1

Introduction

Power electronics applications with power levels in excess of 1 MVA, such as medium-voltage (MV) drives, are introduced in this chapter along with their market and technology trends. The commonly used control and modulation schemes are summarized. An introduction to model predictive control (MPC) is provided, which focuses on the control principle of MPC, and its advantages and challenges. This chapter concludes with a summary of the main results of the book and an outline.

1.1 Industrial Power Electronics

1.1.1 Medium-Voltage, Variable-Speed Drives

A typical representative of an industrial power electronic system is a variable-speed drive (VSD). The block diagram of such a system is shown in Fig. 1.1. It consists of an optional step-down transformer connected to the grid, an (active) rectifier, a dc-link, an inverter, and an electrical machine that drives the mechanical load. Additional components such as the controller, cooling, protection, and switchgear are part of the VSD system, but are not shown in the figure.

A VSD allows the operation of an electrical machine at an adjustable speed and at an adjustable electromagnetic torque. This is achieved by decoupling the grid electrically from the machine. The grid's *fixed* frequency ac quantities, which are either 50 or 60 Hz, are rectified to dc quantities, using either a diode rectifier or an active front end. An inverter transforms these dc quantities back to ac at a *variable* frequency, which is proportional to the rotational speed of the mechanical load. The dc-link acts as an energy storage element and decouples the rectifier from the inverter.

By adjusting the phase and amplitude of the rectifier voltages, the power flow between the grid and the dc-link can be manipulated. Similarly, on the machine side, by adjusting the phase and amplitude of the inverter voltages, the machine currents and thus the electromagnetic torque and magnetization of the machine are controlled.

MV VSDs use line-to-line rms voltages between 690 V and 20 kV, with typical voltages in the range 2.4–6.9 kV. Power ratings are usually in excess of 1 MVA. Because of the

Model Predictive Control of High Power Converters and Industrial Drives, First Edition. Tobias Geyer.

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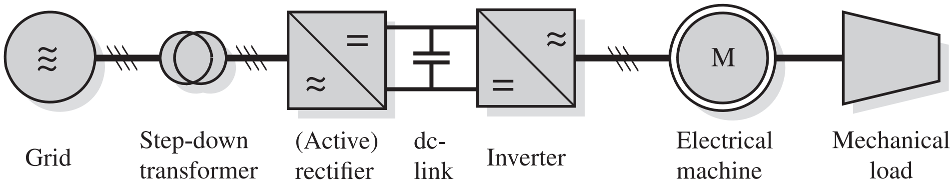
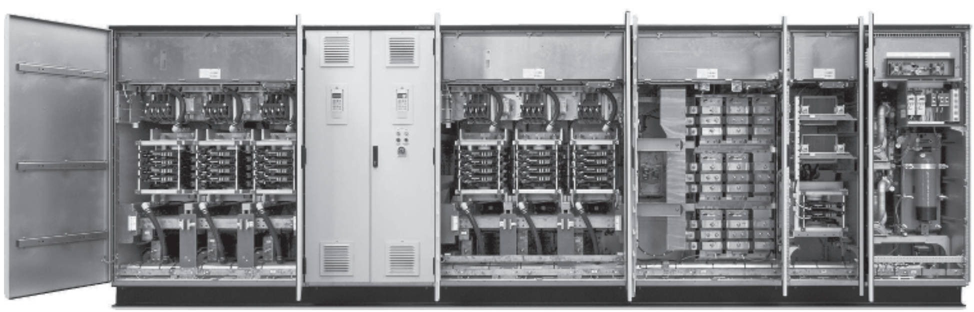


Figure 1.1 Variable-speed drive system

high currents and voltages, high-power semiconductor switches are used in the rectifier and inverter to commutate and control the currents. The semiconductor switches are operated such that the resulting currents approximate, albeit in a coarse manner, sinusoidal waveforms at steady-state operation.

As a well-known example for an MV VSD system, Fig. 1.2 depicts the ACS6000 and a typical MV induction machine. The ACS6000 is based on the three-level neutral-point-clamped (NPC) topology with water-cooled integrated-gate-commutated thyristors (IGCTs).



(a) ACS6000 with an active front end, the terminal and control unit, the inverter unit, the dc-link capacitor bank, a voltage limiter and the water cooling unit

(b) MV induction machine

Figure 1.2 Medium-voltage VSD system. Source: ABB Image Bank. Reproduced with permission of ABB Ltd

It is rated at an output voltage between 2.3 and 3.3 kV. In the single-drive configuration shown in Fig. 1.2(a), the ACS6000 provides 5–12 MVA. Up to 36 MVA is available in the multidrive configuration.

1.1.2 Market Trends

Sale of industrial high-power electronics is experiencing high annual growth rates. For MV drives, for example, the growth rate is consistently above 10% per year, with worldwide revenues of 3.7 billion USD in 2014 [1]. The high growth is driven by four major trends:

1.1.2.1 Electrification

Combustion engines are increasingly being augmented or replaced by electrical drives with the aims of increasing efficiency, reducing emissions, reducing fuel consumption, and removing the clutch and gear box to simplify the mechanical drive train. Examples of this include diesel-electric propulsion systems for trains, large mining trucks, tug boats, and large ships. In the oil and gas industry, gas turbines in compressor trains have traditionally required a starter motor, which—if designed accordingly—may also act as a helper motor, thus augmenting the gas turbine [2]. Furthermore, drives are about to fully replace gas turbines in large liquefied natural gas (LNG) compressor trains. In the low-voltage range, (hybrid) electric automotive vehicles constitute a major and rapidly growing trend.

1.1.2.2 Renewable Power Generation and Energy Storage

Wind turbines have traditionally relied on low-voltage, doubly fed induction machines. Modern wind turbines for the offshore market often exceed 3 MW and have adopted full back-to-back power conversion stages. For higher power ratings, MV generators are used [3]. Pumped hydro storage systems are typically based on MV doubly fed induction machines [4]. Utility-scale photovoltaic plants and large battery energy storage systems are based on MV power converters.

1.1.2.3 Industrial Drive Applications

For industrial drive applications, a distinction between general-purpose and special-purpose drives is generally made [5]. The latter term refers to highly demanding variable-speed and variable-torque applications, such as rolling steel mills, for which a back-to-back power conversion system is mandatory. General-purpose loads, however, such as large pumps, fans, blowers, and compressors, are predominantly connected directly to the grid using standard direct online—rather than inverter-duty—electrical machines. In order to increase their efficiency during partial load operation, many grid-coupled electrical machines are upgraded to VSDs in an retrofit effort [6].

1.1.2.4 Utility-Scale Power Electronics for the Grid

The power system is being overhauled by adding flexible ac transmission systems (FACTS) to it to achieve smart grid capabilities and to enhance the power flow [7, 8]. High-voltage dc (HVDC) systems are installed for bulk power transmission and to connect large offshore wind farms to the grid [9, 10]. Other notable examples for utility-scale, grid-connected power electronics include active voltage conditioners (AVCs) and uninterruptible power supplies (UPSs).

1.1.3 Technology Trends

Industrial power electronic systems in the MV range are influenced by four major technology trends:

1.1.3.1 Multilevel Converter

Over the past 50 years, there has been a continuous shift toward converters with a higher number of output voltage levels [11]. Starting from the two-level converter, the three-level NPC converter was introduced in the early 1980s [12]. Five-level topologies followed around the year 2000. Topologies with a higher number of levels have been available for a few years, which are either based on cascaded H-bridges or the modular multilevel converter (MMC) [13]. The main motivation to adopt these topologies is to achieve higher output power ratings. To keep the currents at bay, this implies increased voltage ratings. Another incentive is to avoid the step-down transformer on the grid side.

1.1.3.2 Product Business

The MV converter business is turning from a project business into a product business, in which MV converters can be bought off the shelf, and installed and commissioned quickly. A relatively large number of competitors coexist, competing with similar products and technologies.

1.1.3.3 Efficiency

Close to 100% efficiency and low losses are paramount for some applications, such as FACTS and photovoltaic systems.

1.1.3.4 Computational Power

The computational power of control hardware is growing exponentially. The observation underlying Moore's law, that the transistor count of integrated circuits doubles every 2 years, still holds true [14]. In industrial power electronics, a transition from relatively small digital signal processors (DSPs) to high-performance DSPs, often augmented by a large field-programmable gate array (FPGA), can be observed. In some cases, multicore processors are adopted as a corner piece of the control hardware.

1.2 Control and Modulation Schemes

1.2.1 Requirements

For industrial power electronic systems, the three pivotal requirements for control and modulation schemes are the following:

1.2.1.1 Low Harmonic Distortions per Switching Losses (or Frequency)

The trade-off between harmonic distortions on one hand and switching frequency or switching losses on the other hand is well known and fundamental to power electronics. The objective is to move this trade-off curve toward the origin, rather than to optimize along the curve; see Fig. 1.3. Lower harmonic distortions allow the reduction or removal of harmonic filters, or the use of standard direct online machines without derating them. Lower switching losses enable either boosting the inverter efficiency or increasing the rating of the inverter. On the grid side, low grid current distortions and compliance with grid codes are required.

1.2.1.2 High Controller Bandwidth

Fast closed-loop control is required to quickly control electrical machines in applications with rapidly changing loads or speed setpoints. This translates into the requirement of fast torque responses of a few milliseconds. Grid-connected power converters often require similarly fast current responses, particularly during power reference steps and faults.

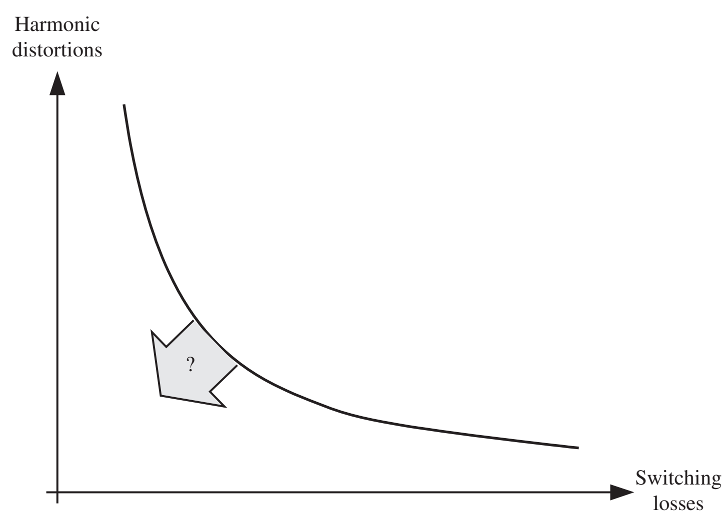


Figure 1.3 Fundamental trade-off between harmonic distortions and switching losses (frequency)

1.2.1.3 Accurate Load Power Control

The load power must be controlled. On the machine side, this implies control of the speed and/or electromagnetic torque of the ac machine. On the grid side, the real and reactive power must be controlled. Typically, the real power is manipulated such that the dc-link voltage is maintained at its nominal level, while the reactive power is set to zero.

Additional requirements include robustness to parameter variations, insensitivity to measurement and observer noise, as well as a high degree of fault tolerance. The computational burden of the control and modulation scheme must be sufficiently low to enable a successful implementation on the available control hardware.

1.2.2 State-of-the-Art Schemes

Almost universally, the controller of an industrial power electronic system is split into a load-side and a grid-side controller. Each controller is subdivided into two cascaded control loops. On the grid side, an outer loop controls the dc-link voltage and manipulates the real power, which is a setpoint for the inner loop. The latter controls the real and reactive power of the converter by manipulating the three-phase converter voltage.

On the load side of a VSD system, the outer loop controls the machine's speed by manipulating the torque reference. The inner loop controls the machine's electromagnetic torque and degree of magnetization by manipulating the voltage applied to the stator windings of the machine. For a grid-connected power electronic system, the load-side controller needs to be designed according to the attached load.

The voltage command of the inner control loop is typically translated into gating signals for the semiconductor switches using a carrier-based pulse width modulator (CB-PWM) [15] or a space vector modulator (SVM) [16]. In both cases, a fast inner control loop is often used, which is typically formulated in a rotating orthogonal reference frame. On the machine side, the reference frame is aligned with a flux linkage vector, leading to the concept of the so-called field-oriented control (FOC) [17, 18]. On the grid side, the reference frame can be aligned with the grid voltage, resulting in voltage-oriented control (VOC), or with a virtual flux vector, giving rise to virtual-flux-oriented control [19].

Lower harmonic distortions per switching frequency can be achieved by using OPPs. Since the related control problem is difficult to solve with a high-bandwidth controller, the commonly used approach is to resort to a slow inner control method, such as scalar or volts per frequency (V/f) control.

A third alternative is to replace the inner control loop by a hysteresis controller. Instead of a modulator, a look-up table is used, which decides the inverter switch positions. Noteworthy examples include direct torque control (DTC) [20] on the machine side, which controls the electromagnetic torque and the magnetization of the machine, and direct power control (DPC) [21] on the grid side, which controls the real and reactive power components. DTC and DPC lead to very fast responses of the controlled variables, but tend to give rise to pronounced harmonic distortions.

Figure 1.4 qualitatively characterizes these three standard control methodologies according to the two control requirements outlined in the previous section. A more comprehensive introduction to the requirements of control and modulation schemes and the state-of-the-art control methods is provided in Chap. 3.

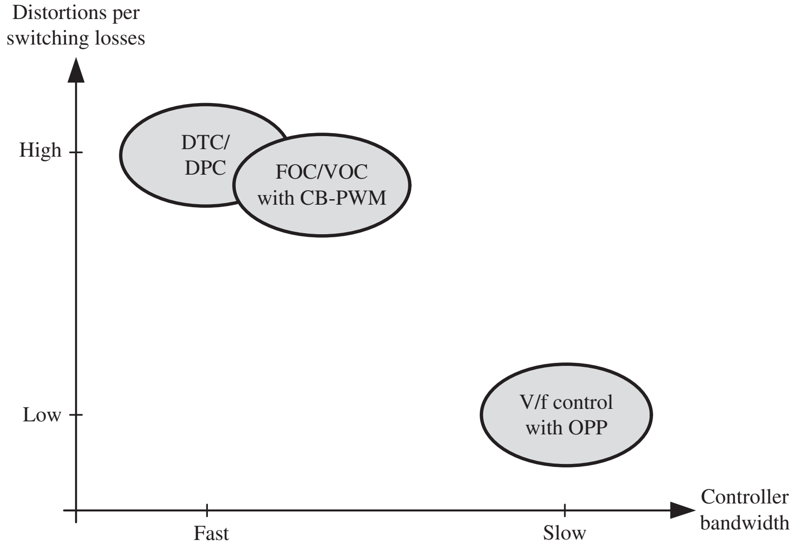


Figure 1.4 State-of-the-art control and modulation schemes for high power converters and industrial drives. These include hysteresis-based control schemes such as direct torque control (DTC) and direct power control (DPC), field-oriented control (FOC) or voltage-oriented control (VOC) with carrier-based pulse width modulation (CB-PWM) or space vector modulation (SVM), and volts per frequency (V/f) control with optimized pulse patterns (OPPs)

In summary, the majority of control and modulation methods used in industry today have the following three attributes: First, the overall multiple-input multiple-output (MIMO) control problem is divided into multiple control loops with single-input single-output (SISO) controllers. These control loops are arranged in a cascaded manner according to the dominant time constant of their loop. Second, the switching behavior of the power converter is neglected through the use of averaging. This allows the use of linear controllers, such as proportional-integral (PI) controllers. These controllers are typically augmented by an additional anti-windup mechanism and a rate limiter. Third, a pulse width modulation (PWM) stage is used to translate the averaged reference quantities into switching signals.

1.2.3 Challenges

Three major challenges can be identified for the design and real-time computation of high-performance control and modulation schemes:

1.2.3.1 Challenge 1: Switched Nonlinear Systems

The main building blocks of power electronic systems are linear circuit elements, such as inductors, capacitors, and resistors, which are complemented by semiconductor switches, which are either active (or controlled) switches or (passive) diodes. For different combinations of switch positions, different system dynamics arise, which can be described by linear functions of time for each combination. As a result, when controlling currents, fluxes, and voltages and manipulating the switch positions, power electronic systems constitute switched *linear* systems, provided that saturation effects of magnetic material, delays, and safety constraints can be neglected [22, 23].

In general, however, power electronic systems represent switched *nonlinear* systems. Nonlinearities arise, for example, when machine variables such as the electromagnetic torque or stator flux magnitude are directly controlled; both quantities are nonlinear functions of currents or flux linkages. For grid-connected converters, the real and reactive power is nonlinear in terms of the currents and voltages. Saturation effects in inductors and current constraints lead to additional nonlinearities.

Averaging [24, 25] is a viable way to conceal the switching behavior, provided that the pulse number is high. A paramount property of CB-PWM is that the ripple current is zero at regular sampling instants, facilitating the use of averaging. For pulse numbers well above 15, CB-PWM results in low current distortions. For low pulse numbers, however, averaging should be avoided and the switching nature of the power electronic system should be addressed by the control and modulation scheme to achieve low current distortions despite the low pulse number. For this, OPPs are the preferred choice. Since sampling instants at which the ripple current is zero in all three phases generally do not exist for OPPs, the concept of averaging is not suitable in the context of OPPs.

1.2.3.2 Challenge 2: MIMO Systems

The decomposition of the MIMO control problem into multiple SISO loops and the use of cascaded control loops greatly simplifies the controller design. This approach works well when the time constants of the cascaded control loops differ by at least an order of magnitude and while operating at (quasi) steady-state operating conditions. During transients and faults, however, the different loops often start interacting with each other in an adverse manner, limiting the achievable performance in terms of controller bandwidth and robustness, and complicating the tuning of the control loops.

For converters with LC filters, for example, the current controller is typically augmented by an active damping loop, with the purpose of dampening the system resonance introduced by the LC filter [26, 27]. To avoid large overshoots during transients, the current response has to be slowed down, for example, by rate-limiting the current reference. For an MMC, a plethora of quantities have to be either regulated along their references or kept at their nominal values. Because of the physical coupling of these quantities, the commonly used approach to control the MMC using multiple SISO loops leads to satisfactory performance only during steady-state operation. Interestingly, few results are available in the literature that showcase a fast dynamic operation of the MMC.

Therefore, for demanding applications, the MIMO characteristic of the power electronic system needs to be addressed by a MIMO controller. The benefit of doing so is a faster dynamic response during transients with less overshoot, as well as a simpler tuning and commissioning procedure.

1.2.3.3 Challenge 3: Short Computation Times

The third challenge results from the short sampling intervals of 1 ms and less that are typically used in power electronic systems. These short sampling intervals limit the time available to compute the control actions. To reduce the cost of power electronic converters sold in high volumes, cheap computational hardware is usually deployed as the control platform. Replacing existing control loops with low computational requirements by new and computationally more demanding methods exasperates the challenge of short sampling intervals. This is particularly the case for direct control methods that avoid the use of a modulator. These methods benefit from very short sampling such as 25 μs.

1.3 Model Predictive Control

Modern control theory formulated in the time domain emerged in the 1960s with the Kalman filter and the linear quadratic regulator [28, 29]. The state-feedback control law of the latter is obtained by minimizing a quadratic cost function over an infinite horizon, subject to the dynamic evolution of a linear system model. The first variants of MPC emerged in the process industry in the 1970s, focusing on nonlinear systems with physical constraints and on a finite horizon formulation.

Traditionally, since its inception 40 years ago, MPC has received little attention from the power electronics community and has been underutilized in this field. Other communities, such as the process industry, had already adopted this concept in the 1980s with great success [30]. Qin and Badgwell report in the late 1990s more than 4500 applications of linear MPCs in various industries, predominantly in refining, petrochemicals, and chemicals. Some applications can also be found in the areas of food processing, aerospace and defence, mining and metallurgy, and the automotive industry [30].

The reasons for the late adoption of MPC by the power electronics community include the limited processing power that was available in the last century to solve the control problem in real time and the very short time constants of power electronic systems necessitating the use of short sampling intervals. The switched (non)linear characteristic of power electronic systems complicates the controller design, analysis, and verification. Nevertheless, some initial investigations in MPC-related concepts for power converters were accomplished in the 1980s. Most importantly, these methods have been successfully implemented and experimentally verified [31, 32].

Over the past decade, however, MPC has rapidly emerged in power electronics. This progress has been facilitated not only by the tremendous increase of the computational power available in the controller hardware but also by the equally significant speed-up of the solvers that compute the solution to the underlying optimization problem. At the same time, complicated, new, multilevel topologies have emerged that require sophisticated control algorithms, the requirements imposed on power electronic systems have become more stringent, and, in the globalized world, companies are facing considerable pressure to retain or regain a competitive edge over their competitors.

1.3.1 Control Problem

Consider a general (power electronic) system with the input vector $\boldsymbol{u} \in \mathbb{R}^{n_u}$ and the output vector $\boldsymbol{y} \in \mathbb{R}^{n_y}$, as shown in Fig. 1.5. Both vectors may contain real-valued and integer components. Physical constraints in the form of actuator limits usually exist on the input. We refer to the system input $\boldsymbol{u}$ as the *manipulated* variable and the system output $\boldsymbol{y}$ as the *controlled* variable.

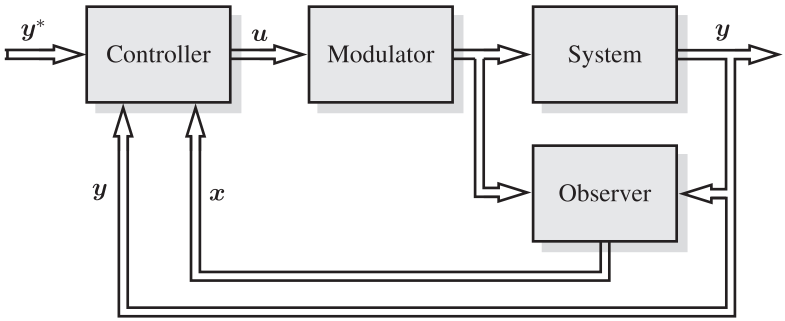


Figure 1.5 Controller regulating the system output $\boldsymbol{y}$ along its reference $\boldsymbol{y}^*$ by manipulating the system input $\boldsymbol{u}$. An optional modulator translates $\boldsymbol{u}$ into the converter switch position. The observer reconstructs the system state $\boldsymbol{x}$

We distinguish between two varieties of the control problem. When a modulation stage is added to the system, the manipulated variable is real-valued and typically a voltage reference. We refer to this as the *indirect* control problem. Averaging can be used to mask the switching phenomenon, and the use of integer variables in the system model can be avoided. On the other hand, when the modulator is removed, the *direct* control problem arises, with the manipulated variable corresponding to the converter switch positions. As a result, averaging cannot be employed, and the system model contains integer variables.

MPC requires the state vector $\boldsymbol{x} \in \mathbb{R}^{n_x}$ of the system. Components of $\boldsymbol{x}$ that cannot be measured, such as the rotor flux linkage, need to be reconstructed by an observer. Using a model of the system that is fed with the system input, the state and the output of the system can be estimated. By feeding back the difference between the measured and the estimated system outputs, observers can be designed such that the estimated states converge to the real states, provided that the observer is asymptotically stable and the system is observable.

The general control problem is to design a controller that achieves the following control objectives: The system output $\boldsymbol{y}$ must be regulated along its reference $\boldsymbol{y}^*$. This can be achieved by feeding back the measured output $\boldsymbol{y}$, comparing it with its reference $\boldsymbol{y}^*$, and manipulating the input $\boldsymbol{u}$ accordingly. This feeding back of the output to the input closes the loop and provides the feedback. The controller also has to guarantee stability and ensure that the constraints are met at all times (constraint satisfaction). These three objectives must be achieved despite disturbances and model uncertainties, necessitating a certain degree of controller robustness.

1.3.2 Control Principle

Over the past decades, MPC has evolved from a collection of control methods into a coherent control paradigm, perhaps even a control philosophy. Several thousand articles have been published on MPC. Despite the different MPC formulations and variations, five key attributes can be identified that are common to the MPC framework. These features are summarized in the following.

1.3.2.1 Internal Dynamic Model

MPC incorporates a dynamic model of the system to be controlled. Let $\boldsymbol{x} \in \mathbb{R}^{n_x}$ denote the state vector of the system, which—in general—includes real-valued and integer components. Starting from the current state, the internal dynamic model enables MPC to predict the sequence of future system states and outputs for a given sequence of manipulated variables.

The dynamic evolution of the system can be described in the continuous-time domain by the state-space representation

$$\frac{\mathrm{d}\boldsymbol{x}(t)}{\mathrm{d}t} = \boldsymbol{f}(\boldsymbol{x}(t), \boldsymbol{u}(t)) \tag{1.1a}$$

$$\boldsymbol{y}(t) = \boldsymbol{h}(\boldsymbol{x}(t), \boldsymbol{u}(t)), \tag{1.1b}$$

where (1.1a) is a nonlinear first-order differential equation that captures the evolution of the state vector over the time $t \in \mathbb{R}$. The outputs $\boldsymbol{y}$ are a nonlinear function $\boldsymbol{h}(\cdot, \cdot)$ of the state and input vectors.

In power electronics, when choosing voltages, currents, or flux linkages as state and output variables, the state-space representation (1.1) is usually linear and we can write it in the following well-known matrix form

$$\frac{\mathrm{d}\boldsymbol{x}(t)}{\mathrm{d}t} = \boldsymbol{F}\boldsymbol{x}(t) + \boldsymbol{G}\boldsymbol{u}(t) \tag{1.2a}$$

$$\boldsymbol{y}(t) = \boldsymbol{C}\boldsymbol{x}(t), \tag{1.2b}$$

with the system matrix $\boldsymbol{F}$, input matrix $\boldsymbol{G}$, and output matrix $\boldsymbol{C}$.

Most linear MPC strategies are formulated in the discrete-time domain, using a constant sampling interval T_s. The manipulated variable is restricted to changing its value only at the discrete sampling instants, that is at the time instants $t = kT_s$, where $k \in \mathbb{N} = \{0, 1, 2, \ldots\}$ denotes the time steps. For the continuous-time state-space model (1.2), the discrete-time representation can easily be computed. Specifically, by integrating (1.2a) from $t = kT_s$ to $t = (k+1)T_s$ and observing that $\boldsymbol{u}(t)$ is constant during this time interval and equal to $\boldsymbol{u}(k)$, we obtain the discrete-time state-space equation

$$\boldsymbol{x}(k+1) = \boldsymbol{A}\boldsymbol{x}(k) + \boldsymbol{B}\boldsymbol{u}(k) \tag{1.3a}$$

$$\boldsymbol{y}(k) = \boldsymbol{C}\boldsymbol{x}(k). \tag{1.3b}$$

The matrices $\boldsymbol{A}$ and $\boldsymbol{B}$ can be computed from their continuous-time counterparts according to

$$\boldsymbol{A} = \boldsymbol{e}^{\boldsymbol{F}T_s} \quad \text{and} \quad \boldsymbol{F}\boldsymbol{B} = -(\boldsymbol{I} - \boldsymbol{A})\boldsymbol{G}, \tag{1.4}$$

where $\boldsymbol{e}$ denotes the matrix exponential, and $\boldsymbol{I}$ is the identity matrix of appropriate dimensions. We refer to this as *exact* discretization.

If the matrix exponentials were to pose computational difficulties, the forward Euler approximation is often sufficiently accurate for short sampling intervals of up to several tens of microseconds in combination with short prediction horizons. In this case, the discrete-time system matrices are given by

$$\boldsymbol{A} = \boldsymbol{I} + \boldsymbol{F}\,T_s \quad \text{and} \quad \boldsymbol{B} = \boldsymbol{G}\,T_s. \tag{1.5}$$

The output matrix $\boldsymbol{C}$ remains the same when deriving the discrete-time system representation.

1.3.2.2 Constraints

Even in cases when the state-space equations are linear as in (1.3), constraints on inputs, states, and outputs

$$u(k) \in \mathcal{U} \subseteq \mathbb{R}^{n_u} \tag{1.6a}$$

$$x(k) \in \mathcal{X} \subseteq \mathbb{R}^{n_x} \tag{1.6b}$$

$$y(k) \in \mathcal{Y} \subseteq \mathbb{R}^{n_y} \tag{1.6c}$$

are usually present, which make the system nonlinear.

For the indirect control problem, when a modulator is added to the system, the real-valued manipulated variable is typically the voltage reference for the PWM. In this case, it is restricted to a bounded continuous set, such as

$$\mathcal{U} = [-1, 1]^{n_u}. \tag{1.7}$$

In contrast to this, for the direct control problem, the switch position of the converter constitutes the manipulated variable, which is constrained to a finite set of integers. A three-level converter, for example, is capable of synthesizing three voltage levels per phase. This characteristic can be captured by the input constraint

$$\mathcal{U} = \{-1, 0, 1\}^{n_u}. \tag{1.8}$$

For a five-level converter, one would have $\mathcal{U} = \{-2, -1, 0, 1, 2\}^{n_u}$. In a three-phase system, the dimension of the input vector is usually $n_u = 3$. The constraints on u are of a physical nature and thus *hard*, implying that they cannot be relaxed.

Constraints on states are sometimes added to prevent the system from operating outside of its safe operating limits. On the converter currents, for example, upper constraints on the absolute value of the currents can be imposed slightly below the trip level to avoid trips and damages due to overcurrents. These constraints are typically imposed in the form of *soft constraints*, which can be slightly violated, albeit at a high cost. Imposing soft rather than hard constraints on state variables is preferable to avoid numerical issues such as the control problem becoming infeasible.

Rather than regulating the controlled variables along their references, controlled variables can be kept within upper and lower bounds by imposing soft constraints on them. In the context of an ac machine, for example, upper and lower bounds can be imposed on the electromagnetic torque and the stator flux magnitude, similar to the hysteresis bounds in DTC.

1.3.2.3 Cost Function

The control objectives are translated into the cost function, which maps the sequences of future states, outputs, and manipulated variables into a scalar cost value. The cost function facilitates the assessment and comparison of the predicted impact the different sequences of manipulated variables (or scenarios) have on the system. This enables MPC to choose the most suitable scenario, which is the one that minimizes the value of the cost function.

A general definition of the cost function is

$$J(\boldsymbol{x}(k), \boldsymbol{U}(k)) = \sum_{\ell=k}^{k+N_p-1} \Lambda(\boldsymbol{x}(\ell), \boldsymbol{u}(\ell)), \tag{1.9}$$

which is the sum of the *stage costs* (or weighting functions) $\Lambda(\cdot,\cdot)$ over the *finite horizon* of N_p time steps. The stage cost penalizes the predicted system behavior, such as the deviation of controlled variables from their references and the control effort, such as the switching frequency. The stage cost is required to be nonnegative. The cost function uses the current state vector $\boldsymbol{x}(k)$ and the *sequence* of manipulated variables

$$\boldsymbol{U}(k) = [\boldsymbol{u}^T(k)\, \boldsymbol{u}^T(k+1)\ \ldots\ \boldsymbol{u}^T(k+N_p-1)]^T \tag{1.10}$$

as arguments. Based on these two arguments, and by using the internal dynamic system model, the future states and controlled variables can be predicted over the prediction horizon and penalized accordingly.

1.3.2.4 Optimization Stage

Minimizing the cost function subject to both the evolution of the discrete-time internal system model over the prediction horizon and the constraints gives rise to a constrained finite-time optimal control problem. The argument of the result is the optimal sequence of manipulated variables, $\boldsymbol{U}_{\text{opt}}(k)$. The control problem predominantly used in this book is based on a linear state-update equation, a nonlinear output equation, and constraints on the manipulated variable, which can be stated as

$$\boldsymbol{U}_{\text{opt}}(k) = \arg \underset{\boldsymbol{U}(k)}{\text{minimize}}\, J(\boldsymbol{x}(k), \boldsymbol{U}(k)) \tag{1.11a}$$

$$\text{subject to} \quad \boldsymbol{x}(\ell+1) = \boldsymbol{A}\boldsymbol{x}(\ell) + \boldsymbol{B}\boldsymbol{u}(\ell) \tag{1.11b}$$

$$\boldsymbol{y}(\ell+1) = \boldsymbol{h}(\boldsymbol{x}(\ell+1)) \tag{1.11c}$$

$$\boldsymbol{u}(\ell) \in \boldsymbol{\mathcal{U}} \quad \forall \ell = k, \ldots, k+N_p-1. \tag{1.11d}$$

In its most general form, with the system model being nonlinear and the system variables containing integers, the optimization problem underlying MPC is a mixed-integer nonlinear program (MINLP). Traditionally, the optimization problem has exclusively been solved online, requiring the solution to be available in real time.

Rather than solving the mathematical optimization problem for the given state vector at the current time step, the optimization problem can be solved offline for *all possible* states. Specifically, the so-called *state-feedback control law* can be computed for all states $\boldsymbol{x}(k) \in \boldsymbol{\mathcal{X}}$ [33–35], by treating the state vector as a parameter and using *multi-parametric programming*, which is akin to a generalization of sensitivity analysis. Time-varying references $\boldsymbol{y}^*$ and additional time-varying parameters can be treated similarly. The explicit control law can be stored in a look-up table, and the optimal manipulated variable can be read from the look-up table in a computationally efficient manner. We refer to this methodology as *explicit MPC*, in contrast to standard MPC.

Explicit MPC might appear to be an attractive choice for systems with very short sampling intervals, such as power electronic systems. It is computationally viable, however, only for systems with a low-dimensional state vector and with few time-varying references and parameters. This makes explicit MPC an inflexible approach that is ill suited to address problems of higher dimensions. The use of integer manipulated variables further complicates the solution. This approach is therefore not pursued in this book. For a summary on the literature on explicit MPC for power electronic systems, the reader is referred to [36]. For an in-depth review of explicit MPC, see [37].

1.3.2.5 Receding Horizon Policy

The solution to the optimization problem (1.11) yields at time step k an *open-loop* optimal sequence of manipulated variables $\boldsymbol{U}_{\text{opt}}(k)$ from time step k to $k + N_p - 1$. To provide feedback, only the first element of this sequence, namely $\boldsymbol{u}_{\text{opt}}(k)$, is applied to the system. At the next time step $k + 1$, a new state estimate is obtained and the optimization problem is solved again over the shifted horizon from $k + 1$ to $k + N_p$. This policy is referred to as *receding horizon control*. It is illustrated in Fig. 1.6.

In summary, the principle of MPC is that at each sampling instant the manipulated variable is obtained by solving a constrained optimal control problem over a finite prediction horizon. An internal dynamic model of the system is used to predict future states and controlled variables, using the current state of the system as the initial state. The control objectives are captured by a cost function, which is minimized subject to the evolution of the internal model and system constraints. The solution to the underlying optimization problem yields an optimal sequence of manipulated variables. A receding horizon policy is employed, that is, only the first element of this sequence is applied to the system, and the sequence of manipulated variables is recomputed at the next sampling instant over a shifted horizon. Hence, MPC combines (open-loop) constrained optimal control with the receding horizon policy that provides feedback and closes the control loop.

In this section, some fundamental principles of MPC have been introduced. For more details on MPC and its mathematical underpinnings, the reader is referred to the vast literature on MPC that has been accrued in the control community. Prominent survey papers include [30, 38–41], and the classic MPC textbooks are [37, 42–45].

1.3.3 Advantages and Challenges

In Sect. 1.2.3, we have identified three major challenges for the design and implementation of high-performance control and modulation schemes when applied to industrial power electronics. In light of the MPC principle outlined in the previous section, we discuss in this section the aforementioned challenges and the ability of MPC to address them. Of the three challenges, the characteristics of power electronic systems being switched nonlinear systems as well as MIMO systems can easily be addressed by MPC, while the third challenge, namely the short computation times available in power electronics, persists as a profound challenge for MPC.

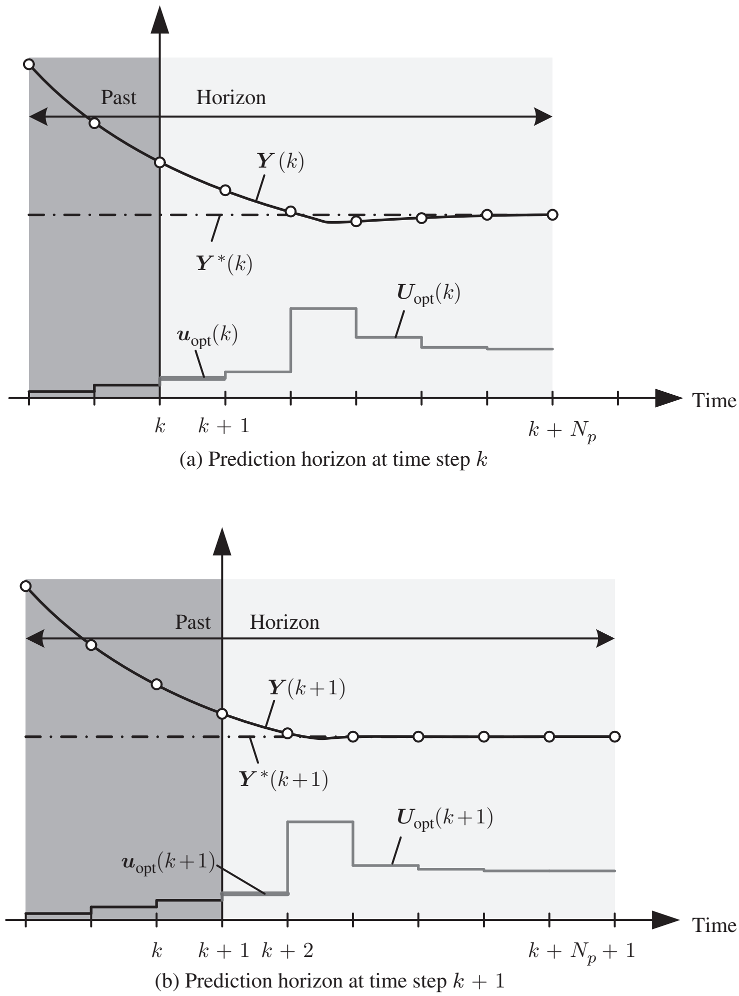


Figure 1.6 Receding horizon policy exemplified for the prediction horizon $N_p = 6$. The optimal sequence of manipulated variables $\boldsymbol{U}_{\text{opt}}$ is chosen such that the predicted output sequence $\boldsymbol{Y}$ tracks the output reference $\boldsymbol{Y}^*$. Out of the sequence $\boldsymbol{U}_{\text{opt}}$, only the first element $\boldsymbol{u}_{\text{opt}}$ is applied to the system

1.3.3.1 Advantages of MPC

First, MPC is formulated in the time domain rather than in the frequency domain. This enables MPC to address nonlinear systems in general—and switched nonlinear systems in particular—in a systematic way. This is achieved by incorporating the nonlinear system behavior into the MPC formulation in the form of an internal dynamic model. Averaging is not required, and the modulation stage can be included in the controller. Moreover, MPC is unique in its ability to systematically cope with hard constraints on manipulated variables, states, and controlled variables.

A vast body of literature has emerged on MPC for switched systems, which are sometimes referred to as *hybrid systems* [46]. Various modeling frameworks exist to describe such systems. This includes piecewise affine (PWA) [47] and mixed logical dynamical (MLD) systems [48] for the modeling of linear hybrid systems. These and other frameworks are reviewed and compared with each other in [49]. MPC can be readily formulated and solved for linear hybrid systems, as shown, for example, in [34, 37]. Many nonlinear (hybrid) systems can be approximated by linear hybrid systems.

The use of a cost function allows one to address diverse and possibly conflicting control objectives. These objectives can be prioritized, thus endowing MPC with the capability of—in effect—incorporating multiple control modes in one MPC controller. Furthermore, soft as well as rate constraints can be added to the control problem formulation.

Second, unlike PI-type controllers, MPC is a multivariable control method that is ideally suited for MIMO systems, particularly for complicated systems such as the various MMC topologies or converter systems with additional passive elements such as LC filters. Contrary to traditional frequency-domain control methods, additional active damping loops or anti-windup mechanisms are not required in MPC—one current control loop suffices. This simplifies the design, analysis, and tuning process. This benefit is sometimes overlooked. Breaking down the control problem into multiple and ideally decoupled SISO loops and designing individual PI loops for each of them might appear to be a straightforward and easy endeavor. In practise, however, these loops tend to interact with each other in an adverse manner, particularly during transients and faults, complicating the design and commissioning of the control loops. Ultimately, this limits the performance that can be achieved by the closed-loop system.

1.3.3.2 Challenges for MPC

Third, however, the effort required to solve the optimization problem underlying MPC is often considerable. Solving the optimization problem in the given time (usually within a part of the sampling interval) constitutes a major challenge. To extend the applicability of MPC from its traditional application domain of systems with long sampling intervals (e.g., in the process industry) to systems with short sampling intervals (e.g., in the automotive industry or power electronics) has spurred significant research effort along three avenues:

- The computation of the state-feedback control law, the explicit solution, for all possible states, references, and parameters. In many cases, however, the parameter space has proven to be of too high a dimension, leading to computationally intractable problems [50].
- The inception of optimization procedures and solvers with fast convergence rates and a low computational burden. Solvers are investigated that are well suited for implementation on embedded systems. For quadratic programs, for example, the fast gradient method appears to be particularly promising when executed on an FPGA, see, for example, [51–53].
- The investigation of new MPC problem formulations and solution methods that are tailored to the specific control problems that arise from power electronic systems. This is the research direction that is predominantly pursued in this book.

We conclude that the effort to formulate MPC control problems is often quite small, while the effort to solve the underlying optimization problem can be daunting. Unfortunately, the computational burden associated with solving the optimization problem underlying MPC increases exponentially with the length of the prediction horizon. Long prediction horizons yield, in general, a better closed-loop performance than short horizons. In particular, the infinite horizon case often ensures closed-loop stability, provided that a solution with a finite cost exists [42, 43]. However, long horizons exasperate the computational issue.

1.4 Research Vision and Motivation

The research vision behind this book is to devise control algorithms so as to maximize the effectiveness of power electronic systems—or equivalently—to design software to fully utilize the capability of power electronic hardware. For a three-phase, three-level inverter topology for example, the proposed control schemes are capable of reducing the switching losses in the semiconductor switching devices by up to 50% when compared to state-of-the-art schemes. In the MV arena, the switching losses are typically of a magnitude similar to the conduction losses; in some cases, they dominate over the latter. When the thermal cooling capability is the limiting factor, lower switching losses enable one to increase the current accordingly. As a result, the power rating of the hardware can be increased; for example, a 5 MVA inverter can be uprated to 6 MVA or more, and sold at an accordingly higher price tag, thus boosting the sales margin.

Alternatively, such control algorithms allow one to reduce the hardware requirements, for example, to reduce or remove harmonic filters, reduce dc-link filter capacitors, and allow standard direct online machines to be used instead of more expensive machines designed specifically for inverters. Moreover, the safe operating limits of the power electronic system can be translated into safety constraints, which can be added to the MPC problem formulation. Such constraints include, for example, upper constraints on the absolute value of the phase current. MPC ensures that these constraints are always met, thus ensuring a safe and reliable operation of the power converter.

Even more importantly, for MPC, a major part of the control effort is shifted from the design stage to the computational stage. As a result, on one hand, the design effort, the time to market, and the commissioning time are significantly reduced. On the other hand, however, a more powerful control hardware is sometimes required that consists not only of a DSP but often also of an additional FPGA that runs computationally intensive calculations. Nevertheless, the cost of an additional FPGA is in most cases negligible when compared to the cost savings that can be achieved when adopting MPC in the context of MV power electronic systems.

1.5 Main Results

The research objective underlying this book is to combine the advantages of DTC or DPC during transients with the benefits of offline computed OPPs during steady-state operation. As shown in Fig. 1.7, the aim is to devise fast current controllers that generate very low switching losses and distortions. To achieve an OPP-like performance at steady-state operation, very long prediction horizons are required. Smart algorithms are needed to solve the underlying

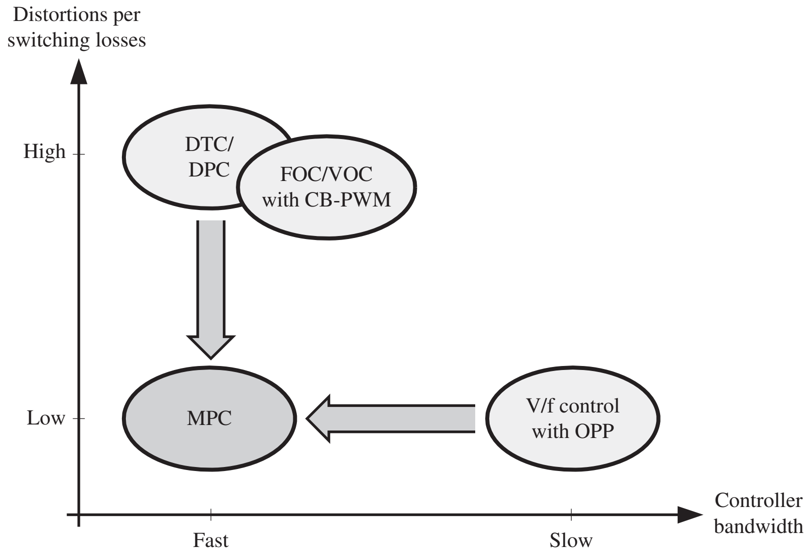


Figure 1.7 Model predictive control combining the merits of DTC or DPC during transients with those of OPPs during steady-state operation

optimization problem in real time, despite the combinatorial explosion of the number of possible solutions in the search space.

Over the past few years, three such schemes have been developed that combine the modulator and inner (current) control loop in one computational stage. These control schemes are based on the key notions of MPC—namely an internal model of the power electronic system to predict the system's response over a prediction horizon, a cost function to assess the predictions, an optimization stage to compute the optimal control action, and a receding horizon policy to provide feedback and robustness [43]. Despite these common characteristics, the three control schemes constitute complementary approaches.

The most commonly used MPC approach in power electronics is to directly manipulate the switch positions of the semiconductors and to formulate the control problem as a reference tracking problem [54]. This approach is often referred to as the *finite control set* (FCS) MPC. Any quantity of a power electronic system, such as a current, electromagnetic torque, angular speed, flux linkage, neutral point potential, real and reactive power, and so on, can be regulated along a given reference, as summarized in Chap. 4. The trade-off between tracking accuracy and switching effort can be adjusted by a tuning parameter. Favorable distortions per switching losses can be achieved when using long prediction horizons. The underlying optimization problem can be solved efficiently by adopting a branch-and-bound method from communication theory called *sphere decoding*, as shown in Chap. 5.

Model predictive direct torque control (MPDTC) is an advance on DTC, where the look-up table is replaced by an online MPC-type optimization stage. MPDTC was developed in early 2004, see [55, 56], experimentally verified on a 2 MVA drive in 2007 [57], and generalized in 2009 to further boost the performance by using even longer prediction horizons, see Chap. 7. Branch-and-bound methodologies can be used to reduce the computational burden by an order of magnitude, as will be shown in Chap. 10. Model predictive direct current control (MPDCC) is a derivative of MPDTC, see Sect. 11.1. Another derivative called model predictive direct balancing control (MPDBC) can be used to balance the internal inverter voltages in multilevel topologies [58].

Model predictive pulse pattern control (MP^{3}C) is based on OPPs [59] that are controlled in an MPC manner. Specifically, offline computed OPPs are modified online to account for transients and model uncertainties, as well as to provide feedback and robustness. MP^{3}C was originally devised for the machine-side inverter in electrical drives [60]. For those, MP^{3}C yields very fast control responses while drastically lowering the switching losses in the converter and/or the current distortions with respect to schemes based on CB-PWM, see Chap. 12.

Although these schemes are based on complementary approaches, they yield very similar closed-loop performances in terms of distortions per switching losses and controller bandwidth. In particular, for three-level MV inverters, the distortions per switching losses are reduced by up to 50% with respect to DTC and CB-PWM or SVM, while for five-level topologies they are reduced by 60% and more, see [61–63]. The current and torque response times are in the range of 1–2 ms. Therefore, at steady-state operating conditions, the resulting distortions per switching losses are similar to those obtained with OPPs. During transients, however, very fast current and torque response times are achieved, similar to deadbeat control.

In all three cases, the key to success was to devise control algorithms that are computationally highly tailored to the specific control problem at hand while utilizing the theoretical foundations of MPC. The standard optimal control approach provides only relatively small performance improvements and is computationally prohibitively demanding, as evidenced by some of the early publications, see, for example, [50, 64, 65]. Very long prediction horizons are required to achieve low distortions per switching losses. A particular effort was required to achieve the solution of these computationally very demanding MPC problems in real time on the commonly available drive control hardware.

1.6 Summary of this Book

The 15 chapters of the book are arranged in five parts.

Part I: Introduction

The first part of this book serves as an introduction, recalling basic power electronic terminology, concepts, and methods. This includes electrical machines, semiconductors, topologies, control, and modulation.

More specifically, following this introductory chapter, industrial power electronic systems are described in detail in Chap. 2. The chapter starts by reviewing some fundamental concepts that will be used throughout the book, such as the per unit system, orthogonal reference frames, and space vectors. State-space models of induction machines are derived, which describe the machines both during steady-state operation and transients. Power semiconductors, such as IGCTs and power diodes, are introduced and their loss models are stated. Three- and five-level voltage source inverters are described and modeled, and four industrial power electronics case studies are defined. The latter refer to MV VSDs and grid-connected converter systems.

After summarizing the requirements that electrical machines, the grid, and converters impose on control and modulation schemes, Chap. 3 reviews the major industrial control and modulation schemes that are used in high-power applications. CB-PWM is explained, its harmonic spectrum is analyzed, and the equivalence with SVM is recalled. A detailed account of OPPs is provided, which includes the derivation of the optimization problem and techniques to solve it in view of multilevel converters. The trade-off between harmonic distortions and the switching effort is shown analytically. In a last step, scalar control, FOC, and DTC are reviewed, which constitute the prevailing control methods used for machine-side converters. An appendix provides an introduction to mathematical optimization.

Part II: Direct Model Predictive Control with Reference Tracking

The second part of this book focuses on direct MPC methods with reference tracking of the output variables.

Chapter 4 introduces the concept of direct MPC by means of a predictive current controller with reference tracking and a prediction horizon of one step. This method is also commonly referred to as *FCS* MPC. Starting with a single-phase inverter with an RL load, the notions of the prediction model, cost function, optimization problem, and enumeration are reviewed. The MPC algorithm is subsequently generalized to the current control problem in three-phase inverter systems. A derivative of this method can be used to solve the torque and flux control problem of VSDs. The similarity between the current and torque controllers is shown by analyzing their cost functions. Moreover, the impact of the tracking error norm on stability is highlighted, and a method is reviewed to compensate for system delays.

Chapter 5 revisits the control problem of regulating the three-phase currents along their references by generalizing the control problem to long prediction horizons. For linear systems with integer inputs, an integer quadratic program results. It is shown that the optimal integer solution lies in a sphere centered on the unconstrained solution—the latter is obtained by relaxing the integer variables to real-valued variables. A branch-and-bound algorithm called *sphere decoding* is adopted that exploits this fact and allows one to quickly solve the underlying optimization problem even for relatively long prediction horizons, such as 10. The sphere decoding principle is illustrated with the help of two examples.

In the next chapter, the performance of long-horizon, direct MPC with reference tracking is evaluated. For an NPC inverter drive system with an induction machine, a horizon of 10 steps reduces the current distortions by 20%, when compared to the horizon 1 case. As a result, long-horizon direct MPC can outperform SVM and CB-PWM during steady-state operation. When an LC filter is added between the inverter and the electrical machine, the performance benefits of long prediction horizons become even more pronounced. Increasing the horizon from 1 to 20, for example, reduces the stator current distortions by up to a factor of 7.

Part III: Direct Model Predictive Control with Bounds

Direct MPC methods that maintain their output variables within upper and lower bounds are described in the third part of the book.

Chapter 7 is devoted to MPDTC. Similar to DTC, MPDTC manipulates the three-phase switch position to keep the controlled quantities, such as the electromagnetic torque, stator flux magnitude, and neutral point potential, within upper and lower bounds. A cost function that captures either the switching frequency or the switching losses is minimized. To render the underlying optimization problem computationally tractable for long prediction horizons, switching is only considered close to these bounds. In between the switching events, the switch position is frozen and the trajectories of the controlled variables are extended in an approximate manner, for example, by using linear or quadratic extrapolation. The cost function, the basic MPDTC algorithm based on enumeration, the corresponding search tree, and different methods of performing extrapolation are described and analyzed.

The closed-loop performance of MPDTC is investigated in Chap. 8. The benefit of adopting long prediction horizons is first shown for an MV NPC inverter drive system operating at steady state. Compared to DTC, the switching losses can be reduced by up to 60% for the same harmonic distortions. In the second part of this chapter, MPDTC is adapted to a five-level inverter drive system, for which the reduction of the harmonic distortions is the main focus. Compared to those of DTC, the harmonic current and torque distortions can be halved for the same—or a slightly lower—switching frequency. During torque transients, both DTC and MPDTC provide excellent results in both case studies.

The next chapter focuses on advanced topics regarding MPDTC. The bounds on the torque and stator flux magnitude form a target set, within which DTC and MPDTC maintain the stator flux vector. The offline computation of the control law facilitates the analysis and illustration of the decision-making process underlying MPDTC as well as the impact of different cost function formulations. The phenomenon of infeasible states or deadlocks is analyzed, and an effective deadlock resolution scheme is proposed. With the aim of inhibiting MPDTC from running into deadlocks, several such methods are proposed and their effectiveness is analyzed in the last part of the chapter.

The focus of Chap. 10 is on reducing the computational burden of MPDTC by an order of magnitude to enable the use of very long prediction horizons in real-time implementations. To this end, a branch-and-bound method is proposed that extends the MPDTC algorithm and computes the optimal switching sequence while exploring only a small part of the search tree. Upper and lower bounds on the cost function are introduced that allow the algorithm to identify and prune suboptimal parts of the search tree without explicitly exploring them. To limit the maximum number of computations, the optimization procedure can be stopped if the number of computational steps exceeds a certain threshold. Despite the possibility of suboptimal solutions, the performance impact is shown to be small, provided that the threshold is chosen carefully.

Chapter 11 generalizes the MPDTC concept and presents two derivatives. MPDCC controls the currents rather than the torque and stator flux magnitude. It is suitable for machine-side and grid-side converters. Thanks to the shape of its current bounds, it tends to achieve lower current distortions per switching losses than MPDTC. Model predictive direct power control (MPDPC) controls the real and reactive power components in a grid-connected converter setup. Both MPDCC and MPDPC are introduced in this chapter along with detailed performance evaluations. The chapter concludes with a comparison of the shape of the bounds of MPDTC, MPDCC, and MPDPC.

Part IV: Model Predictive Control based on Pulse Width Modulation

The fourth part of this book focuses on MPC methods that are based on PWM. These methods are complementary in their approach to the direct MPC techniques discussed in the previous two parts.

Chapter 12 proposes the concept of $\mathrm{MP^3C}$. By definition, offline computed OPPs provide the minimal current distortion for a given switching frequency. Integrating the three-phase voltage waveform of the OPP over time leads to the optimal stator flux trajectory. By manipulating the switching instants of the OPP, the stator flux vector of the electrical machine can be regulated along the optimal flux trajectory, thus achieving fast closed-loop control of the machine. Adopting the notion of MPC, in particular the receding horizon policy, two computational variations of $\mathrm{MP^3C}$ are proposed. The first one is based on a quadratic program and uses a long prediction horizon. The second variation is a deadbeat controller that is computationally simple and achieves almost as fast a torque response as DTC. To improve the performance during transients, additional switching transitions can be inserted when the stator flux error exceeds a certain threshold.

The performance of $\mathrm{MP^3C}$ is evaluated in Chap. 13 through simulations and experiments on MV drives. Simulation results are provided for an NPC inverter drive system during steady-state operation and transients. When compared to SVM operating at the same switching frequency, $\mathrm{MP^3C}$ reduces the current distortions by up to 50%. The benefit of inserting pulses during transients is illustrated. Experimental results for a five-level active NPC inverter drive system are shown in the second part of the chapter, with the MV induction machine operating at up to 1 MVA. A summary and discussion of the main benefits and characteristics of $\mathrm{MP^3C}$ is provided at the end of the chapter.

Chapter 14 focuses on an MMC that is controlled by an indirect MPC scheme with CB-PWM. The nonlinear MMC model is derived and linearized, based on which a linear MPC scheme is formulated. By manipulating the reference voltages of the modulator, the controller regulates the phase currents along their references, controls the branch energies, and imposes soft constraints on the branch currents, dc-link current, and capacitor voltages. A subsequent balancing controller maintains the capacitor voltages of the modules around their nominal values. The main benefit of this two-tiered controller is its ability to provide very fast responses during transients while operating the converter within its safe operating limits.

Part V: Summary

The last part of this book provides a performance comparison, summary of the results, conclusions, and an outlook for MPC of high power converters and industrial drives.

An extensive performance comparison is provided in Chap. 15, in which the principal direct MPC schemes discussed in this book are benchmarked with SVM. These direct control schemes include one-step predictive current control, MPDTC, MPDCC, and $\mathrm{MP^3C}$. When minimizing the switching losses in the cost function and adopting long prediction horizons, MPDCC tends to slightly outperform $\mathrm{MP^3C}$, albeit only in terms of harmonic current distortions per switching losses. Correspondingly, long-horizon MPDTC achieves lower torque distortions per switching losses than $\mathrm{MP^3C}$. An in-depth assessment of the proposed control and modulation follows, which discusses their benefits and challenges and highlights promising application areas for each method. The outlook proposes a number of possible future research directions.

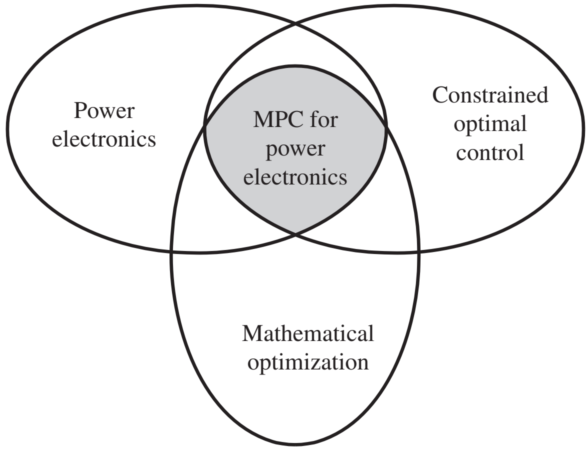


Figure 1.8 The focus of this book is on MPC for power converters and industrial drives, which is a field at the intersection of power electronics, constrained optimal control theory, and mathematical optimization

1.7 Prerequisites

This book is intended for researchers in academia and industry who are interested in an introduction to and a summary of the MPC methods available today for industrial power electronic systems. This includes university students at or above the MSc level, academics, and engineers in industry focusing on research and development. As shown in Fig. 1.8, the field of MPC for power electronics is at the intersection of power electronics, constrained optimal control theory, and mathematical optimization. Specifically, strong domain knowledge in power electronics is required to understand the system and the control problem at hand, MPC theory is required to formulate the control problem, and mathematical optimization is needed to solve it.

The reader is expected to be familiar with power electronics, modern control methods, and the basic notions of mathematical optimization. This includes three-phase machines, multilevel voltage source inverters, PWM, linear systems, linear algebra, state-space representation, discrete-time systems, optimal control, MPC, and quadratic programming.

Some of these prerequisites are covered by the following textbooks. For an introduction to high-power electronics and ac drives, the reader is referred to [66]. PWM is described and analyzed in depth in [15]. Detailed dynamic models of three-phase machines are derived in [67]. For a survey on multilevel converters, the reader is referred to [5, 11].

Linear systems and the state-space representation are described in detail in [68]. Discrete-time systems are explained in [69], while [70] is an excellent textbook on linear algebra. Regarding MPC, [43, 37] are recommended. An introduction to convex optimization is provided in [71]. For an encyclopedia on optimization, the reader is referred to [72].

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