting factor calculation is to become a fast and accurate surrogate of the system model with the ability to calculate the system performance metrics for different cost function parameters as shown in Fig. 3 workflow. In order to create the surrogate, a system simulation model can be used to collect the data for training the ANN. Alternatively, for more accuracy, experimental data can be used. However, it is more time-consuming and requires a human supervision. The training data of interest are the performance metrics such as torque and stator current rms errors ($T_{\mathrm{err}}, \Psi_{s\,\mathrm{err}}, I_{s\,\mathrm{err}}$), average switching frequency ($f_{\mathrm{sw\,avg}}$) obtained for different cost function parameters. The MPTC cost function for controlling the torque, stator flux, and the average switching frequency can be defined as

$$g = \left(T_e^* - T_e^{k+1}\right)^2 + \lambda_\psi \left(\Psi_s^* - \Psi_s^{k+1}\right)^2 + \lambda_{\mathrm{sw}}\, n_{\mathrm{sw}} + h_{\mathrm{lim}} \tag{12}$$

$$n_{\mathrm{sw}} = \sum_{x=a,b,c} \left| S_x^k - S_x^{k-1} \right| \tag{13}$$

where h_{lim} is limiting the stator current, λ_Ψ and λ_{sw} are the weighting factors, and n_{sw} defines the number of switching transitions. Thus, S_x^{k-1} is the switching state applied in the previous sampling period and S_x^k is the current switching state.

When collecting the performance metrics for different cost function parameters λ_Ψ, λ_{sw}, and Ψ_s^*, the range of the parameters should be defined to only sweep combinations that can lead to a successful drive start and steady-state operation. A feed-forward ANN configuration was used with a back-propagating training algorithm to tune the parameters of the ANN. Once trained ANN can be used to calculate the performance metrics for all weighting factors within the defined range of the cost function parameters. Afterward, a fitness function is defined using the performance metrics to find the cost function parameters that will provide the desired control performance. An example of a fitness function for different loading conditions is shown here

$$f_{\mathrm{ANN}} = \Psi^2_{s\,\mathrm{error}} + I^2_{s\,\mathrm{error}} + T^2_{s\,\mathrm{error}} + (f_1 - f_{\mathrm{sw\,avg}})^2 \tag{14}$$

where f_1 is the average switching frequency for which the optimum parameter values will be calculated and it is chosen arbitrary. By repeating the procedure in Fig. 3 for different operating conditions of the motor drive, the performance can be optimized for wide operating range of the motor drive. As it was shown in [26], the size of the optimum parameter region depends both on the load and the speed reference.

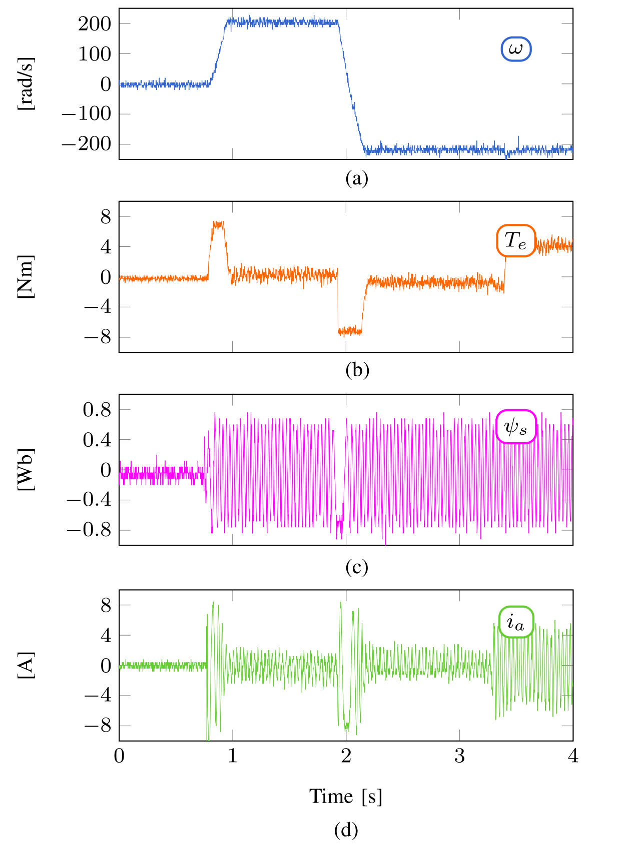

Fig. 4. Experimental waveforms of drive speed, torque, stator flux, and current for f_{ANN} as per (14) and $T_{\mathrm{load}} = 5$ N·m, $f_1 = 2.5$ kHz, $\lambda_\Psi = 9.64$, $\lambda_{\mathrm{sw}} = 0.13$, and $\Psi_s^* = 0.65$ Wb.

B. Design Validation

Fig. 4 shows the experimental waveforms obtained using λ_Ψ, λ_{sw}, and Ψ_s^* that were calculated with (14) for the frequency $f_1 = 2.5$ kHz and the load torque of 5 N·m. It can be observed that the design allows a fast start, successful speed reversing, and good steady-state performance of the drive.

C. Analytical Tuning for MPTC

As discussed above, the weighting factors' choice for MPTC strategy-and thus the tuning procedure-may be difficult because one has to decide on the relative importance between the torque error and the flux magnitude error. This tradeoff also affects the stator current distortions, which are typically higher than the ones obtained with MPCC. Recently, in [39] and

[60], the value of the weighting factors that minimize the current distortions are analytically derived. However, MPCC still achieves lower current distortions, particularly at nonzero torque reference and low switching frequencies. To overcome this issue, a slight modification to the conventional MPTC is proposed in [40]. Here, the MPTC is made equivalent to MPCC by tracking the rotor flux magnitude Ψ_r^* instead of the stator flux magnitude Ψ_s^*. As a result, analytical expressions for the weighting factors can be derived, ensuring the same closed-loop performance as MPCC. Consequently, the proposed model predictive torque and flux controller achieves the same low current and torque distortions as MPCC, without requiring an outer field-oriented controller that sets the current references (see Fig. 1).

IV. MPC Without Weighting Factors

As discussed in Section III, the selection of weighting factors for a multiobjective cost function does not have an analytical solution. Its selection has been through a heuristic search and currently with advanced techniques such as ANN, which goes in the opposite direction of the conceptual simplicity of predictive control. It is for this reason that many authors have proposed techniques to avoid the use of weighting factors. In [61], a MPTC with multiobjective optimization based on a ranking table is proposed, achieving an independence of the weighting factor, however, a relative magnitude errors are missed and changed for discrete table. In [51], the electrical torque and stator flux magnitude references are converted into an equivalent reference vector of stator flux. There are also works that propose to control the torque and stator flux in an indirect way controlling the direct and quadrature stator current [62], in this way, the cost function has objectives with the same magnitude. A modified MPTC is proposed in [63], where the electrical torque and stator flux are controlled through the control of torque and reactive torque, both have the same order magnitude so a weighting factor is not required. A deadbeat predictive DTC is proposed in [64], achieving control of torque and flux through the tracking of voltage vectors. One of the latest multiobjective control strategies for motor drives is the sequential predictive control [54]. This method achieves torque and flux control by evaluating two cost functions sequentially. Because it is intuitive and straightforward, this strategy has been implemented in other applications [65], improved with more sophisticated techniques [66], and analyzed in depth [53], [68].

The sequential MPTC (SMPTC) proposed in [54] is illustrated in Fig. 5. As shown in this figure, the SMPTC strategy has two control objectives: the electromagnetic torque and amplitude of the stator flux, controlled using two cost functions sequentially

$$g_T = (\Delta T_e)^2 = \left(T_e^* - T_e^{k+1}\right)^2 \tag{15}$$

$$g_\Psi = (\Delta \Psi_s)^2 = \left(\Psi_s^* - \Psi_s^{k+1}\right)^2. \tag{16}$$

SMPTC as well as any finite-set MPTC needs a discrete model to predict the behavior of variables. The prediction of electric torque and stator flux of the machine is based on (9) and (10), considering the forward Euler discretization as presented in [69]– [71].

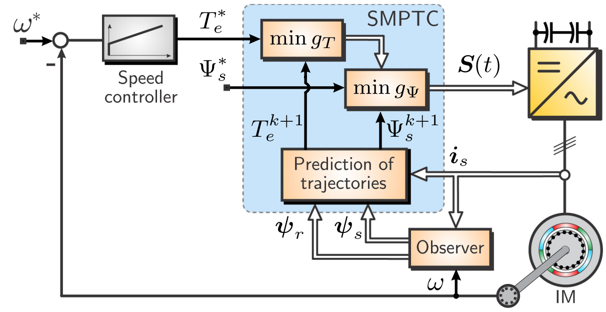

Fig. 5. Sequential model predictive flux and torque control.

In summary, the SMPTC can be described in the following three simple steps.

1) The electric torque is predicted for the $(k+1)$th instant considering all the possible vectors of the 2L-VSI using the discrete-time model of the stator flux and torque.
2) The cost function g_T in (15) is evaluated. The two vector that minimizes the cost function will be considered for the next optimization stage.
3) The two optimal vectors found in the previous step are evaluated in the cost function g_Ψ, (16). The vector that minimizes g_Ψ will be the optimal vector and will be applied in the 2L-VSI in the next sampling time.

Thus, using the SMPTC strategy, weighting factors are avoided while keeping good performance in the motor drive.

An inversion speed maneuver from nominal speed to negative nominal speed in an IM controlled with SMPTC is depicted in Fig. 6. This figure shows the good behavior of this control technique, where the electric torque and the stator flux have a good dynamic and stationary behavior. The electric torque allows the speed inversion to be carried out with good dynamic performance. Simultaneously, the magnitude of the stator flux remains controlled and constant at all times, showing that there is no coupling between both control objectives.

Nevertheless, as analyzed in [72], the simplicity of SMPTC removes degrees of freedom that can be exploited to improve the overall system efficiency. This feature limits the controllability of the torque and machine magnetization, what can lead to suboptimal performance. As shown in [72], when the torque and flux terms are minimized sequentially higher current distortions result over the whole range of switching frequencies.

V. Multistep FCS-MPC

Multistep FCS-MPC has recently gained attention due to its role as a key enabler for efficiency improvement, specially in high power electrical drives [42], [72] since it has the potential to reduce the stator current THD while retaining the power converter switching frequency. This leads to a power loss reduction in the electric machine, improving thus the overall system efficiency [42]. To achieve this, the control input in the problem formulation is either the switch positions [42] or the distinctive output voltage levels [16]. For the multistep case, the optimal control input vector, $\boldsymbol{u}_{\text{opt}}(k)$, is the first element of the optimal

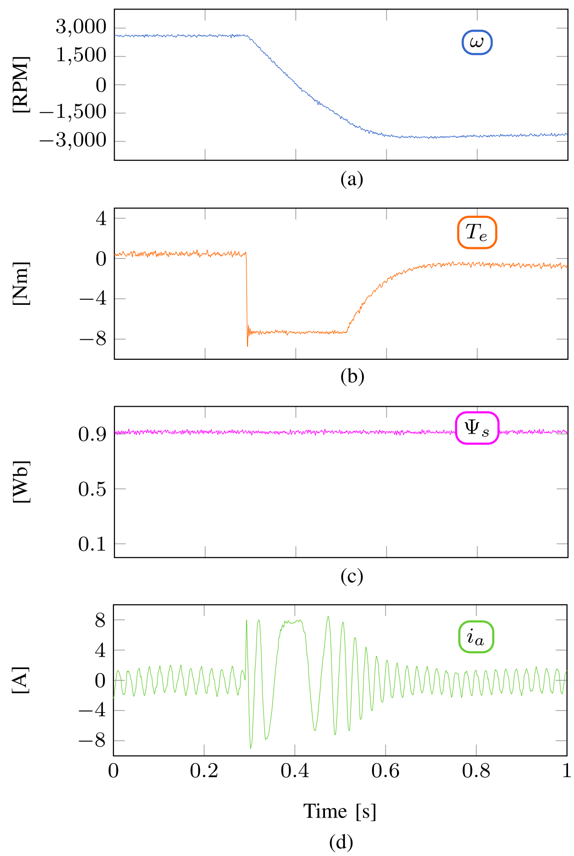

Fig. 6. SMPTC during speed reversal maneuver. (a) Motor speed ω. (b) Electric torque T_e. (c) Stator flux magnitude $|\boldsymbol{\psi}_s|$. (d) Stator current i_α.

control input sequence

$$\boldsymbol{U}_{\text{opt}} = [(\boldsymbol{u}_{\text{opt}}(k))^T \cdots (\boldsymbol{u}_{\text{opt}}(k+N-1))^T]^T. \tag{17}$$

The vector $\boldsymbol{U}_{\text{opt}}$ is found formulating a standard multistep MPC problem that minimizes the stator current tracking error versus switching effort, $\Delta\boldsymbol{u}(\ell) = \boldsymbol{u}(\ell) - \boldsymbol{u}(\ell-1)$, over an extended prediction horizon N, i.e.

$$\min_{\boldsymbol{U}} \sum_{\ell=k}^{k+N-1} \left\|\boldsymbol{i}_s(\ell+1) - \boldsymbol{i}_s^*(\ell+1)\right\|_2^2 + \lambda_u \left\|\Delta\boldsymbol{u}(\ell)\right\|_2^2$$
$$\text{s.t.} \quad \boldsymbol{U} \in \mathbb{U}^{3N} \text{ and } \|\boldsymbol{\Delta u}(\ell)\|_\infty \leq 1 \tag{18}$$

where $\boldsymbol{U}$ is the multistep decision variable and $\lambda_u > 0$.

The first constraint in (18) can consider either the switching states or voltage levels, while the second constraint limits the output voltage level transitions to avoid internal damage in the converter and excessive dV/dt in the load.

Normally, to find $\boldsymbol{U}_{\text{opt}}$, it is required to evaluate all the possible combinations. However, for the multistep case, the number of combinations exponentially increases with N, leading to a high computational burden. Recently, [14] and [15] have shown that the control problem (18) can be reformulated as an integer least squares optimization problem. Then, a sphere decoding algorithm (SDA) enables microprocessors to efficiently solve (18) in real-time to obtain the multistep optimal control vector $\boldsymbol{U}_{\text{opt}}$ [16]–[19].

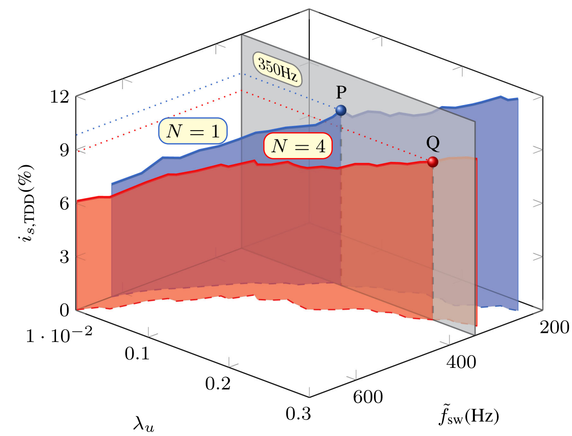

Fig. 7. Experimental sweep of the weighting factor λ_u for the prediction horizon $N = 1$ and 4, and sampling interval $T_s = 125\ \mu$s [17].

To do this, the SDA forms an initial sphere centered in $\boldsymbol{U}_{\text{unc}}$, which is the well known explicit unconstrained optimal solution. The initial sphere radius, ρ_{ini}, is determined as the Euclidean distance between $\boldsymbol{U}_{\text{unc}}$ and an initial suitable candidate, $\boldsymbol{U}_{\text{ini}}$, chosen from the pool of available input combinations. Then, using a branch-and-bound technique, the SDA quickly discards all input combinations that lie outside of the initial sphere. As soon as the SDA finds a candidate inside the initial sphere, a new smaller sphere is formed and the process is repeated by evaluating the remaining candidates. Finally, the optimal solution $\boldsymbol{U}_{\text{opt}}$ is found when the sphere cannot be further shrink, so its first element, $\boldsymbol{u}_{\text{opt}}(k)$, is taken to synthesize the switching state $\boldsymbol{S}$ applied to the converter.

Similar to the system shown in Fig. 1, but considering a multistep MPCC, the best tradeoff between performance, weighting factors, sampling interval, optimality, and length of the prediction horizon was obtained considering that transients are one of the main causes of impracticability due to the SDA initialization [73]–[75]. Thus, a selective initialization approach choose the box-constrained initialization during transients while preserving the well-known dynamic performance of FCS-MPC at minimum suboptimality cost, without affecting the steady-state performance. Fig. 7 shows the results of multistep FCS-MPC reducing the stator current total demand distortion (TDD) ($i_{s\text{TDD}}$), defined by

$$i_{s\text{TDD}} = \frac{1}{\sqrt{2}I_{\text{nom}}}\sqrt{\sum_{h\neq 1}(\hat{i}_{s,h})^2} \tag{19}$$

where I_{nom} refers to the nominal current of the IM and $\hat{i}_{s,h}$ is the amplitude of the hth stator current harmonic. The points P and Q in Fig. 7 are selected to demonstrate that for the same average switching frequency of $\tilde{f}_{\text{sw}} = 350$ Hz, $i_{s\text{TDD}}$ is reduced by 10.6% for a prediction horizon $N = 4$. Finally, Fig. 8 shows a typical speed reversal maneuver, which demonstrates that the dynamic performance of the algorithm remains unaltered; see [17] for further details.

An FPGA implementation of the SDA is detailed in [19] achieving prediction horizons of up to five steps. Multistep

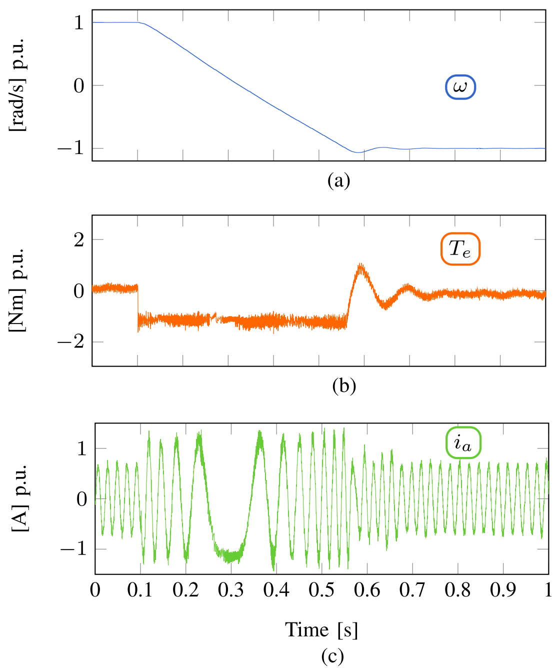

Fig. 8. Typical speed reversal maneuver using multistep FCS-MPC [17].

FCS-MPC is particularly beneficial for higher order systems, such as converters with *LC* filters. As shown in [76], the current distortions can be reduced by an order of magnitude when using long prediction horizons of 15–20 steps.

VI. Model Predictive Pulse Pattern Control

Optimal pulse patterns (OPP) allow the current distortion in the load to be minimized for a specific switching frequency [77]. Consequently, OPPs are a very attractive choice for medium-voltage drives because they achieve a substantial reduction of the switching frequency at comparable harmonic distortion [78]. The OPP's switching angles α_j with $j \in \{1, \ldots, d\}$ are calculated offline and stored in the memory of the real-time control platform as functions of the modulation index m and the pulse number d, [79]. Fig. 9 shows the three-level OPP for $m = 0.7$ and $d = 5$; the corresponding stator flux reference trajectory is illustrated in Fig. 9(b).

The use of OPPs provides optimal performance under steady-state conditions. However, undesired transients are observed whenever the operating point is changed, or transitions between different pulse patterns occur. To overcome this problem, closed-loop control strategies have been proposed in the literature [21]–[23], [78]–[81]. Initial concepts use deadbeat controllers to track a current reference trajectory [80], [81] or stator flux reference trajectory to improve the robustness under parameter variations [78], [79]. However, these methods require a dedicated observer to identify the instantaneous fundamental components of the stator currents and flux linkage vectors. More recently, a model predictive controller, referred as model predictive pulse pattern control (MP^{3}C), has been introduced in [21]–[23] to control the instantaneous stator flux instead of its fundamental component.

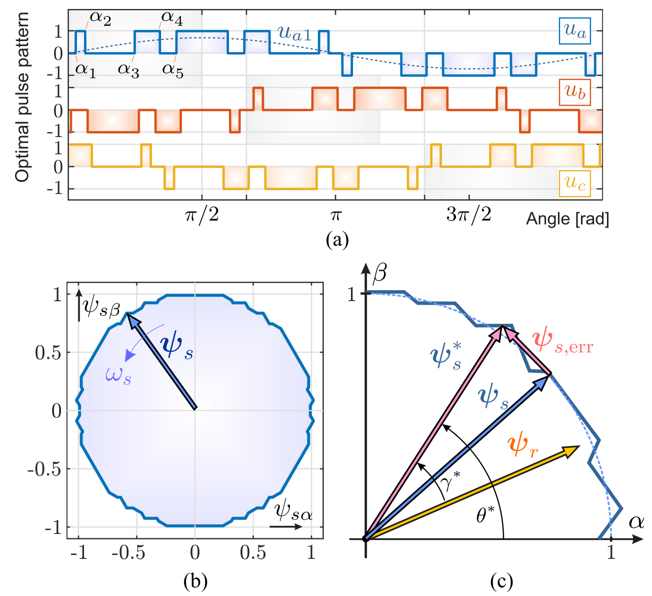

Fig. 9. (a) OPP for $d = 5$ switching angles and $m = 0.7$. (b) Reference trajectory for the OPP shown in (a). (c) Control principle of MP^{3}C.

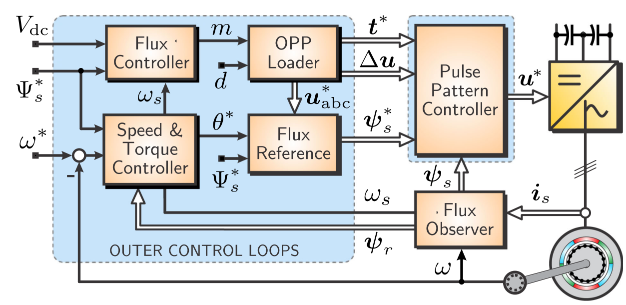

Fig. 10. MP^3 C scheme for IM.

As a result, a simple and standard flux observer can be used, making the implementation much simpler.

A. *MP^{3}C Control Strategy*

Starting with the initial version in [21], the MP^{3}C strategy has been extended and revised during the past decade [21]–[23], [82]–[89]. To explain the MP^{3}C fundamentals, the three-level NPC converter will be used in this review. The block diagram of the overall MP^{3}C scheme is shown in Fig. 10.

1) Outer Control Loops: As depicted in Fig. 10, the speed ω is regulated by manipulating the reference torque T_e^*, which in turn is translated into the reference angle between the stator and rotor flux vectors γ^*, as illustrated in Fig. 9(c). Then, the angular position of the stator flux reference is determined as

$$\theta^* = \angle \boldsymbol{\psi}_r + \sin^{-1}\left(\frac{T_e^*}{k_T \Psi_s^* \Psi_r}\right) \qquad (20)$$

where Ψ_s^* is the desired stator flux magnitude, $\Psi_r = \|\boldsymbol{\psi}_r\|$ is the estimated rotor flux vector magnitude provided by the flux observer and the parameter $k_T = \frac{3}{2} p \frac{k_r}{\sigma L_s}$.

In its simplest form, the modulation index is determined by the flux controller from the angular stator frequency $\omega_s = 2\pi f_s$

and the dc-link voltage V_{dc} as $m = \omega_s \Psi_s^*(2/V_{\mathrm{dc}})$. The pulse number d is computed from the maximal allowed switching frequency of the semiconductor devices f_{sw} according to $d = \mathrm{floor}(f_{\mathrm{sw}}/f_s)$, where f_s is the fundamental stator frequency. Thus, by using the inputs d and m, the switching sequence of the OPP in the $\alpha\beta$ frame can be stated as $\boldsymbol{u}_s^* = \mathbf{T}_{\alpha\beta}\boldsymbol{u}_{\mathrm{abc}}^*$, where $\mathbf{T}_{\alpha\beta}$ is the Clarke transformation. Then, if the IM is fed by the OPP, the stator flux space vector should track the following trajectory:

$$\boldsymbol{\psi}_s^*(\theta) = \boldsymbol{\psi}_s(0) + \frac{\Psi_s^*}{m}\int_0^\theta \boldsymbol{u}_s^*(\vartheta)\mathrm{d}\vartheta. \tag{21}$$

Therefore, under ideal conditions, the stator voltage matches precisely the OPP voltage waveform $\boldsymbol{v}_s = \boldsymbol{u}_s V_{\mathrm{dc}}/2$, and consequently, the stator current distortion is minimized. Nevertheless, the dc-link voltage ripple, voltage drop over the stator resistance, and the nonlinear effects of the inverter produce deviations of the stator flux space vector from its reference trajectory. Trajectory deviations also occur during transients or transitions between different pulse patterns, among other disturbances. Therefore, a closed-loop controller must be implemented to compensate these errors quickly and to ensure the proper operation of the drive.

To this end, an MPC strategy is designed, which operates at regularly spaced sampling instants kT_s, where $k \in \mathbb{N}$ and T_s is the sampling interval. A variable-length prediction horizon N is utilized such that this time interval includes at least one switching transition per phase. The switching instants of the pulse pattern are shifted forward or backward such that the stator flux error is corrected within the horizon N to achieve fast closed-loop control of the stator flux space vector.

2) Pulse Pattern Controller: Modifying the switching instants of the OPP, the following stator flux correction is obtained:

$$\Delta\boldsymbol{\psi}_s(\Delta\boldsymbol{t}) = -\frac{V_{\mathrm{dc}}}{2}\mathbf{T}_{\alpha\beta}\mathbf{N}\Delta\boldsymbol{t}, \tag{22}$$

with $\mathbf{N} = \mathrm{diag}\{\Delta\boldsymbol{u}^T\}$ and $\Delta\boldsymbol{u} = \begin{bmatrix}\Delta\boldsymbol{u}_a^T & \Delta\boldsymbol{u}_b^T & \Delta\boldsymbol{u}_c^T\end{bmatrix}^T$, where $\Delta\boldsymbol{u}_x \in \{-1,1\}^{n_x}$ comprises the n_x switching transitions for the phase $x \in \{a,b,c\}$ within the prediction horizon. The correction of the switching instants $\Delta\boldsymbol{t} = \boldsymbol{t} - \boldsymbol{t}^*$ contains all modifications from the OPP's nominal switching times in the vector $\boldsymbol{t}^* = \begin{bmatrix}\boldsymbol{t}_a^{*T} & \boldsymbol{t}_b^{*T} & \boldsymbol{t}_c^{*T}\end{bmatrix}^T$. Thus, by using $\Delta\boldsymbol{t}$ as the decision variable, the MP³C problem is formulated as follows:

$$\begin{aligned}\min_{\Delta\boldsymbol{t}} \quad & \left\|\boldsymbol{\psi}_{s,\mathrm{err}} - \Delta\boldsymbol{\psi}_s(\Delta\boldsymbol{t})\right\|_2^2 + q\left\|\Delta\boldsymbol{t}\right\|_2^2 \\ \text{s.t.} \quad & \boldsymbol{t} = \Delta\boldsymbol{t} + \boldsymbol{t}^* \in \mathbb{T}\end{aligned} \tag{23}$$

where $\boldsymbol{\psi}_{s,\mathrm{err}} = \boldsymbol{\psi}_s^* - \boldsymbol{\psi}_s$ is the instantaneous stator flux error. The flux reference $\boldsymbol{\psi}_s^*$ is obtained by substituting the reference stator flux angle (20) in (21). Notice that vectors $\boldsymbol{t}^*$ and $\Delta\boldsymbol{u}$ are determined by the OPP, and consequently, they are provided by the OPP Loader block in Fig. 10, and then used as parameters in (23). To ensure that the MP³C-based switching instants $\boldsymbol{t}^\star = \Delta\boldsymbol{t}^\star + \boldsymbol{t}^*$ occur within the prediction horizon N in ascending order but before the first switching transition beyond N (transition with the nominal time $t_{x[n_x+1]}^*$), the set constraint $\mathbb{T}$ in (23) is defined as $\mathbb{T} = \mathbb{T}_a \times \mathbb{T}_b \times \mathbb{T}_c$, where for each phase

$$\mathbb{T}_x = \left\{\boldsymbol{t}_x \in \mathbb{R}^{n_x} \mid 0 \le t_{x1} \le \cdots \le t_{x[n_x]} \le t_{x[n_x+1]}^*\right\}. \tag{24}$$

Solving (23) provides a tradeoff between the flux error correction and modification to the nominal OPP. The scalar $q > 0$ is used to adjust this compromise.

In summary, the MP³C problem in (23) is a small-scale quadratic program that can be solved in real-time by adopting the active set method or a fast gradient method [83], [90]. Its solution provides a sequence of optimal control actions within the horizon and, following the receding horizon policy, only the first control action of this sequence (the pulse pattern over T_s) is applied to the drive system. Noteworthy extensions of the trajectory control principle have been developed, such as the optional insertion of additional switching transitions to shorten torque transients [23]. The pulse insertion provides the controller, when required, with an additional degree of freedom to remove the flux error as quickly as possible. On the other hand, to address the balancing of the NP potential of an NPC converter in the MP³C strategy, the cost function (23) is extended to also control the predicted error of the NP voltage at the end of the prediction horizon to zero [88]. As a result, the stator flux trajectory control and NP balancing are treated in a single control loop by modifying the switching instant of the OPP.

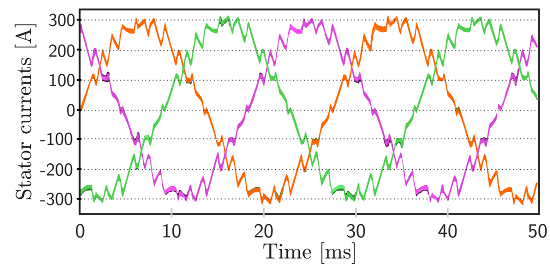

Fig. 11. Medium-voltage experimental results: steady-state stator currents when operating with MP³C at 30 Hz with $d = 5$.

B. Experimental Results

Experimental results for a medium-voltage NPC inverter driving a 3.3 kV IM rated at 1140 kVA are summarized in this review (further details can be found in [85]). To evaluate the performance of the drive system, the current TDD is utilized.

The stator current waveforms are depicted in Fig. 11, showing operation with MP C at a fundamental frequency of 30 Hz and 60% of the rated machine torque. For a pulse number equal to 5, the resulting switching frequency is 150 Hz and the current TDD is 8.7%.

The current TDD is depicted in Fig. 12 for two upper bounds on the switching frequency (150 and 250 Hz) when the drive operates at various fundamental frequencies and rated torque. The current TDD that results from the MP³C strategy (solid lines) is compared with the theoretical one from the OPP at open-loop (dash-dotted line). As shown in Fig. 12, the difference between the measurement and the theoretical TDD is less than

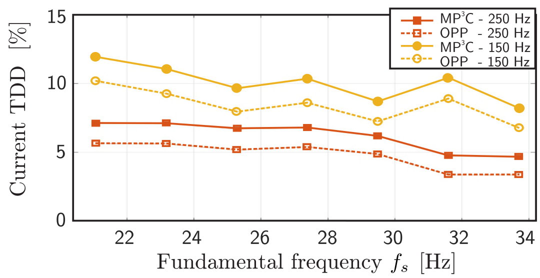

Fig. 12. Medium-voltage experimental results: measured versus theoretical OPP current TDD at rated torque when varying the fundamental frequency, [85].

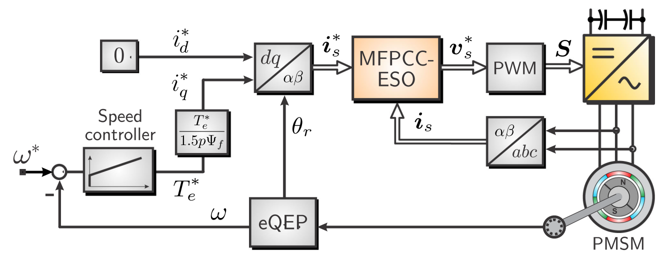

Fig. 13. Control diagram of the PMSM drive system with an ESO based on an ultra-local model.

1.85%. This discrepancy tends to increase with the torque setpoint. Thus, the results depicted in Fig. 12 correspond to the worst-case at which the IM operates, i.e., at rated torque.

VII. Model-Free MPC

The performance of MPC will be degraded if the system parameters used in the controller are different from the actual system parameters [91]. For example, the stator resistance and dq-axis inductance of a PMSM may vary with the operating point and environment. If the machine parameter variations are not taken into account, the current will show a steady-state error and the noise will increase during the operation of the machine [92].

Various methods have been proposed in the literature to tackle the problems of machine parameter variations, including online parameter identification [93], disturbance observer-based methods [94], and model free control [28], [95]–[98]. These methods differs in operating principle, complexity and computational burden. However, one of the main differences is that the online identification and disturbance observer-based methods are still using the mathematical model of machines, while model free control does not use the actual machine models. This feature distinguishes model free control from other kinds of methods due to its universality and flexibility.

Recently, model free control has been introduced in MPC and is gaining increasing attention. The early work on model free MPC in [95] simply uses the current difference in the past to predict the future current. Although the principle is simple, it requires high sampling frequency and the performance is affected by the updating rate of current difference table. Furthermore, the use of only one voltage vector during one control period limits its steady-state performance.

The other work on model free MPC uses the so-called ultra-local model developed by Michel Fliess [99]. As pointed in [99], in most cases the physical system can be described using the first/second order ultra-local model. For example, the PMSM can be described by a first-order ultra-local model using complex vector in stationary frame as [97]

$$\frac{\mathrm{d}\boldsymbol{i}_s}{\mathrm{d}t} = \alpha \boldsymbol{v}_s + \mathbf{F} \tag{25}$$

where $\mathbf{F}$ represents the known and unknown part of the system, which can be summarized as a total disturbance; α represents a nonphysical scaling factor selected by the designer; $\boldsymbol{v}_s$ and $\boldsymbol{i}_s$ are the stator voltage vector (input) and stator current vector (output), respectively. According to [99], the total disturbance $\mathbf{F}$ can be estimated from the input and output using a differential algebra method as

$$\hat{\mathbf{F}} = -\frac{6}{L}\int_{t-L}^{t} (L-2\sigma)\boldsymbol{i}_s(\sigma) + \alpha\sigma(L-\sigma)\boldsymbol{v}_s(\sigma) d\sigma \tag{26}$$

where $L = n_F T_{sc}$ and n_F is the number of control periods in the integral step L. Owing to the existence of n_F, a lot of past information is used in the differential algebra method. This will affect the dynamic response of the system. In [97], an extended state observer (ESO) is employed to observe the total disturbance. However, it should be noted that the ESO is still based on the ultra-local model rather than real machine model. After estimating $\mathbf{F}$, one can track the stator current reference using deadbeat control based on SVM or FCS MPC. The control diagram of the PMSM drive system with an ESO based on ultra-local model is shown in Fig. 13.

The dynamic responses of a PMSM drive based on model free MPC are illustrated in Fig. 14, where $\mathbf{F}$ is estimated using differential algebra method in (a)–(c) and using ESO in (d)–(f). From top to bottom, the curves shown in Fig. 14 are the rotor speed, the reference, and the actual values of the q-axis current, and the a-phase stator current. The permanent magnet flux and inductance in the controller are twice of the actual value. It is seen that model-free MPC can achieve accurate tracking of q-axis current with machine parameter mismatches. It is worth to highlight that, by estimating $\mathbf{F}$ using ESO instead of differential algebra method, much lower dynamic overshoot is achieved in the current.

VIII. Challenges and Future Work

MPC has shown a high degree of flexibility, allowing the control of torque, flux, and currents, generating different control schemes that are easy to implement. Table I summarizes the main characteristics of the different MPC strategies described in the previous chapters. According to the experience of these researchers, MPC still has to overcome some challenges in terms of behavior. One of the challenges is the operation at very low speed, including developing full torque at zero speed. In the case of sequential MPC, it is important to gain more practical experience concerning the selection of the sequence: first selecting the torque and then the flux or vice versa is an

TABLE I
MAIN CHARACTERISTICS OF MPC STRATEGIES

	MPCC	MPTC	SMPC	Multi-Step	MP^{3}C	Model-Free
Need of weighting factors	✓✓	✗	✓✓	✗	✓✓	✗
Harmonic distortion	✓	✓	✗	✓	✓✓	✓
Low switching frequency	✗	✗	✗✗	✓✓	✓✓	–
Calculation and complexity	✓	✓	✓✓	✗	✓	✗✗
Parameter robustness	✓	✓	✓	✗	✓	✓✓

Scaled from best ($\surd\surd$) to worst (✗✗), (–) not studied.

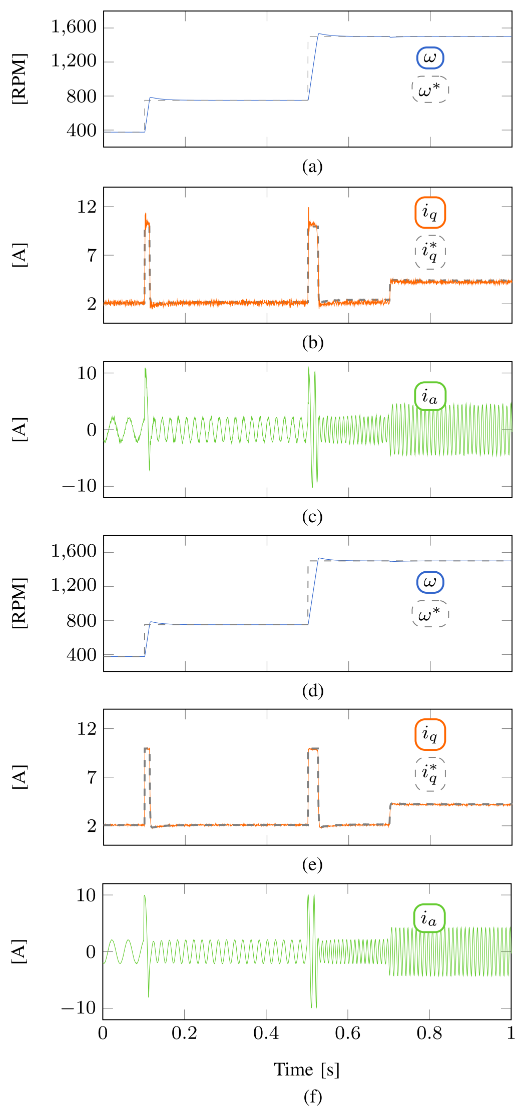

Fig. 14. Experimental results of model-free MPC during a dynamic process with mismatched parameters at $1R$, 2ψ, $2L$ under the condition of 10 kHz sampling frequency. (a)–(c) F estimated using differential algebra method. (d)–(f) F estimated using ESO [97].

aspect that needs more maturity. Also, the number of voltage vectors that are chosen at each stage of the sequence is a matter that needs further investigation.

To reduce the intrinsic dependence that MPC has on the motor parameters, model-free predictive control appears as an incipient and very attractive alternative, which needs further investigation regarding the implementation, observation techniques, and experimental results. In particular, the performance to parameter mismatch of model-free predictive control should be compared to the one obtained using FOC (with linear control).

Another future research is the study of MP^{3}C for higher order systems, such as drives with LC output filter. However, the optimal dynamic response using multistep prediction should be subject of additional study.

Finally, AI techniques are being considered to be applied in power converters [100]. In principle, MPC is appropriate for AI techniques because it works with basic models and instantaneous variables. However, this is a new line of research that must be explored in the future.

IX. CONCLUSION

This article showed that MPC is being used successfully in high-performance motor drive applications. With little effort, MPC has been applied in FOC and direct control of flux and torque.

Two different and interesting strategies have solved the classical problem of weighting factor calculation in the cost function when using predictive control. The first method uses sequential predictive control to avoid the use of weighting factors. This solution is straightforward to understand and implement without sacrificing the drive's high-quality transient behavior. The second strategy uses ANNs to obtain the optimal value for the weighting factor, introducing AI techniques in the core of the control method, which opens a very attractive area for future research.

The use of a multiple-step prediction has reduced the distortion of the load current generated by the inverter. Besides, for higher power motor drives, optimized pulse patterns can be integrated with predictive control to further reduce the distortion in the load current while operating with a low switching frequency.

Finally, the model-free strategy has demonstrated that it is possible to control the machine with high quality, without the need for a precise model, which offers a significant opportunity to improve the drive's robustness, introducing modern estimation techniques into the control algorithm.

These selected advanced topics showed that the application of MPC opens the possibility to continue improving the behavior of high-performance motor drives, including more intelligent techniques and advanced optimization algorithms.

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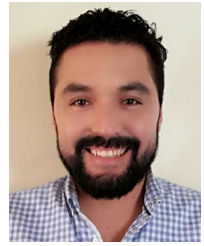

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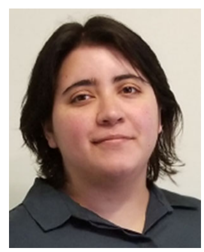

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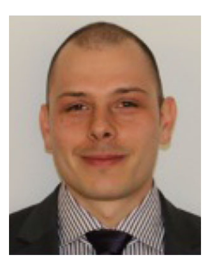

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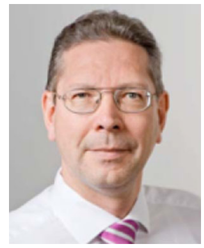
Dr. Geyer was a recipient of the Semikron Innovation Award and the Nagamori Award, both in 2021. He is also the recipient of the 2017 First Place Prize Paper Award in the Transactions on Power Electronics, the 2014 Third Place Prize Paper Award in the Transactions on Industry Applications, and of two Prize Paper Awards at conferences. He is a former Associate Editor for the *Transactions on Industry Applications* (from 2011 until 2014) and the *Transactions on Power Electronics* (from 2013 until 2019). He was an international program committee vice chair of the IFAC conference on Nonlinear Model Predictive Control in Madison, WI, USA, in 2018. He is a Distinguished Lecturer of the Power Electronics Society in the years 2020 and 2021.



Ralph Kennel (Senior Member, IEEE) was born in Kaiserslautern, Germany, in 1955. He received the Diploma and the Dr.-Ing. (Ph.D.) degrees from the University of Kaiserslautern, Kaiserslautern, Germany, in 1979 and 1984, respectively, and the Doctoral degree honoris causa from Universitatea Stefan cel Mare, Suceava, Romania, in 2018.

From 1983 to 1999, he worked on several positions with Robert BOSCH GmbH (Germany). Until 1997, he was responsible for the development of servo drives. He was one of the main supporters of VECON and SERCOS interface, two multicompany development projects for a microcontroller and a digital interface especially dedicated to servo drives. Furthermore, he took actively part in the definition and release of new standards with respect to CE marking for servo drives. Between 1997 and 1999, he was responsible for "Advanced and Product Development of Fractional Horsepower Motors" in automotive applications. His main activity was preparing the introduction of brushless drive concepts to the automotive market. From 1994 to 1999, he was appointed as a Visiting Professor with the University of Newcastle-upon-Tyne, U.K. From 1999 to 2008, he was a Professor of electrical machines and drives with Wuppertal University, Germany. Since 2008, he has been a Professor of electrical drive systems and power electronics with Technische Universitaet Muenchen, Germany. His main interests include sensorless control of ac drives, predictive control of power electronics, and hardware-in-the-loop systems.

Dr. Kennel is a Fellow of IET (former IEE) and a Chartered Engineer in the U.K. Within IEEE, he is a Treasurer of the Germany Section as well as a Distinguished Lecturer of the Power Electronics Society (IEEE-PELS). He was a recipient of the Harry Owen Distinguished Service Award from IEEE-PELS, in 2013, the EPE Association Distinguished Service Award in 2015 as well as the 2019 EPE Outstanding Achievement Award. He was appointed "Extraordinary Professor" by the University of Stellenbosch (South Africa) from 2016 to 2019 and as "Visiting Professor" with the Haixi Institute by the Chinese Academy of Sciences from 2016 to 2021.

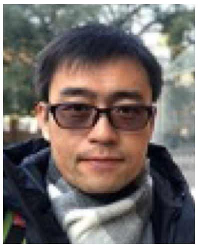
Davood Arab Khaburi was born in 1965. He received the B.Sc. degree in electronic engineering from the Sharif University of Technology, Tehran, Iran, in 1990, and the M.Sc. and Ph.D. degrees in electrical engineering from ENSEM, INPEL, Nancy, France, in 1994 and 1998, respectively.

He joined the University of Technology of Compiègne (UTC), Compiegne, France, for one year (1998–1999). Since January 2000, he has been a Faculty Member with Electrical Engineering Department, Iran University of Science Technology (IUST), where he is currently an Associate Professor. He is one of the founders of Iranian Association of Power Electronics and currently a board member of this association. He is also a member of Center of Excellence for Power Systems Automation and Operation. He is currently the Head of power group with IUST. His research interests include power electronics, motor drives, and digital control.

Mohamed Abdelrahem (Senior Member, IEEE) was born in Assiut, Egypt, in 1985. He received the B.Sc. (Hons.) and M.Sc. degrees from Assiut University, Assiut, Egypt, in 2007 and 2011, respectively, and the Ph.D.(Hons.) degree from the Technical University of Munich (TUM), Munich, Germany, in 2020, all in electrical engineering.

Since 2019, he has been the Head of the Research Group "Renewable Energy Systems" with the Institute for Electrical Drive Systems and Power Electronics (EAL), TUM. Since 2020, he has been an Assistant Professor with Electrical Engineering Department, Assiut University. His research interests include power electronics, predictive and encoderless control of variable-speed wind generators, photovoltaic energy systems, and energy storage systems.

Dr. Abdelrahem was a recipient of Walter Gademann Prize from the Faculty of Electrical and Computer Engineering, TUM, in recognition of his excellent Ph.D. dissertation entitled "Predictive Control and Finite-Set Observers for Variable-Speed Wind Generators," in 2020. Furthermore, he was a recipient of a number of Best Paper Awards from high prestigious international conferences of the IEEE. Dr. Abdelrahem is recorded in the world's top 2% scientist's list by Stanford University.



Zhen Zhang (Senior Member, IEEE) received the B.Eng. and M.Eng. degrees in automation from Tianjin University, Tianjin, China, in 2004 and 2007, respectively, and the Ph.D. degree in electrical engineering from The University of Hong Kong, Hong Kong, in 2014.

He is currently a Professor of electrical engineering with the School of Electrical and Information Engineering, Tianjin University. His research interests include the advanced control for power conversion with emphasis on wireless power transfer and motor drives.

Dr. Zhang is currently the Chair of IEEE Beijing Section IES Chapter and an Associate Editor for the IEEE Industrial Electronics Magazine, IEEE Transactions on Industrial Electronics, and IEEE Transactions on Industrial Informatics. He is the recipient of the IEEE J. David Irwin Early Career Award, Humboldt Research Fellowship, and 2020 Best Paper Award for IEEE Transactions on Industrial Electronics.

Nenad Mijatovic (Senior Member, IEEE) received the Dipl.Ing. degree in electrical power engineering from the University of Belgrade, Belgrade, Serbia, in 2007, and the Ph.D. degree from the Technical University of Denmark, Kongens Lyngby, Denmark, for his work on technical feasibility of novel machines and drives for wind industry.

Upon completion of his Ph.D., he continued work within the field of wind turbine direct-drive concepts as an Industrial Postdoctoral Researcher. He is currently an Associate Professor with the Technical University of Denmark, where he is in charge of managing research projects and education related to the field of electrical machines and drives, power electronic convertors, motion control, application of energy storage and general applications of low-frequency electromagnetism with main focus on emerging eMobility and renewable energy generation. His research interests include novel electrical machine drives/actuator designs, operation, control and diagnostic of electromagnetic assemblies, advance control of drives and grid-connected power electronics, energy storage, and eMobility.

Ricardo P. Aguilera (Member, IEEE) received the B.Sc. degree in electrical engineering from the Universidad de Antofagasta, Antofagasta, Chile, the M.Sc. degree in electronics engineering from the Universidad Tecnica Federico Santa Maria, Valparaíso, Chile, and the Ph.D. degree in electrical engineering from The University of Newcastle (UoN), Newcastle, NSW, Australia, in 2003, 2007, and 2012, respectively.

From 2012 to 2013, he was a Research Academic with UoN, where he was a part of the Centre for Complex Dynamic Systems and Control. From 2014 to 2016, he was a Senior Research Associate with The University of New South Wales, Australia, where he was a part of the Australian Energy Research Institute. Since September 2016, he has been with the School of Electrical and Data Engineering, University of Technology Sydney, Australia, where he currently holds a Senior Lecturer position. His main research interests include theoretical and practical aspects on model predictive control with application to power electronics, renewable energy integration, and microgrids.