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Model-Free Predictive Control of Motor Drives and Power Converters

A Review

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Model-Free Predictive Control of Motor Drives and Power Converters: A Review

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ABSTRACT Predictive control has emerged as a promising control method in a variety of technological fields. Model predictive control, as one of the subdivisions of this control method, has found a growing number of applications in power electronics and motor drives. In practical implementations, model predictive control faces performance degradation of the controlled plant due to its dependency on a model. There are considerable numbers of review papers that are devoted to the different points of view of predictive control. However, the existing literature lacks a review study that addresses the solutions for parameter dependency of the model predictive control method. Recently, model-free predictive control has been used in drives and power electronics as a solution for dealing with the model-dependency of the model predictive control method. There are many papers that have used such methods. In this paper, a classification is proposed for the different implementation types of model-free predictive control or similar methods that address model parameter uncertainties. Additionally, a comparison between the methods is also presented.

INDEX TERMS Control systems, estimation, inverters, motor drives, power conversion, power electronics, predictive control.

I. INTRODUCTION

Predictive control has been considered as a part of optimal control theory since 1960s [1]. The model predictive control (MPC), a branch of predictive control, has found growing applications in motor drives and power electronics. MPC implies the idea of employing a model of a plant under control to predict the future behavior of the control system's output. The prediction provides the capability to solve optimal control problems for minimizing the tracking error of the predicted output with respect to a desired reference [2].

During the last two decades, several reviews have been conducted of the MPC literature from various points of view. One of the earliest survey studies reviewed MPC theory and design techniques [3]. A part of that review deals with the robustness issues, indicating that this has been an important topic since the very beginning. Robust MPC theory and implementation methods are presented and surveyed in [2], [4]. The theory allows for the systematic handling of

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system uncertainties. The early approach of robust MPC is based on min–max optimal control problem formulations in which the controller acts according to the worst-case evaluations of the cost function. The constraints of the optimal control problem must be satisfied for all possible uncertainty realizations [5]. However, designing the controller for the worst case may be overly conservative. The nominal performance may have to be compromised in order to achieve the best possible robustness [6]. Offline MPC has also been reviewed. It allows the optimization to be carried out offline, thus reducing the time-consuming calculations, which is one of the drawbacks of the conventional MPC [7]. Another review surveys the three decades of development of the model predictive control; this paper divides the growth of the method into three steps, each belonging to one decade [8].

The application of MPC method in its different forms is also addressed in the field of drives and power electronics, including active filters, distributed generation, and renewable energy, etc. [9]–[12]. In [13], two different MPC schemes, namely, finite control set (FCS) (direct) and continuous control set (using PWM), are studied and compared by

implementing the controllers via the explicit form of MPC. In addition, three strategies for reducing the computational complexity of the MPC are studied [14]. In [15], a survey on predictive control methods in power electronics and drive systems is presented with an informative classification. It emphasizes that the control system's performance generally depends on the accuracy of the plant model. The paper [16] offers a similar review, including the latest developments, but it does not address robustness against model parameter mismatch. The MPC schemes in motor drive applications are comparatively studied with an emphasis on the control of medium-voltage induction motors in [17]. In addition, three different approaches for the predictive current control of permanent magnet synchronous (PMS) machines are discussed in [18]. Another comparative study, regarding the control objective, is conducted to investigate the FCS model predictive torque and model predictive current control schemes of induction motor drives in [19]. Although the effect of parameter mismatch is studied for both schemes, indicating that some cases of mismatch lead to instability of the control system, solutions to improve the robustness against parameter mismatch are not discussed. Four different schemes of the FCS model predictive torque control of PMS motors are also reviewed in [20]. The schemes are compared according to the results of experimental tests. However, the dependency of the control system on the accuracy of the model is not investigated. The review study [21] discusses the application of MPC in wind turbines. It concludes that there is great potential to effectively use the vast literature on robust MPC in wind energy applications.

The theory of model-free predictive control (MFPC) has emerged in the field of control as an alternative to robust MPC method to cope specifically with the issues caused by the model-based nature of MPC [22]. That the performance of a plant under MPC relies heavily on accurate knowledge of the model is a well-known fact. Nevertheless, it is quite challenging to achieve model accuracy in real-world applications. The challenges are due to two main facts. Firstly, the model parameters usually vary from their nominal values during the system operation under the influence of different factors, including operating point and ambient conditions. Additionally, the parameters of the model may be unknown in, for example, plug-and-play applications. Therefore, lessening the dependency of the control system on the model is now an emerging area of research. The theory is based on the idea of a model-on-demand framework. Instead of estimating a global model, the input and output data corresponding to a small neighborhood around the operating point are exploited to estimate the system dynamics locally and on-demand when the need for a model arises [22]. Unlike the robust MPC method, the optimization problem in the MFPC method is the same as that in the MPC method. As is extensively reviewed in the next section, the MFPC method is increasingly applied to motor drives and power electronic applications. This is particularly due to the emerging applications in technologies

such as drones, electric vehicles, and wireless power transfer systems that have widely variable operating points working in harsh ambient conditions. Many papers investigate different methods of MFPC of motor drives and power electronic converters. Nevertheless, to the best of the authors' knowledge, no review papers or tutorial work is available in the literature in this field.

This paper first presents the basic formulation and structure of major MFPC strategies according to a novel comprehensive classification and then addresses various methods of MFPC as applied to motor drives and power electronic converters. It elaborates on the basic analytical and implementation aspects of the control methods by introducing a novel classification. It also describes the methods' similarities and differences, rather than providing detailed formulations of each method. Of course, space limitations preclude mentioning all research activities in this area. Nevertheless, the authors attempt to review many major developments in the field during the past decade.

The paper is organized as follows. A literature review on the application of MFPC in power electronics and drives is presented in section II. Section III concisely outlines the MPC theory. Section IV presents the principles of MFPC and a classification of its application in power electronics and drives; this section builds on the literature review of Section II. Section V discusses the implementation of three major MFPC schemes using mathematical equations and system block diagrams. The section ends with a comparison between the different schemes. Concluding remarks are given in section VI, where some unresolved challenges and practical issues are mentioned.

II. LITERATURE REVIEW

As one of the earliest implementations of the MFPC method in the field of motor drives, a current control method is proposed for IPM motors with a simple but effective structure [23]. The method does not require any prior knowledge of the controlled motor's parameters. Only one switching state is actuated by the inverter in each control period as the method works based on the FCS predictive control. The variations of the current vector components over a control period, provided by the corresponding inverter switching states, are stored in the look-up table. The look-up table must be continuously updated every time that the switching state of the inverter changes. The idea is to use the stored input and output data for predicting the future variations of the current vector. The key point is that the variations are almost constant over a short period (e.g., a couple of control periods). Therefore, the stored data can be used for the predictions of the next sampling period. In this method, current sampling is conducted twice per switching interval in order to calculate the current variation. A similar method is adopted for controlling a three-phase voltage source inverter driving a three-phase load in [24] and a dual air-gap transverse-flux permanent magnet brushless motor in [25]. Furthermore,

the method is applied to a synchronous reluctance motor drive with some improvements in [26]; this method adopts one current sampling per switching interval.

In the methods discussed above, if a voltage vector is not applied for a while, its corresponding data in the look-up table cannot be updated. The old data stored in the look-up table may no longer be accurate for the predictions due to the possible change of the operating point, such as the rotation of the rotor. In some cases, the inaccuracy is so severe that it results in instability in the control system. A solution is proposed to overcome this drawback in [27]. In this approach, if a switching state has not been applied over a predefined number of sampling periods, it is actuated regardless of which state is designated by the optimization. However, applying the non-optimal voltage vectors results in considerable performance deterioration. The same method is also used for controlling a three-phase AC/DC converter in [28] and a dual air-gap transverse-flux six-phase permanent magnet machine in [29]. The method is further improved by utilizing more synthesized voltage vectors instead of just seven by using two of the inverter basic voltage vectors in one sampling period [30], [31]. Although this may lead to a lower torque ripple and current THD, measuring the current difference would be challenging in practical implementations. In other words, the lower the current components' ripple, the more difficult it would be to detect the current difference over a sampling period.

The authors of [32] propose a solution to overcome the look-up table updating issue in the aforementioned model-free predictive current control methods. Current variations corresponding to all of the inverter switching states are estimated by using data of only the three most recent sampling periods. As a result, the stagnation of the look-up table updating problem is resolved by guarantying continuous updating without actuating any non-optimal switching state of the inverter. However, the proposed method imposes an excessive computational burden on the CPU due to the reconstruction of current variations. The reconstruction results in 210 possible combinations of three switching states, which can be gathered together in six different groups. A faster algorithm for the reconstruction that is based on the voltage vectors' group identification is introduced to deal with such a time-consuming solution [33]. Additionally, an improved version of the approach described in [33] has been published; it proposes a method for compensating for the effect of the rotor movement on the current predictions [34].

Another model-free predictive current control method for PMS motors is proposed in which a data-driven ultra-local model of the motor with parametric uncertainties and inverter nonlinearities is established via input and output data of the drive system [35]. The method estimates an uncertain term of the derived model through algebraic parameter identification techniques. Then, the model is used to calculate reference voltage vectors in a deadbeat fashion. The reference voltages are then synthesized using the SVM technique. Hence, the method needs a voltage modulator. A similar approach is

also used to improve the robustness of the motor drive control against mechanical parametric uncertainties [36]. This method adopts an ultra-local model through the input and output data of the speed loop under parametric uncertainties and external disturbances. Then, the derived model is used to generate the torque reference command in a predictive manner. The ultra-local model is further used as the predictive model to achieve another model-free predictive current control for PMS motor [37]. The difference between this method and those previously mentioned is the way in which the voltage vector is synthesized. The phase and magnitude of the reference voltage vector are optimized in a two-sequence optimization algorithm. The Lagrange interpolation polynomial is used to optimize the phase of the voltage vector, and the optimum magnitude of the voltage vector is then determined by minimizing a cost function. Finally, the optimal voltage vector is synthetized by using three of the inverter basic voltage vectors. A model-free predictive current control based on the discrete SVM is proposed to reduce the switching frequency compared to continuous SVM-based methods; it does so while maintaining a steady-state performance that is better than those seen in non-modulator-based methods [38]. The ultra-local model is also utilized to determine a reference voltage vector based on the principles of deadbeat current control. The voltage sector containing the reference voltage vector is divided into nine sub-sectors. Finally, the optimal voltage vector, which is a combination of three basic voltage vectors of the sector, is obtained and applied to the inverter. Furthermore, a two-level cost function is proposed for the sequence optimization of the selected basic voltage vectors in the combination. The method is effective in reducing the inverter's average switching frequency. The use of observers such as sliding mode and extended state observers instead of using the algebraic parameter identification techniques are also adopted to estimate the uncertain terms [39]–[43].

The measured current variations in previous successive sampling periods are used to achieve correct predictions without using the motor parameters [44]–[46]. Unlike the conventional model-free predictive current control [23], these methods do not use a look-up table for storing the related data of all switching configurations. Thus, they do not face the stagnation problem. Four parameters related to the current vector variation, two for each component, are continually estimated online. The current variation (output variation) and the applied voltage vector (input) data of two consecutive sampling periods are used for the estimation [44]. It is important to filter the estimated values digitally to avoid spikes. A similar approach is also proposed for model-free predictive torque control of PMS motors [47], [48] and direct power control of grid-connected converters [49]. The recursive least square method is adapted to model-free predictive current control of synchronous motors as an alternative estimation technique by using the data from at least two previous sampling periods [45].

MFPC method is adapted to different power electronic converters [41], [43], [49]–[56]. An improved model-free

predictive current control of a PWM rectifier is proposed to reduce the prediction error [56]. To do so, the difference between the measured current in the present sampling period and the predicted current at the previous sampling period for the existing instance is added to the next step prediction as compensation. The errors are multiplied by a factor that should be carefully tuned. However, the prediction errors of the inverter switching configurations differ from one another. Hence, adding the prediction error related to a switching configuration to the prediction related to another switching configuration using a constant gain would not be a proper solution.

There are some predictive control methods in which, instead of directly predicting the control variable by using the MFPC approach, the measurement data is used to correct prediction errors [57]–[60]. The methods are not, however, completely model-free. By using a two-degree-of-freedom control, the robustness of the predictive torque control of PMS motors is improved via feed-forward compensation while maintaining a strong reference tracking performance [57]. A predictive current control method for PMS motors is proposed in which the prediction errors of current components in each sampling period are stored in a look-up table [58]. The motor's initial parameters (ideal model) are used for the predictions. Then in each sampling period, the difference between measured current components and the predicted ones are stored in the look-up table as the prediction errors. The look-up table consists of the inverter's main switching configurations and the corresponding current components' prediction errors. When a switching configuration is followed in a sampling period, the provided prediction error corresponding to that configuration is updated in the look-up table. The next time the same configuration is applied, the corresponding error value stored in the look-up table is used to compensate for the conducted prediction. A proportional gain is also used to adjust the impact of the compensation. The same error suppression solution is also applied to predictive torque control of the surface-mounted PMS motors [59]. The corrected predicted current components are used in predictions related to the torque calculation. However, this method is not robust against the mismatch in permanent magnet flux and winding resistance parameters [60]. Additionally, two latter methods suffer from the problem of stagnation of look-up table updating, as previously discussed, when some of the inverter switching configurations are not actuated for a while [60]. The problem is resolved by using the prediction error data of two consecutive previous sampling periods to compensate for the predictions of the next sampling period [60]. The look-up table is therefore no longer needed in this method. Two coefficients are estimated in each sampling period; they can be used to correct the errors related to all of the inverter voltage vectors. These coefficients are updated continually in each sampling period.

A variety of solutions for the reduction of model dependency of the predictive control was surveyed in this section for motor drives and power electronic converters.

Considering the similarities and differences in how they are implemented, a classification method is proposed in this paper.

III. PRINCIPLE OF MODEL-BASED PREDICTIVE CONTROL

The basic principles of model-based predictive control are briefly presented here [1]. The method predicts future performance of the system. An optimal control is then adopted to force the system to produce the desired performance. The MPC, which is one of the predictive control methods, makes use of a model of the plant under control for the predictions. The model in discrete-time state-space form can be presented as [1]:

$$\hat{x}(k+1) = Ax(k) + Bu(k), \qquad (1)$$

$$y(k) = Cx(k) + Du(k), \qquad (2)$$

where $x(k)$ and $\hat{x}(k+1)$ are the system state vectors at the current and the next instants, respectively. Also, $u(k)$ and $y(k)$ are input and output vectors, respectively, at the current instant. A, B, C, and D are the system, input, output, and disturbance matrices, respectively. An objective function, J, which is a function of system states and inputs, is defined to formulate the system's desired performance as:

$$J = f(x(k), u(k), \ldots, u(k+N)), \qquad (3)$$

where N is a positive number known as the prediction horizon and is the number of future instances over which the control can predict the system's performance. The vector $u(k+N)$ is the system input at the instance $k+N$. The sequence of the inputs prior to $u(k+N)$ is also included in J, as shown in Fig. 1 [1]. The figure shows the reference and actual states of the system in addition to the discrete inputs in consecutive instances from the past up to instance $k+N$. It can be seen that the system error decreases as time goes on, and the actual state gets closer to the reference. Commonly, J includes the absolute or the square tracking error between a reference and a predicted value of the system output. The objective function may include other parts to fulfill non-regulatory desirable objectives. It is common to define the objective function as a weighted sum of different objectives. The optimization problem is to find the inputs such that J is minimized, subject to the system's restrictions. The system model presented by (1) and (2) is used in finding the solution. A general solution is complicated. A simple solution, however, is to evaluate the value of J for all possible inputs in each sampling period. Then, the lowest value of J determines the best input for the next period. The solution consists of a sequence of optimal input signals. However, the controller will apply only the first element of the sequence. Once the selected input is applied to the system, the system model and the objective function are updated by using the most recently measured data. Therefore, the predictive horizon is regarded as a moving window of instances [1].

As per the descriptions presented above, a functional block diagram of general model-based predictive control is shown
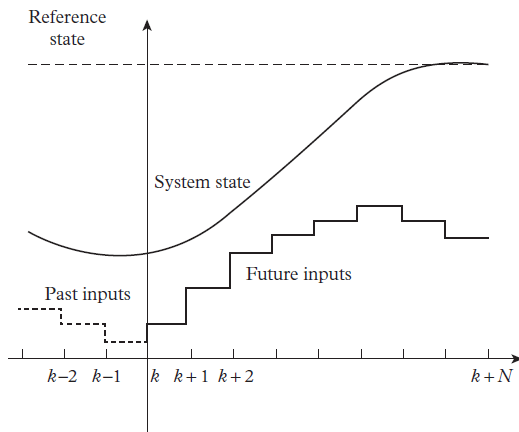
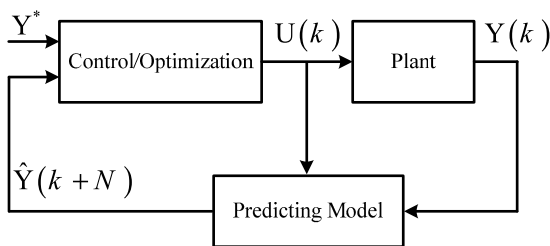**FIGURE 1.** Working principles of model-based predictive control [1].

FIGURE 2. A functional block diagram of general model-based predictive control.

FIGURE 3. A functional block diagram of general MFPC method.
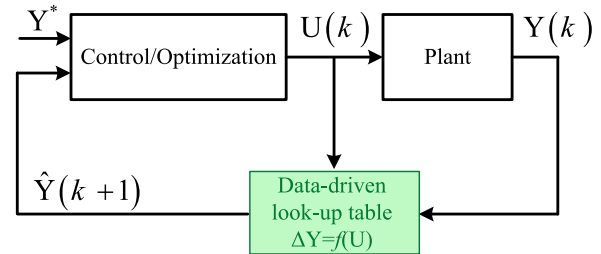
FIGURE 4. A simple block diagram of Type I MFPC method.

in Fig. 2, where the tasks of prediction and optimization are distinguished. The superscript ''*'' is used for the reference value, whereas a hat symbol indicates predicted or estimated variables.

IV. PRINCIPLES OF MODEL-FREE PREDICTIVE CONTROL

It is evident from the previous section that the performance of the MPC algorithm heavily depends on the knowledge of the system model, i.e., (1) and (2). However, the parameters of the system usually vary over time. Therefore, a practical model should be time-varying. However, such a model cannot be obtained without excessive computational burden, which is not desirable in the actual implementation of the control system. Furthermore, a perfect initial parameter identification procedure for an unknown plant is also another issue. Mismatch between the model and the controller parameters may lead to performance degradation, and even in some cases, the instability of the control [19].

An alternative approach is to use an on-demand model to handle the predictions [22]. The basic idea is to store the system's performance information in a database and use it for predicting system dynamics instead of using a constant model [22]. In fact, the input-output information from a small neighborhood in the vicinity of the current operating point is used to predict a local model of the system instead of estimating a large global model covering the entire operating range. In some MFPC methods, this data-driven model is replaced by a look-up table containing the input and output
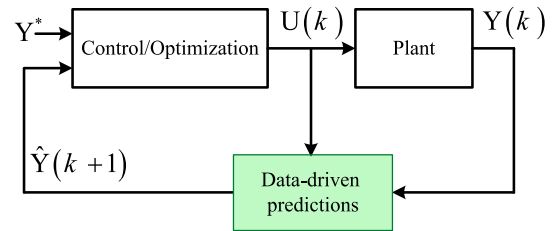
data of the control system. The data-driven model/look-up table is updated continually during each sample time. It is then linearized and used in predicting the system's behavior. A general block diagram of the control system is shown in Fig. 3. Here, the ''predicting model'' block of Fig. 2 is replaced with ''data-driven predictions''.

MFPC methods have recently seen increasing applications in the field of power electronics and drives with different schemes. Although the approaches and formulations are different, they share the common idea of making the predictions free of a system model or at least less dependent on it. For this purpose, in some cases, the data-driven model/look-up tables are directly used for predictions, and in some other cases, they are used for modifying the predictions or system inputs. Here, the methods are categorized into three main groups according to the extent to which they are model-free.

A. TYPE I—TOTALLY MODEL-FREE

Type I methods do not use any model for predictions [23]–[34]. Instead, the predictions are carried out by directly using the system's previous input and output data, which are stored in a look-up table. The look-up table contains the values of the output variations corresponding to all available finite numbers of the control system inputs. The stored data may be provided by directly measuring the output in each sampling period or estimating it by using some output measurements and the appropriate mathematical equations. Fig. 4 shows a simplified block diagram of this type of MFPC method.

B. TYPE II—USING AN ULTRA-LOCAL MODEL

The methods of this group are more similar to the basic MFPC approach that adopts an ultra-local model for the predictions. They use a model with one or more uncertain terms that should be estimated continually via the system's input and
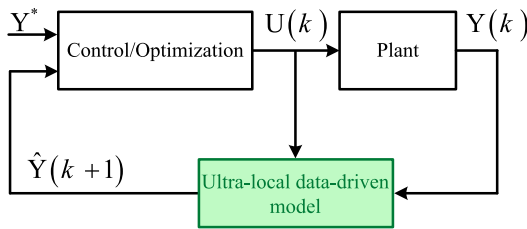
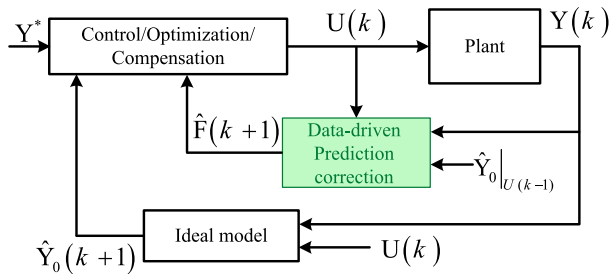**FIGURE 5.** A simple block diagram of the Type II MFPC method.

FIGURE 6. A simple block diagram of Type III MFPC method.

FIGURE 7. Different approaches of Type III MFPC methods. (a) Compensation of predicted output. (b) Compensation of calculated control input.

output data. The model is then utilized in the control system's prediction stage [35]–[49], [54], [55]. A general block diagram of this type is shown in Fig. 5. It can be seen that there is no need for a look-up table. Hence, these methods do not face the problem of stagnation of look-up table updating.

C. TYPE III—PREDICTION CORRECTION

The third category is devoted to the methods in which an ideal model of the plant is used. However, by using the input, output and previous prediction data of the system, some correction factors are estimated to compensate for the predictions [56]–[61]. Another approach is to compensate for the control inputs that are going to be applied to the control plant in the upcoming sampling period [62]–[71]. A general block diagram is illustrated in Fig. 6. In addition, two different approaches for correcting the prediction are shown in Fig. 7. In the figures, $\hat{Y}_0$ is the output predicted by an ideal model of the plant with nominal parameters. The correction can be made by modifying the ideal prediction conducted using the nominal model, as shown in Fig. 7(a), or by modifying the inputs, as illustrated in Fig. 7(b).

V. MODEL-FREE PREDICTIVE CONTROL OF DRIVES AND POWER CONVERTERS

The mathematics and some detailed description of each type of MFPC method introduced in the previous section, are adapted to drives and power electronics as summarized in this section. The last subsection contains a comparative table of the surveyed control schemes, which serves as the conclusion of this section.

A. TYPE I—TOTALLY MODEL-FREE

The idea is that the output (e.g., components of the current vector) variation provided by each input, i.e., an inverter
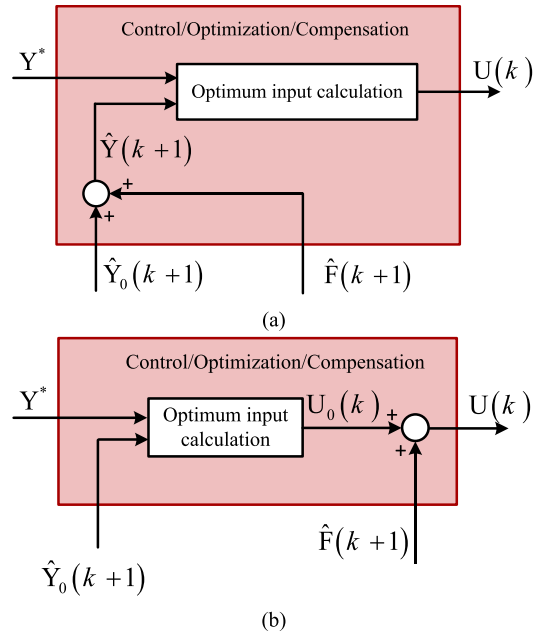
voltage vector, can be considered constant for that input, over a couple of sampling periods, when the sampling time is reasonably short. Therefore, the output variations are stored in a look-up table for each of the corresponding inputs. The data-driven look-up table, instead of using the system model, can be used to predict the value of the output for the next sampling period [23], [34]. Fig. 4 shows a simple block diagram of this type of model-free method. The data in the look-up table should be updated continuously. In each sampling period, when an input is applied to the plant under control, the output variation corresponding to that input is updated in the look-up table. A problem arises when using the look-up table for methods in which the output variations for all available inputs are directly measured [23]–[31]. In fact, if an input is unapplied to the system for some successive sampling periods, its corresponding data in the look-up table cannot be updated. When the obsolete data is used for the predictions, it may result in performance degradation or even instability in the control system [27], [45]. This problem is known as stagnation of the data updating and is shown in Fig. 8. It shows the periodic stagnation of data updating in the look-up table for an output variation (Δi_d) corresponding to the voltage vector of number 1 during the steady-state operation of a drive system. The applied voltage vectors are also shown in Fig. 8(a). It is seen from Fig. 8(b) that the corresponding data field in the look-up table cannot be updated when voltage vector number 1 does not drive the output in some periods.

As a solution, some methods have been proposed in which the look-up table is updated using the estimated variation
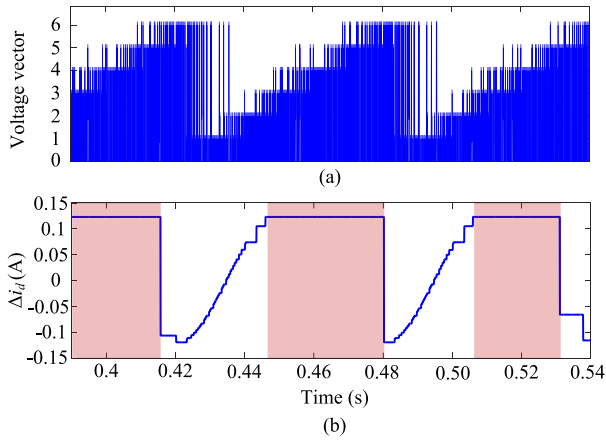
FIGURE 8. An example of look-up table updating stagnation. (a) Applied voltage vectors, (b) Look-up table data of d-axis current component variation corresponding to voltage vector number 1.

FIGURE 9. A block diagram of Type I MFPC system based on the method proposed in [23].

of the output for unapplied inputs [32]–[34]. It helps the continuity of the look-up table updating mechanism.

Type I MFPC method is well-suited to FCS predictive control due to the limited numbers of system inputs (inverter voltage vectors) and the lack of a voltage modulator. As an example, the basics of the method are described for the predictive current control of a PMS motor with a two-level inverter based on the method proposed in [23]. A block diagram of the control system is illustrated in Fig. 9. In this control system, the stator current is the system output. The control inputs are selected according to the inverter's eight possible switching configurations. Considering the one-step delay of the digital processor [72], [73], a cost function is defined to minimize the tracking errors of the inputs as:

$$J_u = \left| i_a^*(k) - \hat{i}_a(k+2) \right|_u \Big| + \left| i_b^*(k) - \hat{i}_b(k+2) \right|_u \Big| + \left| i_c^*(k) - \hat{i}_c(k+2) \right|_u \Big|, \quad (4)$$

where $u \in \left\{ \vec{v}_0, \dots, \vec{v}_7 \right\}$ is a basic voltage vector of the inverter. The phase current can be predicted as:

$$\hat{i}_x(k+1) \Big|_u = i_x(k) + \widehat{\Delta i_x}(k) \Big|_u, \quad x \in \{a, b, c\}, \quad (5)$$

where $\widehat{\Delta i_x}(k) \Big|_u$ is the predicted variation of a phase current over one sampling period. The calculation of this term is performed using the motor model in MPC. However, under the MFPC method, the prediction can be conducted using the input and output data of the control system without the need for a model. In this method, it is assumed that for a short interval, each voltage vector can provide a specific variation for each of phase currents that is nearly constant over the sampling periods within the interval. Thus, the variations of the phase currents in a sampling period are stored in a look-up table for corresponding voltage vectors. Based on the aforementioned assumption, the current variation can be extracted from the look-up table for an intended voltage vector. In other
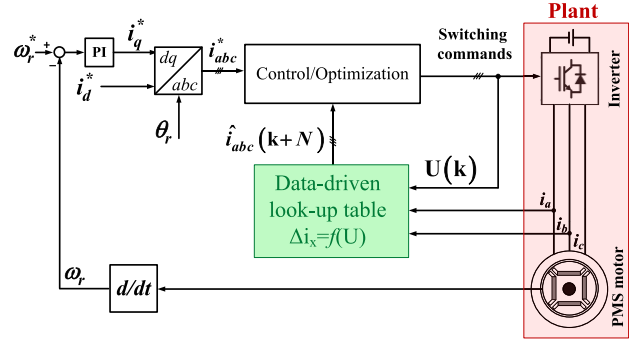
words:

$$\Delta i_x(k) \Big|_u \approx \Delta i_x^{LUT} \Big|_u, \quad u \in \left\{ \vec{v_0}, \dots, \vec{v_7} \right\}, \quad (6)$$

where $\Delta i_x^{LUT} \Big|_u$ is the stored data of one-period variation of the phase currents in the look-up table. Finally, substituting (6) into (5) gives:

$$\hat{i}_x(k+1) \Big|_u = i_x(k) + \Delta i_x^{LUT} \Big|_u, \quad x \in \{a, b, c\}, \quad (7)$$

By using (7), the stator current is predicted without using the motor model. The predicted values can be used to evaluate the cost function of (4) in order to select the optimal voltage vector.

B. TYPE II–USING AN ULTRA-LOCAL MODEL

An ultra-local, data-driven model is used for the predictions in this type of MFPC method. The derived model typically contains one or more uncertain terms that should be estimated continually via the input and output data of the control system. The estimation methods can be classified into two approaches. The first approach uses algebraic parameter identification techniques [35]–[38], [55], or observers [39]–[43], and the second one exploits the inherent nature of the control variable ripples (output ripples) to estimate uncertain parts of the ultra-local model [44]–[49], [54] instead of adopting observers. The stability of the control system in the first approach where the observers are used may be an issue that should be considered.

In the first approach, the ultra-local model can be described in a general form as:

$$\frac{dY(t)}{dt} = F(t) + \alpha U(t), \quad (8)$$

where $Y(t)$ and $U(t)$ are the system output and input vectors, respectively, and $F(t)$ refers to the known and unknown parts of the system containing uncertain terms. There is also a scaling factor, α, which should be chosen by the designer. To describe some details of this approach, the predictive current control of a surface-mounted PMS motor is considered [35].

Accordingly, (8) is modified as:

$$\frac{di_x(t)}{dt} = f_x(t) + \alpha_x u_x(t), \quad x \in \{d, q\}. \tag{9}$$

where α_x ensures that di_x/dt and $u_x(t)$ have the same order of magnitude. It can be set as $1/L_s$, and L_s is the stator inductance of the motor. Furthermore, $f_x(t)$ can be expressed as:

$$\begin{cases} f_d(t) = \dfrac{-R_s}{L_s} i_d + \omega_r i_q - \left(V_{d,par} + V_{d,dead}\right)/L_s \\ f_q(t) = \dfrac{-R_s}{L_s} i_q - \omega_r i_d - \dfrac{\omega_r \lambda_m}{L_s} - \left(V_{q,par} + V_{q,dead}\right)/L_s \end{cases} \tag{10}$$

where $V_{d,par}$ and $V_{q,par}$ are the disturbance voltages caused by parametric uncertainties. In addition, $V_{d,dead}$ and $V_{q,dead}$ denote inverter dead-time and nonlinearities. The parameter R_s is the winding resistance, and ω_r is the angular frequency of the rotor flux vector. Considering the reference current constant over two sampling periods and discretizing (9) results in:

$$u_x^* = \frac{1}{2T_s \alpha_x} \left(i_x^*(k+2) - i_x(k)\right) - \frac{\hat{f}_x(k)}{\alpha_x}, \quad x \in \{d, q\}. \tag{11}$$

The uncertain term, $\hat{f}_x(t)$, which is assumed to be constant over a short period of T_F, should be estimated using the voltage and current data of the motor. The algebraic parameter identification techniques from [35], [74] are used for the estimation resulting in:

$$\hat{f}_x = -\frac{3!}{T_F^3} \int_0^{T_F} \left[(T_F - 2\delta) i_x(\delta) + \alpha_x \delta (T_F - \delta) u_x(\delta) \right] d\delta, \quad x \in \{d, q\}. \tag{12}$$

where $T_F = n_F T_s$ is the window sequence length. This means that the estimation is made by using the data of $n_F + 1$ sampling periods. Additionally, the compound trapezoidal formula is used to calculate the integrator in (12), and the real-time implementation in the digital controller is described in [35]. Substituting (12) into (11) for a given current reference, one can obtain the reference voltage vector components that should be synthesized and applied to the inverter through a voltage modulator. Although this method's estimation improves the robustness of the control system, the choice of parameter α_x requires initial knowledge of the motor inductance parameter. Hence, this is a shortcoming of this approach compared to the Type I MFPC methods.

The second approach of Type II estimates all of the uncertain terms of a derived ultra-local model using the inherent ripples of the output [44], [45], [47], [49]. Thus, this approach is well-suited for FCS predictive control. The general formulation of the model is:

$$\frac{dY(t)}{dt} = F_1(t)U(t) + F_2(t), \tag{13}$$

where $F_1(t)$ and $F_2(t)$ are the varying uncertain functions that are estimated online using the input and output data of the

control system without requiring any knowledge of the plant parameters [44], [45]. Two implementations are described here for predictive current control of the PMS motor drives. Accordingly, (13) is modified as:

$$\frac{di_x(t)}{dt} = f_{1x}(t) u_x(t) + f_{2x}(t), \tag{14}$$

The terms $f_{1x}(t)$ and $f_{2x}(t)$, where $x \in \{d, q\}$, are defined as:

$$\begin{cases} f_{1d}(t) = 1/l_d\left(i_d, i_q\right) \\ f_{2d}(t) = \left(\omega_r i_q L_q\left(i_d, i_q\right) - R_s i_d\right)/l_d\left(i_d, i_q\right) \\ f_{1q}(t) = 1/l_q\left(i_d, i_q\right) \\ f_{2q}(t) = \dfrac{-\left(\omega_r \lambda_m + \omega_r i_d L_d\left(i_d, i_q\right) - R_s i_q\right)}{l_d\left(i_d, i_q\right)}, \end{cases} \tag{15}$$

where L_x and l_x are apparent and incremental inductances of the motor, respectively. They can vary due to saturation or cross-saturation effects. A discrete form of (14) is obtained as:

$$\hat{i}_x(k+1) = i_x(k) + f_{1x} u_x(k) + f_{2x}, \quad x \in \{d, q\}. \tag{16}$$

Due to the high sampling frequency of the FCS predictive control, it can be assumed that the values of f_{1x} and f_{2x} are constant over a couple of consecutive sampling periods. Hence, an estimation method that typically uses the current variation and voltage data of only the two most recent sampling periods has been proposed for f_{1x} and f_{2x} [44]. The estimation uses only input and output data of the control system as:

$$\begin{cases} \hat{f}_{1d} = \dfrac{\Delta i_d(k-1) - \Delta i_d(k-2)}{T_s V_m \left[\cos \vartheta(k-1) - \cos \vartheta(k-2)\right]} \\ \hat{f}_{2d} = \Delta i_d(k-1)/T_s - \hat{f}_{1d} V_m \cos \vartheta(k-1) \\ \hat{f}_{1q} = \dfrac{\Delta i_q(k-1) - \Delta i_q(k-2)}{T_s V_m \left[\sin \vartheta(k-1) - \sin \vartheta(k-2)\right]} \\ \hat{f}_{2q} = \Delta i_q(k-1)/T_s - \hat{f}_{1q} V_m \sin \vartheta(k-1), \end{cases} \tag{17}$$

where $V_m = 2V_{dc}/3$. Substituting the estimated values of (17) into (16), the current components can be predicted without using any of the motor parameters. By applying a two-step prediction to compensate for the one-step delay of the digital controller [35], one can derive a reference voltage vector corresponding to the control input reference, i.e., i_x^* as:

$$u_x^* = \left[i_x^*(k+2) - \hat{i}_x(k+1) - T_s \hat{f}_{2x}\right]/T_s \hat{f}_{1x}. \tag{18}$$

Finally, instead of evaluating a cost function, the inverter voltage vector that is the nearest one to the reference voltage vector is selected as the optimal input to be applied to the motor in the next sampling period. It is important to digitally filter the estimated values so as to ensure a good performance despite the non-idealities in the measurements. A flowchart of the method is given in Fig. 10.

Another manner for estimating ultra-local model uncertain terms is adopted based on the recursive least square (RSL) method [45]. This method is suited to the estimation of
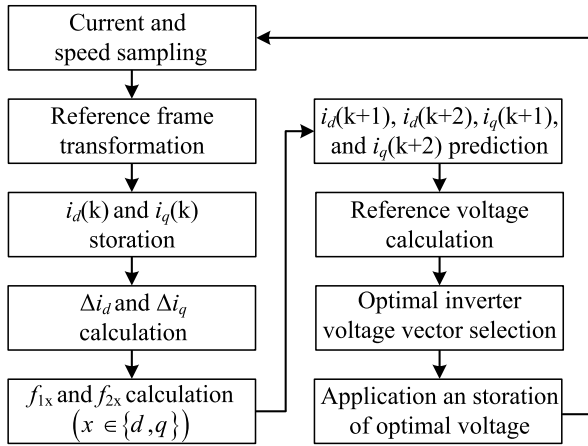
FIGURE 10. A flowchart of one of the Type II approach 2 MFPC methods proposed in [44].

FIGURE 11. A block diagram of the predictive current control of PMS motors implemented based on Type II MFPC method.

FIGURE 12. Steady-state experimental waveforms of the d- and qaxis components of a motor current under 100% error in the motor inductance values [44].

parameters during normal operations of a process with a varying operating point structure. In a discrete form, (11) can be rearranged as:

$$\frac{\Delta i_x}{T_s} = \begin{bmatrix} u_x(k) & 1 \end{bmatrix} \begin{bmatrix} f_{1x} & f_{2x} \end{bmatrix}^T = \phi_x^u F_x, \quad (19)$$

where ϕ_x^u and F_x are the regressor and uncertain coefficient vectors, respectively. According to the standard RSL algorithm, a set of equations that should be solved recursively is given as:

$$\begin{cases} G_x(k) = Q_x(k-1)\,\Phi_x^T \left(\Phi_x Q(k-1)\,\Phi_x^T + \chi I \right)^{-1} \\ \hat{F}_x(k) = \hat{F}_x(k-1) + G_x(k)\left(\delta_x(k) - \Phi_x \hat{F}_x(k-1) \right) \\ Q_x(k) = (Q_x(k-1) - G_x(k)\,\Phi_x Q_x(k-1))\big/\chi \end{cases} \quad (20)$$

Matrix $G_x(k)$ is a gain matrix for weighting the errors between measurements and estimations made by using the coefficients' vectors. Additionally, Φ_x is the regressor matrix that contains all the regressor vectors related to the current components' variations involved in estimating $\hat{F}_x(k)$, i.e., those related to measurements vector $\delta_x(k) = \begin{bmatrix} \Delta i_x(k)/T_s, \Delta i_x(k-1)/T_s, \dots \end{bmatrix}^T$. The estimation error covariance matrix is denoted $Q_x(k)$ by. In addition, a forgetting factor, χ, is used in (20) in order to weight the old estimation data. By substituting the estimated coefficients into (19), the current components' variations are calculated; thus, the current vector can be predicted without any knowledge of the motor parameters. Finally, the predictions are evaluated in a cost function to select the optimal voltage vector for the inverter.

A simple block diagram of the implemented control systems of Type II model-free predictive current control of PMS motors is shown in Fig. 11.

Experimental results of the *d*- and *q*- axis components of the current vector of a motor drive with certain specifications are shown in Fig. 12 under 100% mismatch in the model-based predictive current controller inductances [44]. This
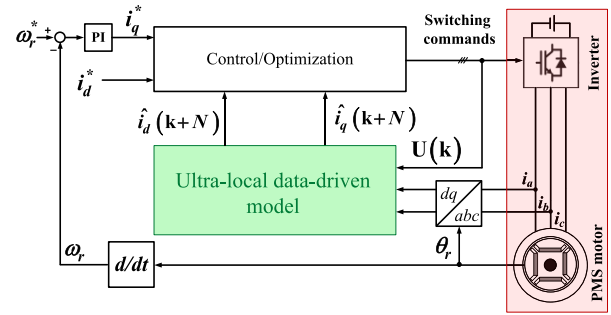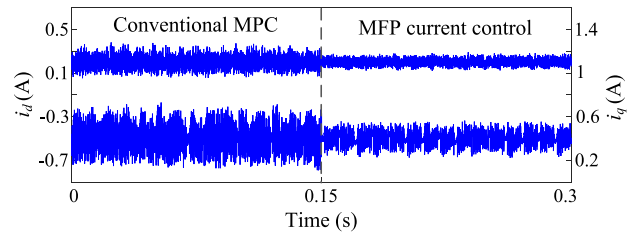
kind of mismatch may happen in the case of improper parameter identification of the motor or under a deep saturation. It can be seen that the performance improves considerably after the model-free predictive current control method is enabled.

C. TYPE III—PREDICTION CORRECTION
The third type of MFPC adopted in power electronics is based on the correction of calculations conducted using the nominal parameters of the controlled plant. Using the input, output and previous predictions of the system, some correction factors are estimated in order to compensate for the next sampling period's predictions [56]–[61], or reference voltages [62]–[71]. Compensation for the predicted output has been adopted mainly in the FCS predictive control, whereas the compensation for the calculated control input (voltage) is commonly applicable in modulator-based predictive control methods such as deadbeat predictive control.

In order to compensate for the output prediction error, which is caused by using the ideal model of the controlled plant, a lumped disturbance term that contains the mismatch value between the ideal model and the real one is defined. This term is then estimated and added to the upcoming predictions to minimize the prediction error, as shown in Fig. 7(a).

The literature provides a variety of methods for estimating the correction term. A simple solution has been proposed to improve the robustness of the FCS predictive torque control of the PMS motors [56]. A systematic change in the controller structure from feedback to partial feedforward improves the closed-loop robustness against model mismatch.

The controller uses the error between the predicted and the measured current at the end of the previous sampling period. However, the error is not the same for different voltage vectors [58]. Therefore, using the calculated error from the previous sampling period to compensate for the prediction error in the next sampling period, in which a different voltage vector may be applied, is not the best solution. Finding the right value to be added as a compensation term motivated the authors of [58], [59] to propose that the prediction error corresponding to all voltage vectors be stored in a look-up table. The prediction error data related to a voltage vector in the look-up table is updated when the vector is applied to the motor. Hence, the look-up table is continually updated during the operation of the control system. The prediction error in each sampling period is calculated by simply subtracting the measured current from the predicted current. The last prediction error of every voltage vector, which is stored in the look-up table, is used in the prediction stage for the same voltage vector to compensate for the related prediction error.

The ideal model of a surface-mounted PMS motor used for primary output prediction is given as:

$$\begin{cases} \dfrac{di_d}{dt} = -\dfrac{R_{s0}}{L_{s0}}i_d + \omega i_q + \dfrac{v_q}{L_{s0}} \\ \dfrac{di_q}{dt} = -\dfrac{R_{s0}}{L_{s0}}i_q - \omega i_d + \dfrac{v_q}{L_{s0}} - \dfrac{\omega \lambda_{m0}}{L_{s0}}. \end{cases} \quad (21)$$

where subscript "0" denotes a nominal parameter value. Applying the forward Euler approximation for a sampling period of T_s gives the uncompensated predicted current components as:

$$\begin{cases} \hat{i}_{d0}(k+1)\Big|_u = i_d(k) \\ \quad + \dfrac{T_s}{L_{s0}}\left(-R_{s0}i_d(k) + L_{s0}\omega i_q(k) + v_d|_u\right) \\ \hat{i}_{q0}(k+1)\Big|_u = i_q(k) \\ \quad + \dfrac{T_s}{L_{s0}}\left(-R_{s0}i_q(k) - L_{s0}\omega i_d(k) - \omega \lambda_{m0} + v_q|_u\right), \end{cases} \quad (22)$$

where $u \in \{V_0, \ldots, V_7\}$. This uncompensated model, which uses constant motor parameters, results in a prediction error at the end of each sampling period, as the motor parameters have a different value from the model parameters. This error can be calculated as:

$$\varepsilon_x(k)|_u = \hat{i}_{x0}(k) - i_x(k), \quad x \in \{d, q\}, \quad (23)$$

where $\hat{i}_x(k)$ is a predicted current component for kth sampling instance. This prediction is conducted at the $(k-1)$th sampling period. It should be noted that $i_x(k)$ is a current component of the measured motor currents. A key point that this method is based on is that although the prediction error differs for variant voltage vectors, the error for a given voltage vector is nearly constant during a short interval. In other words, for each voltage vector, the error between the predicted and measured values of the current components does not change significantly in comparison with the last time that particular voltage vector was applied. The prediction errors
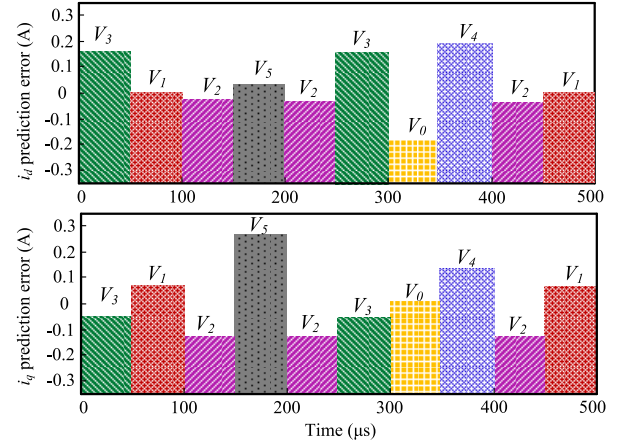

FIGURE 13. Prediction error for different voltage vectors.

of the d- and q-axis current components over ten successive sampling periods are shown in Fig. 13. The figure also indicates the voltage vectors that are applied. It can be seen that the errors are nearly equal for the same voltage vectors over a short period in which the rotor rotation can be neglected. For instance, the prediction errors are nearly equal for all three times that V_2 is applied to the motor during 0.5 s. Therefore, the last prediction errors corresponding to each voltage vector are stored in a look-up table. They are used to compensate for the prediction of the corresponding voltage vector as:

$$\hat{i}_x(k+1)\Big|_u = \hat{i}_{x0}(k+1)\Big|_u + \hat{F}_x(k+1)\Big|_u, \quad (24)$$

where the compensating term, $\hat{F}_x(k+1)\Big|_u$, is expressed as:

$$\hat{F}_x(k+1)\Big|_u = k_x\, \varepsilon_x|_{LUT:u}, \quad (25)$$

in which, k_x is a weighting factor between 0 and 1. The error values are taken from the look-up table.

Fig. 14 shows the simulation results of a PMS motor current components under the conventional MPC and the proposed Type III MFPC method in [58] when there is a 150% error in the inductance parameter. The effectiveness of the proposed method of [58] can be seen in this figure.

The look-up table is continually updated during every sampling period. However, if a voltage vector is not applied for a dozen sampling periods, its related error data in the look-up table cannot be updated. Therefore, as in Type I MFPC methods, this outdated data affects the predictions and cost function evaluations which in turn results in a deteriorated performance. To avoid this problem, a method has been proposed to estimate the error terms without using a look-up table [60]. The prediction errors of two consecutive sampling periods are used to estimate the compensation term for the prediction of the next sampling period. The method is explained for the current control of a surface-mounted PMS motor. In a space vector form, the predicted current vector
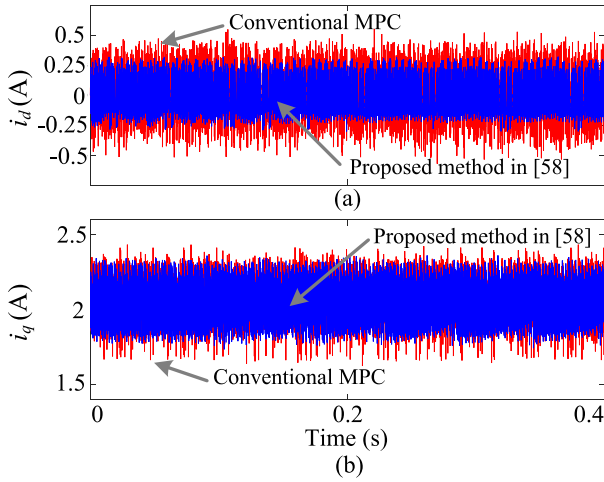
FIGURE 14. Steady-state simulation waveforms of the d- and q-axis components of a motor current under 150% error in the motor inductance values [58].
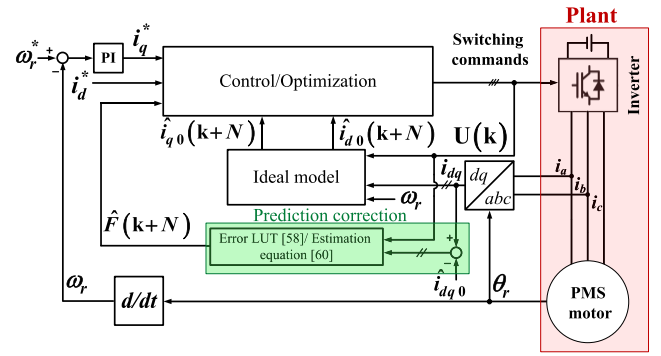

FIGURE 15. A block diagram of the predictive current control of PMS motors implemented based on Type III MFPC method.

using the initial motor parameters, $\hat{\bar{I}}_s$, is obtained as:

$$\hat{\bar{I}}_s (k + 1) = \bar{I}_s (k) + \frac{T_s}{L_{s0}} \left(\bar{U} (k) - R_{s0}\bar{I}_s (k) - j\lambda_{m0}\omega e^{j\theta_r} \right),$$

$$(26)$$

where $\bar{U}(k)$ is the inverter voltage vector applied at the kth sampling period. The prediction error that results from the model parameter mismatch can be expressed as:

$$\bar{\varepsilon}_I (k)|_{\bar{U}} = \left(\frac{T_s}{L_{s0}} - \frac{T_s}{L_s} \right) \bar{U} (k - 1)$$
$$- \left(\frac{R_{s0}T_s}{L_{s0}} - \frac{R_sT_s}{L_s} \right) \bar{I}_s (k - 1)$$
$$- \left(\frac{\lambda_{m0}T_s}{L_{s0}} - \frac{\lambda_mT_s}{L_s} \right) j\omega e^{j\theta_r} \qquad (27)$$

The error difference between the prediction errors of two consecutive sampling periods can be calculated as:

$$\overline{\Delta\sigma} = \bar{\varepsilon}_I (k) - \bar{\varepsilon}_I (k - 1). \qquad (28)$$

As the variations of the second and the third terms of (27) during a short period can be assumed negligible in comparison with the first term, substituting (27) into (28) results in:

$$\overline{\Delta\sigma} \cong \left(\frac{T_s}{L_{s0}} - \frac{T_s}{L_s} \right) \left(\bar{U} (k - 1) - \bar{U} (k - 2) \right). \qquad (29)$$

By defining K_1 as $T_s \left(1/L_{s0} - 1/L_s \right)$, it can be estimated without using the model parameters as:

$$\hat{K}_1 = \overline{\Delta\sigma} / \left(\bar{U} (k - 1) - \bar{U} (k - 2) \right). \qquad (30)$$

The second and third terms of (27) can be denoted by K_2 as:

$$K_2 = - \left(\frac{\lambda_{m0}T_s}{L_{s0}} - \frac{\lambda_mT_s}{L_s} \right) j\omega e^{j\theta_r}$$
$$- \left(\frac{R_{s0}T_s}{L_{s0}} - \frac{R_sT_s}{L_s} \right) \bar{I}_s (k - 1). \qquad (31)$$

The coefficient K_2 can be estimated as:

$$\hat{K}_2 = \Delta\bar{I}_s(k) - \hat{K}_1 \bar{U} (k - 1). \qquad (32)$$

The prediction error compensation vector can be expressed as:

$$\hat{\bar{F}}(k + 1) = -\hat{K}_1 \bar{U}(k) - \hat{K}_2, \qquad (33)$$

Finally, according to Fig. 7(a), the compensated predicted current vector is obtained as:

$$\hat{\bar{I}}_s(k + 1) = \hat{\bar{I}}_{s0}(k + 1) + \hat{\bar{F}}(k + 1), \qquad (34)$$

As mentioned before, since the method does not utilize a look-up table, it does not face the problem of stagnation of the look-up table updating. A block diagram of the latter two methods is shown in Fig. 15.

Disturbance observer (DOB) techniques for compensation of the predictions have also been adopted as another solution to improve the robustness against model mismatch. A method is proposed for FCS model predictive torque control of an induction motor using DOB [61]. The method not only improves the robustness against mechanical load disturbances but also compensates for model uncertainties in torque, flux and current predictions. The equations of rotor flux and stator current observers are given as:

$$\begin{cases} \dfrac{d\hat{\bar{\lambda}}_r}{dt} = \dfrac{L_mR_r}{L_r}\bar{i}_s - \left(\dfrac{R_r}{L_r} - j\omega \right).\bar{\lambda}_r \\ \qquad + K_{\lambda rp} \left(\bar{\lambda}_r - \hat{\bar{\lambda}}_r \right) + \hat{f}_{\lambda r} \\ \dfrac{d\hat{f}_{\lambda r}}{dt} = K_{\lambda ri} \left(\bar{\lambda}_r - \hat{\bar{\lambda}}_r \right), \end{cases} \qquad (35)$$

$$\begin{cases} \dfrac{d\hat{\bar{i}}_s}{dt} = \dfrac{T_sL_r}{L_m^2 - L_rL_s} \left(R_s\bar{i}_s - \bar{v}_s \right) \\ \qquad - \dfrac{T_sL_m^2R_r}{\left(L_m^2 - L_rL_s \right) L_r}\bar{i}_s - \dfrac{T_sL_m}{L_m^2 - L_rL_s} \left(\dfrac{R_r}{L_r} - j\omega \right) \bar{\lambda}_r \\ \qquad + K_{isp} \left(\bar{i}_s - \hat{\bar{i}}_s \right) + \hat{f}_{is} \\ \dfrac{d\hat{f}_{\lambda r}}{dt} = K_{isi} \left(\bar{i}_s - \hat{\bar{i}}_s \right), \end{cases} \qquad (36)$$

TABLE 1. Comparison of the reviewed MFP control methods in the field of power electronics.

Approach	Type I		Type II		Type III	
	1	2	1	2	1	2
Requires a model	No	No	Ultra-local data driven	Ultra-local data driven	Ideal model	Ideal model
Utilization of look-up table	Yes	Yes	No	No	Yes	No
Stagnation problem of look-up table	Yes	No	No	No	Yes	No
Relative Simplicity of algorithm	Very High	Middle	Middle	High	High	Low
Requires gain tuning	No	No	Yes	No	Yes	Yes
Computational burden	Low	Middle	Middle	Low/High*	Low	Middle
References	[23]-[31]	[32]-[34]	[35]-[43], [55]	[44]-[49], [54]	[56]-[61]	[62]-[71]

* Recursive solutions impose a high computational burden.

where L_s, L_r and L_m are stator, rotor and mutual inductances, respectively, and R_r is the rotor resistance. The vectors $\bar{i}$ and $\bar{\lambda}_r$ are the stator current and rotor flux space vectors, respectively. In addition, $\hat{f}_{\lambda r}$ and $\hat{f}_{is}$ are lumped disturbances of the rotor flux and stator current, respectively. The coefficients $K_{\lambda rp}$, $K_{\lambda ri}$, K_{isp} and K_{isi} are observer gains. The details of the observer gain design and the stability of the observer can be found in the paper [61].

Many classic methods have also been proposed to improve robustness of modulator-based predictive control [62]–[71]. They mostly operate as depicted in Fig. 7(b). As they have reached a relatively mature level and their approaches are outside the scope of this paper, i.e., MFP control, they are not discussed in detail here.

D. COMPARATIVE STUDY
In this subsection, the aforementioned methods of MFPC in motor drives and power electronics are briefly compared to one another. Three types of control method are represented in TABLE 1. Each type is divided into two approaches according to how it is implemented. It is worth noting that approach 2 of Type I control scheme comprises the methods based on look-up tables that adopt output variation estimation for the non-applied control inputs over a control period [32]–[34].

It is seen in the table that Type I methods do not require any mathematical model in their implementation. Instead, they adopt the data-driven look-up table that is updated continually. Type II method uses an ultra-local data-driven model for the predictions. The model has some uncertain terms that are estimated continually using the system input and output data. The plant parameters are rarely included in the model. However, the nominal parameters of the plant are exploited in the model used in Type III MFPC methods. There are some compensating schemes to correct the prediction errors aroused from using the ideal model instead of the model with actual parameters of the plant. Type II methods do not adopt a loo-up table so they are immune to the problem of data stagnation. Approach 1 of Type II and most of the methods of Type III MFPC need gain tuning. Care must be taken particularly in gain selection for observer-based methods. Improper gain tuning may result in instability issues. TABLE 1 also compares the methods in terms of the computational burden

imposed on the processor. The look-up table-based methods have the advantage of simplicity and low computational burden. In fact, their computation burden is nearly the same as the one of conventional FCS-MPC method, which is fairly low for a two-level three-phase inverter, owing to the development of high-speed processors. However, approach 2 of Type I needs extra computations for data reconstruction to overcome the stagnation problem. On the other hand, recursive solutions in some methods of Type II, approach 2, need a relatively higher computations compared to other methods of this type. Also, different kinds of observers used in approach 2 of Type III MFPC methods impose more computational burden to the processor compared to the solution adopted in the methods of approach 1 of this type.

VI. CONCLUSION
This paper studies different types of model-free predictive control methods in motor drives and power electronic converters. The brilliant advantage of these methods is nullifying the effects of model parameter mismatch in the predictive control. This parameter robustness results in improved performances and enhanced stable systems under different operating points. The paper also introduces a classification system for discussed methods that is based on their implementation and formulation. Different aspects are taken into consideration in order to draw comparisons between them. Type I control methods benefit from not requiring a model of the controlled plant. Furthermore, their calculation burden is low. However, these methods generally face stagnation of the data updating. Type II methods utilize an ultra-local model to make predictions. The model is derived from the input and output data of the control system. No look-up table is needed. Hence, Type II methods do not face the stagnation problem of data updating. Type III methods use the input and output of the control system to compensate for the prediction error or modification of the reference voltage vector. They need the nominal parameters of the control plant model.

It seems that the current measurement is the most challenging step in the implementation of the model-free methods. Any inaccuracy in the measurement affects the control method and derived ultra-local model (where required). Since the current variation over a sampling period should be measured in most of these methods, the measurement would be

more challenging at high sampling frequencies considering the acquisition latency. In addition to the short control interval, which results in difficulties in current variation detection, the inverter dead-time is another issue that should be dealt with. Another critical issue that needs to be further researched in light of model-free predictive control of motor drives is the robustness of the control system against load disturbances. Few papers have addressed this issue and have proposed some model-free solutions. Nonetheless, robustness against mechanical disturbances needs much more attention especially in speed-controlled plug-and-play motor drives.

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