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Review

Smart grid evolution: Predictive control of distributed energy resources—A review

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ABSTRACT

As the smart grid evolves, it requires increasing distributed intelligence, optimization and control. Model predictive control (MPC) facilitates these functionalities for smart grid applications, namely: microgrids, smart buildings, ancillary services, industrial drives, electric vehicle charging, and distributed generation. Among these, this article focuses on providing a comprehensive review of the applications of MPC to the power electronic interfaces of distributed energy resources (DERs) for grid integration. In particular, the predictive control of power converters for wind energy conversion systems, solar photovoltaics, fuel cells and energy storage systems are covered in detail. The predictive control methods for grid-connected converters, artificial intelligence-based predictive control, open issues and future trends are also reviewed. The study highlights the potential of MPC to facilitate the high-performance, optimal power extraction and control of diverse sustainable grid-connected DERs. Furthermore, the study brings detailed structure to the artificial intelligence techniques that are beneficial to enhance performance, ease deployment and reduce computational burden of predictive control for power converters.

1. Introduction

A smart grid is an electricity grid with bidirectional power/data flow [1], and integrated advanced information/communication, sensing, measurement and control technologies. These features facilitate the smart grid's flexible, reliable, resilient, stable, and sustainable operation [1,2]. The concept of a modern grid was motivated by the need to [2]: (1) improve efficiency of electricity production and distribution, (2) improve reliability, (3) empower electricity users with information to control their electrical power usage and costs, and (4) mitigate the climatic impacts of the electrical power industry. These led to industrial, research and regulatory actions for the evolving smart grid.

Four elements enable the smart grid to deliver the afore-described functionalities, viz., distributed energy resources (DERs), information communication technologies and sensors, vehicle-to-grid infrastructure, and electricity markets. Fig. 1 shows the electrical infrastructure at the generation, transmission, distribution and consumption stages of the grid. In the smart grid, these elements interact by the bidirectional dataflow of control signals and measurement data from sensors and smart meters over secure information and communication channels. Internet of things (IoT) facilitates the cyber–physical monitoring and control of smart grid elements (see Fig. 1).

The large number of control variables for the diverse smart grid elements and timescales of control require optimal control techniques. Among several candidate methods, model predictive control (MPC) has been gaining increasing popularity among researchers who work on different aspects of the smart grid. MPC facilitates the superior performance of the multivariable constrained optimization of several applications, namely: microgrids [3,4], smart buildings [5–7], grid ancillary services [8], industrial automation [9,10], plug-in electric vehicles (PEV) [11,12], and grid-connected DER power electronics converters [13].

Microgrids are intelligent and automated modular grids which operate autonomously, and can be connected to the main grid too [14]. They comprise DERs, distribution feeder lines and diverse kinds of loads. The application of MPC to AC and DC microgrids facilitates multivariable and multi-time-scale implementation in primary, secondary and tertiary hierarchies [15]. Primary control via MPC attends to voltage/current, frequency, power sharing, virtual impedance, ESS

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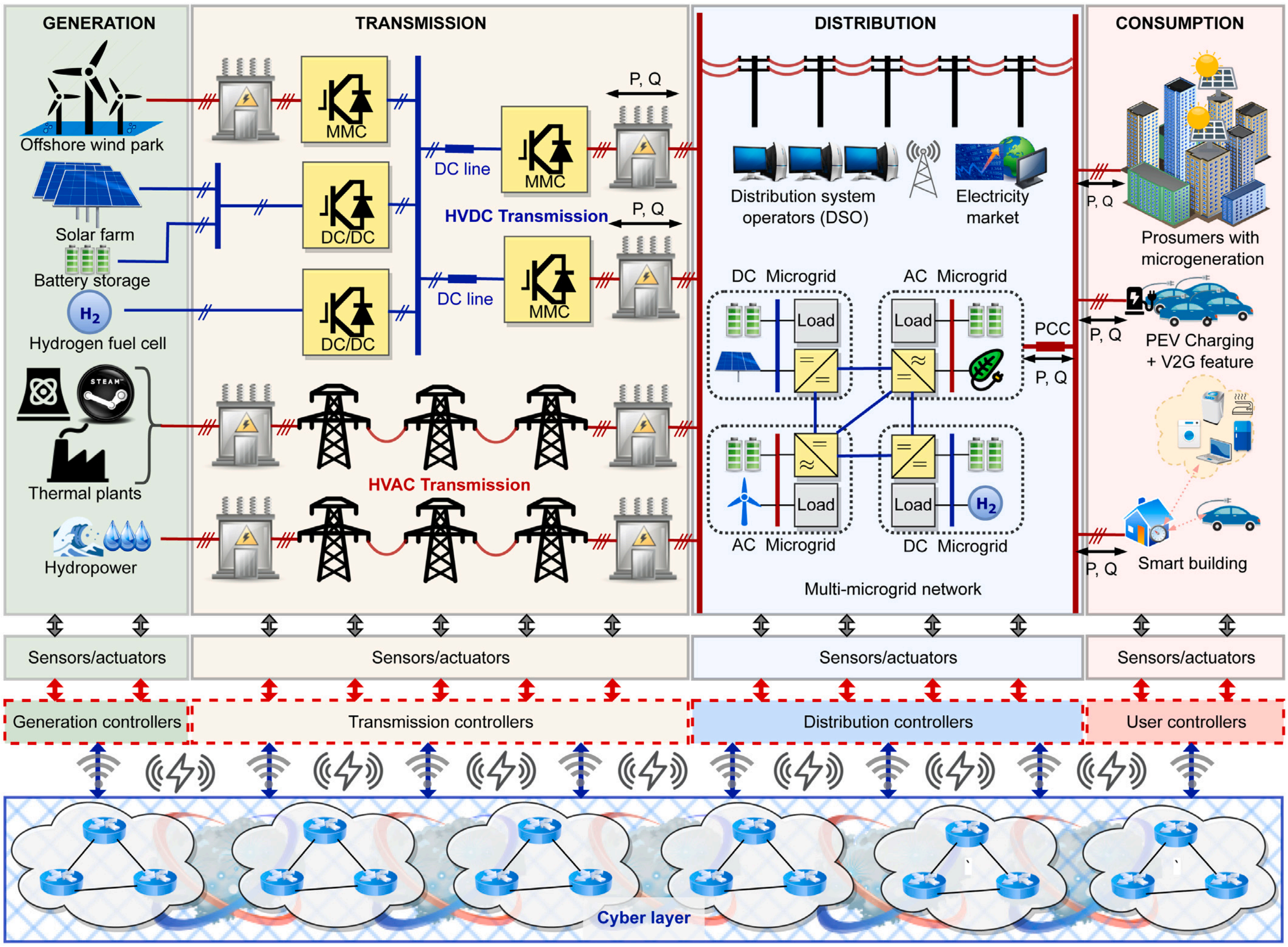


Fig. 1. Overview of the smart grid showing the cyber–physical layers.

management, and power quality control. Secondary control regulates the compensation of voltage/frequency deviations, optimal power flow and black start management [16–19]. The tertiary level attends to market participation [20], multi-microgrid coordination [21,22] and optimal power dispatch [22,23]. Details on these topics can be found in related review articles [3,4].

Smart building MPC applications are implemented for demand response, i.e., price-based and incentive-based programs [24]. Higher electricity prices are associated with peak-demand period, and incentivization is an added program for users who reduce loading during peak hours. It operates by the DSO broadcasting an emergency signal (with energy price and duration of scheduled load shedding) to all clients for load shedding or shifting. At this point, smart controllers (using convex optimization or other optimization techniques) at the user's end effect the request on electrical devices. Demand response problems can be solved with MPC formulated as convex optimization problems (for improved stability and robustness) [24]. MPC can provide optimal allocation of power references for building energy flexibility (from energy storage, heat pump with thermal storage, plug-in EVs), and load power consumption [25]. Furthermore, additional objectives including pricing and CO_2 intensity (of hybrid energy sources) can be included in the cost functions [26].

Ancillary services are specialty services which facilitate reliable power supply in the grid. They are supplied by specialty providers to the system operator [27]. The most essential are frequency and voltage control services. Frequency control involves maintaining the frequency at regulatory levels by ensuring balance between active power generated and consumed [27]. The deployment of positive and negative frequency control reserves helps to achieve this goal. Voltage control service regulates participating devices which generate or absorb reactive power as a means to control voltage levels [28–30]. As the smart grid accommodates an increasing number of converter-interfaced DERs, MPC becomes beneficial to implement optimal frequency [31,32] and voltage control [33,34]. The predictive control of a large number of heterogeneous thermostatically controlled loads to provide ancillary service was also validated in [35]. It was shown that by engaging ancillary services within an MPC framework, the microgrid operating expenses can reduce by almost 25% [8].

MPC has been also demonstrated for the performance enhancement of high power, medium voltage drives used in industrial machines. In particular, it has faster and more robust responses than linear cascaded control schemes like field-oriented control [36]. Nonetheless, with high power drives, lower power converter switching frequencies are necessary to reduce the switching losses. Hence, multi-step (or long) prediction horizons are favored [37,38]. It was reported that an algorithm with comparable performance to the multi-step methods, namely, MPC with *optimized pulse patterns*, has been commercially deployed by ABB [10].

The optimal scheduling of plug-in electric vehicle (PEV) charging constitutes a multi-objective problem with constraints, and can be solved with predictive control. The objectives are to charge numerous PEVs connected to the distribution network, while maintaining the bus voltage level within the regulatory limits. These are considered in different studies which carry out combined charging scheduling and power control [39], plug-and-play [40], and demand response participation [41]. The cyber–physical configurations of PEV charging stations can be grouped into three: centralized, hierarchical [42], and decentralized [11,12]. Centralized control configuration has a central control hub where all optimization control for the operation of the numerous charging stations is carried out subject to several constraints including grid constraints and user constraints. This method faces severe limitations as the scale of charging points increases. Therefore, hierarchical centralized control provides a solution to the challenge of scale by reducing both processing hardware and communication requirements [11]. This involves grouping the charging stations into local charging units, area charging centers and wide area charging centers. The decentralized configuration operates with a more democratic control structure; each charging unit has the ability to communicate intelligently (through is onboard controller) with the grid and dictate how it wants to operate. Customer preference can be prioritized and communicated to the distributed system operator. Also, the control scheme is more robust to communication channel disturbances than centralized and hierarchical control methods.

The smart grid has several options for the sustainable distributed generation of electrical energy from DER such as solar photovoltaic (PV), wind, fuel cell, ocean, tidal, wave, bioenergy, and energy storage systems (ESS). These DERs usually need to be operated at their operating points of maximum power extraction. Hence, MPC enables high performance control of power electronic conversion for solar photovoltaic (PV) systems [43], wind energy conversion systems (WECS) [44], fuel cells [45] and energy storage systems (ESS) [13].

Authors in [46] studied MPC applications for PV systems only, and did not provide further information for other renewable sources. The review of optimal energy management in microgrids [47], and MPC for microgrids in primary, secondary and tertiary hierarchical levels were reported in [3,4]. However, only microgrid applications were covered. The use of MPC in optimal energy management was reviewed by [48]; but it only applies to the tertiary control of energy sources. The review of MPC for power converters in electric drives was reported in [36]; but it mainly applies to industrial drives. A recent review covered MPC's applications to microgrid DERs [49]. This study investigated MPC's high performance control of PV, wind and energy storage systems. Nonetheless, the study excludes several mathematical details, and does not include grid-connected converters and artificial intelligence-based MPC for DERs.

Motivated by the literature gap, the objective of this article is to provide a comprehensive review on the state-of-the-art of MPC applications to power electronic converter interfaces for DERs' grid integration. The scope of this study covers the following related fields: (i) renewable energy (and energy storage) technologies [50,51], and their integration in modern power systems [52]; (ii) new smart transmission grid technologies for ancillary services support in power systems [53–55]; (iii) smart distributed and autonomous energy systems [56], including AC and DC microgrids [3,4,57], and DERs [58]. The rest of the article is organized as follows: The introduction to MPC is discussed in Section 2. The applications of MPC to converter-interfaced DERs is covered in Section 3. The predictive control of grid-connected DER-converters is covered in Section 4. Artificial intelligence techniques for predictive control are discussed in Section 5. MPC-based control of virtual power plants and grid ancillary services is discussed in Section 6. Open issues and future trends are discussed in Section 7. Finally, the conclusion is drawn in Section 8.

2. Preliminaries on MPC for DER systems

Fig. 2 depicts a typical DER (comprising wind, solar PV, fuel cells and battery energy storage (BESS)) and interfacing systems which facilitate its connection to the grid. The stages of the system include primary energy source and storage, the interfacing power converters (back-to-back DER-side and grid-side), and grid-connected filter. At the DER, MPC can regulate maximum power-point tracking (MPPT) for optimal power extraction from the DER. The grid-end converter MPC regulates optimal power exchange with the grid. Bidirectional energy flow is necessary for energy storage charging and discharging cycles (wind turbines with regenerative capability also cause bidirectional flow). The focus systems in this study are the power converters directly connected to the DER, and the grid-connected converter, as highlighted in Fig. 2.

2.1. Introduction to model predictive control

Model predictive control (MPC) is a nonlinear control technique which emerged in the process industry in the 1970s [10]. It has emerged as a popular control technique with application in cross-disciplinary domains. This is due to its high dynamic performance, and capability for constrained optimization [3]. Over the past half-century, it has found industrial relevance to petrochemical, aerospace and automotive processing and manufacturing.

MPC is an optimization-based control technique that utilizes a dynamic process model to predict the future evolution of the system's state and output. The control objectives are formulated as optimization problem with the system inputs being the optimization variables. At each time step, this problem is solved over the prediction horizon whereby the process model yields the effect of the input sequence on the objective function. Finally, the first input value is applied to the real system. MPC has the inherent ability to handle multiple-input and multiple-output control problems and takes constraints regarding actuators, states, and outputs into consideration. For all MPC algorithms, there are common elements, namely: the prediction model, and objective function (or cost function in the case of minimization problem). These will be discussed in the following.

2.2. System prediction model

The generic discrete model of a physical system or process requiring regulation is given by (1), where $k \in \mathbb{N}$ is the discrete time step, $\mathbf{x}$ is the state vector (with state variables $x \in \mathbf{x}$), $\mathbf{y}$ is the output vector (with output variables $y \in \mathbf{y}$).

$$\mathbf{x}(k+1) = \mathbf{f}(\mathbf{x}(k), \mathbf{u}(k)), \tag{1a}$$

$$\mathbf{y} = \mathbf{x}(k). \tag{1b}$$

Given a sequence of input variables over a prediction horizon $N_p \in \mathbb{N}$ time steps. We can define a sequence of possible control input states that the controller could implement as [10,59]:

$$\mathbf{U}(k) = [\mathbf{u}^T(k) \;\; \mathbf{u}^T(k+1) \;\; \dots \;\; \mathbf{u}^T(k+N_p-1)]. \tag{2}$$

The predictive controller seeks an optimal control input sequence

$$\mathbf{U}_{\mathrm{opt}}(k) = \min_{\mathbf{U}(k)} J, \quad \text{s.t. } x(k) \in \mathcal{X}, u(k) \in \mathcal{U} \tag{3}$$

where J is the cost function that captures the control objectives for the optimization problem, $\mathcal{X}$ and $\mathcal{U}$ are the state and input constraints sets respectively. The control objective would be to track a reference $\mathbf{y}^*(k+1)$ by minimizing the tracking error magnitude as [10]

$$J = \sum_{k=1}^{k+N_p-1} \|\mathbf{y}^p(k+1) - \mathbf{y}^*(k+1)\|_{\mathbf{Q}}^2 + \lambda_{\mathrm{u}} \|\Delta u(k)\|_2^2, \tag{4}$$

where $\mathbf{Q}$ is the penalty matrix on the tracking error, $\mathbf{y}^p$ is the predicted output which is derived from the system's mathematical model, $\mathbf{y}^*$ is the reference, λ_{u} penalizes the control effort $\Delta u(k)$, and $\Delta u(k) := u(k) - u(k-1)$. MPC is a receding horizon scheme; therefore, only the first term of the sequence $\mathbf{U}_{\mathrm{opt}}(k)$ is applied to the plant. Recalculation of the next sampling instant's predictions and optimal sequence is done after updated estimates of the states. Fig. 3 depicts how MPC is applied to a typical plant in the smart grid.

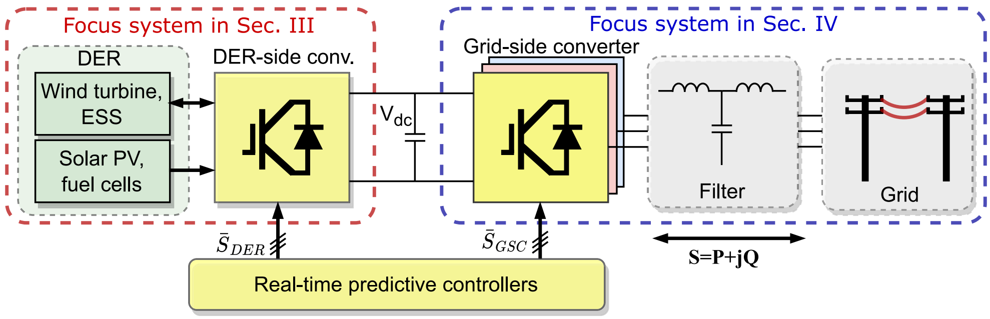


Fig. 2. Power electronic conversion system for grid-connected DER.

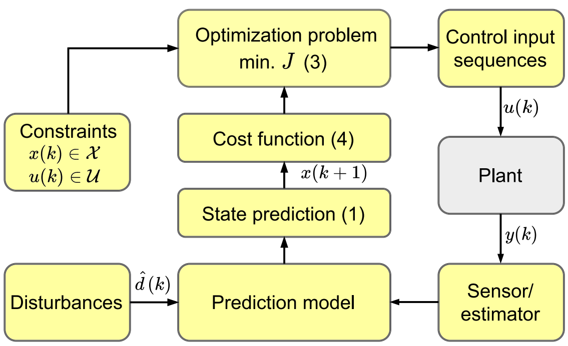


Fig. 3. Model predictive control of a plant in the smart grid [5]. Plant represents different DERs, grid-connected filters and electrical loads.

3. Predictive control of distributed energy resources

The smart grid has several options for the sustainable distributed generation of electrical energy from DER such as solar photovoltaic (PV), wind, fuel cell, ocean, tidal, wave, bioenergy, and energy storage systems (ESS). These DERs need to be operated at their operating points of maximum power extraction. Hence, MPC enables optimal high performance control of power electronic conversion for solar photovoltaic (PV) systems [43], wind energy conversion systems (WECS) [44], fuel cells [45] and energy storage systems (ESS) [13]. Fig. 4(a) depicts the MPC-based regulation of modular multi-level power converters (MMC) for high voltage DC (HVDC) transmission of electrical energy from offshore wind farms to the grid. MMC inner structure is depicted in Fig. 4(b).

In the following subsections, the theory and application of MPC to power electronic converters for WECS, ESS, fuel cells and solar PV will be covered in detail. Table 1 presents comparative details of MPC applications to different types of DER converters.

3.1. Predictive control of generator-side WECS converters

In this subsection, applications of MPC to DER-side power converters for wind energy conversion systems (WECS) will be discussed in detail.

Electricity generated from wind turbines in 2020 was 1270 TWh, representing 3.7-fold increase from 2010 [111]. This is because between 2010 to 2020, the cost of generating electricity from onshore wind, and offshore wind systems fell by 56% and 48% respectively [112]. Wind generators are commercially made as squirrel-cage induction generator (SCIG), wound rotor induction generator (WRIG), doubly-fed induction generator (DFIG), permanent magnet synchronous generator (PMSG) and wound rotor synchronous generator (WRSG) [113]. Among these, PMSG and DFIG are commonly studied in the literature, and will be further discussed in this article. This study focuses on the application of predictive control to WECS; details on WECS hardware configurations can be found in [113].

Fixed-speed ($\pm 1\%$) generators are the oldest form of WECS, and they have limitations which include [113]: (i) lower energy conversion efficiency, (ii) wind speed variability impacts grid frequency directly, (iii) mechanical stresses on the WECS mechanical components during grid faults. On the other hand, variable-speed WECS (especially those with full-variable speeds of $0-100\%$), overcome these challenges by (i) higher conversion efficiency, (ii) decoupling the wind speed variations from grid frequency, (iii) reducing wear and tear of mechanical components (e.g., a PMSG can be directly coupled without a gearbox), (iv) improving power quality, and (v) reducing acoustic noise [114]. Nonetheless, because they require power electronic converters, they cost more than their fixed-speed counterparts. The generator-side converter – voltage source rectifier (VSR) – facilitates the operation of the wind-turbine generator at variable wind speeds/frequencies, therefore, extending the efficiency of wind energy conversion.

3.1.1. Permanent magnet synchronous generator

PMSGs have their rotor excitation supplied by permanent magnets, saving about 30% of generator losses (arising from DC excitation) [115]. Thus, they have high power density and efficiency, with low lifetime costs. PMSGs used for direct-driven WECS are usually smooth-surface multi-pole machines, also having negligible salience [116]. There are two common converter topologies on the WECS generator-side [117]: (i) voltage source active-front-end rectifier (with maximum power-point tracking (MPPT) control), and (ii) passive rectifier and DC/DC boost converter (with MPPT control).

MPC for multi-level boost converter for PMSG WECS. The MPPT algorithm maximizes the reference speed to the PMSG for variable wind speed.

Control objectives and cost function: Let us consider a generic voltage source converter with N_L voltage levels (where N_L is a positive integer greater than or equal to 2). The control objectives for the direct model predictive power control (DMPPC) of the N_L-level converter include: (i) the tracking of the power reference; (ii) balancing of the DC-link capacitor voltages (in the case when $N_L > 2$), and (iii) minimization of the control input (switching frequency). The DMPPC scheme will be regulated by the cost function J_p in Table 2, where each term represents objectives (i)-(iii) respectively. Further details on the model can be found in [118].

Direct model predictive torque control (DMPTC) of PMSG WECS. First, the classical DMPTC is discussed, and two variants are introduced afterwards.

Control objectives and cost function: Let us consider a generic rotor-side voltage source converter (VSC) with N_L voltage levels (where N_L is a positive integer greater than or equal to 2). The control objectives for the DMPTC of the N_L-level converter are (i) tracking of the torque reference, (ii) tracking of PMSG current reference, (iii) maintenance of maximum torque T_e^{max} constraint, and (iv) balancing of the DC-link

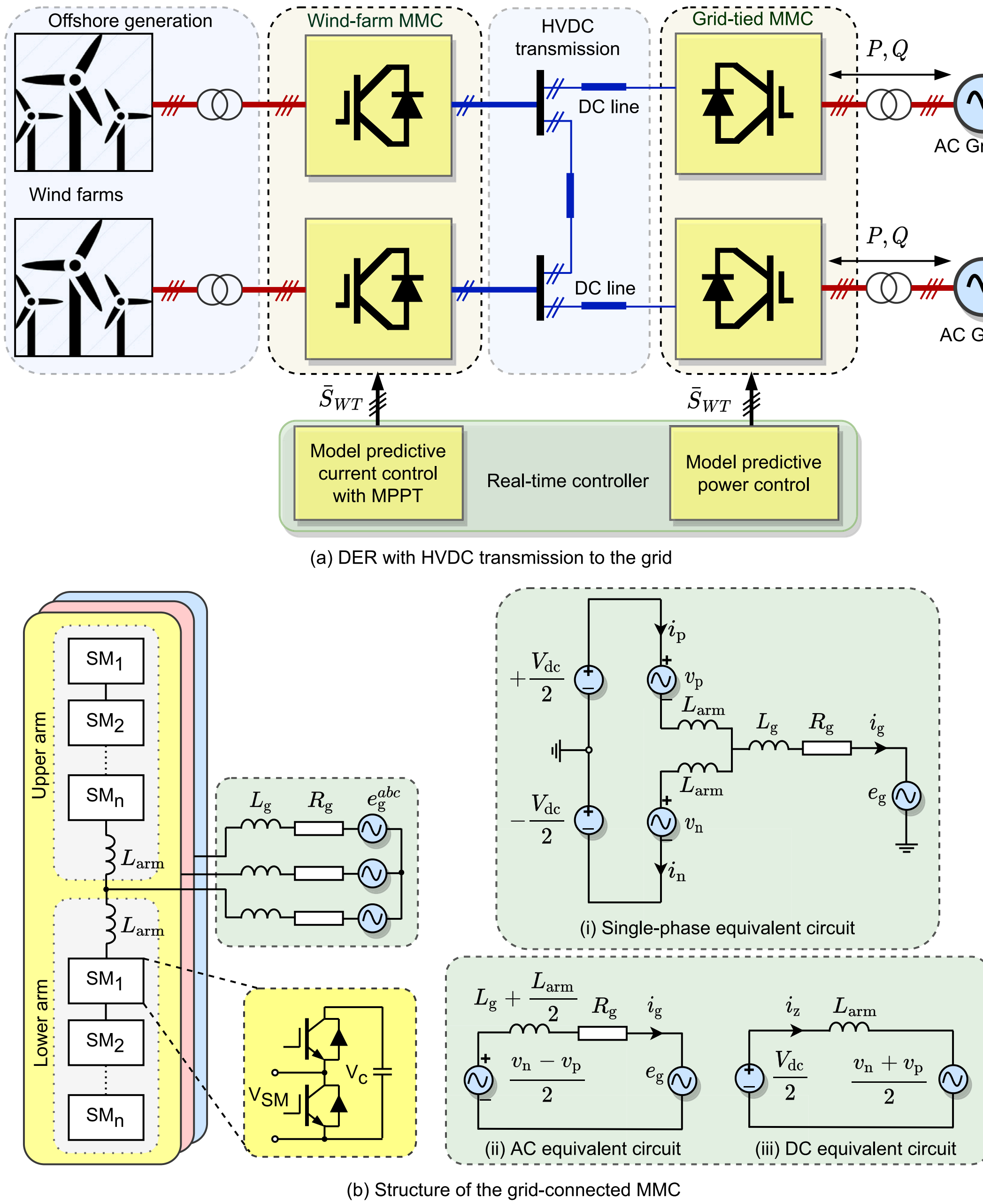


Fig. 4. Predictive control of grid-connected DER with HVDC transmission.

capacitor voltages (in the case when $N_L > 2$). The DMPTC scheme will be regulated by cost function J_{DMPTC} in Table 2 where each term represents objectives (i)-(iv) respectively.

Classical DMPTC: Consider the case of a two-level converter; DMPTC will evaluate the cost function for the finite set of applicable voltage vectors $\mathbf{u}_i \in \mathbf{U} := \{\mathbf{u}_0, \mathbf{u}_1, \ldots, \mathbf{u}_7\}$. A single optimal voltage vector $\mathbf{u}_{opt}$ is applied over the entire sampling duration T_s.

$$\mathbf{u}_{opt} := \arg\min J(\mathbf{u}_i)(i_m(k+1), T_e(k+1)) \tag{5}$$

Nonetheless, this method has limitations because the chosen vector could be distant from the ideal (which may lie in-between the finite voltage vectors), resulting in relatively high ripples. Thus, the dual-vectors DMPTC scheme gives a better performance.

Dual-vectors DMPTC: This is an improvement over the classical DMPTC through the application of two voltage vectors within a sampling interval, which has two variants. The first utilizes an active and a zero vector [119]. Through duty cycle optimization, a fraction of control period is designated for an active (non-zero) voltage vector and the remaining time for a zero vector. This method faces severe limitations in that the resultant voltage vector always lies in phase with the active vector, resulting in sub-optimal phase [120]. The second variant utilizes two active voltage vectors, producing optimal length and phase, and with lower ripples [121,122]. The latter selects the optimal pair from any neighboring active vectors. Let the chosen optimal active vectors be $\{\mathbf{u}_q, \mathbf{u}_r\}$. Their optimal application times will be [121,122]

$$\frac{\partial J(\mathbf{i}_m(k+1), T_e(k+1), (\mathbf{u}_q, \mathbf{u}_r))}{\partial t_q, \partial t_r} = 0 \tag{6}$$

s.t. (i) $t_q + t_r = T_s$, (ii) $t_q, t_r \in [0, T_s]$,

$$\frac{\partial J(i_m(k+1), T_e(k+1), (\mathbf{u}_q, \mathbf{u}_r))}{\partial t_q, \partial t_r} = 0, \tag{7}$$

Table 1
Applications of predictive control techniques to DER converters.

DER Type	Control Method	Feature	Application
Wind energy conversion system (WECS)	Single-vector predictive control	✓One voltage vector per sampling period. ✓Higher ripple content.	✓PMSG [60–65] ✓DFIG [66,67]
	Multiple-vector predictive control	✓Two or more voltage vectors per sampling period. ✓Lower ripples and tracking errors.	✓PMSG [68,69] ✓DFIG [70–72]
	Computationally efficient DMPC	✓Reduces computational efforts. ✓Utilizes hexagon or triangle candidate region, discrete space vector modulation (SVM) etc. ✓Constant switching frequency with SVM	✓PMSG [64,73–76] ✓DFIG [72,77,78]
Solar PV	FCS-MPC-MPPT	✓Improved conversion efficiency, fast dynamic response, than linear control. ✓Negligible oscillations around the maximum power point.	✓Buck converter [79] ✓Flyback converter [80–84] ✓Boost converter [85]
	CCS-MPC-MPPT	✓More grid-friendly frequency spectrum than FCS-MPC-MPPT	✓Boost converter [86,87]
	DO-MPC-MPPT	✓Performs better than FCS-MPC-MPPT under rapidly changing weather conditions.	✓Flyback converter [88,89] ✓Boost converter [90]
Energy storage system (ESS)	FCS-MPC	✓Faster control dynamics than linear control. ✓Optimized transient performance within system constraints.	✓Multilevel flying-capacitor converter [91–93] ✓Buck converter [94,95] ✓Buck-boost [96,97] ✓Dual active bridge converter [98] ✓Boost converter [99] ✓Pulsed power loads [100,101] ✓Constant power loads [102,103]
Fuel cell	MPC	✓Increases life span of the fuel cell. ✓Maximizes the active catalytic surface area.	PEMFC [104,105]
Hybrid DER management	MPC	✓Optimal energy management and power sharing for hybrid energy storage system.	✓PV–wind–battery [106] ✓PV–wind–hydrogen fuel cell [107,108] ✓PV-ESS [109,110]

FCS-MPC is finite control set MPC, CCS-MPC is continuous control set MPC, DO-MPC is discrete observer MC, MPPT is maximum power point tracking, PMSG is permanent magnet synchronous generator, and PV is photovoltaic.

Table 2
Cost functions for power converters in distributed energy resources.

Application	Equation	Description
Boost Converter Permanent Magnet Synchronous Generator (PMSG) WECS	$J_p = \left(P^*_{dc}(k+1) - P_{dc}(k+1)\right)^2$ $+\lambda_{vc}(v_o(k+1))^2 + \lambda_{sw}u^2_{sw}(k+1)$	$P_{dc}(k+1) := v_{dc}(k+1)i_{dc}(k+1)$ is the extrapolated reference power, $u_{sw}(k+1) = \sum_{x=1,2,3}\lvert u_x(k+1) - u_x(k)\rvert$, v_{dc}, i_{dc} are predicted boosted converter input voltage and current respectively, and the voltage difference between the upper and lower dc link capacitors $v_o(k+1) = v_{c1}(k+1) - v_{c2}(k+1)$.
DMPTC PMSG WECS	$J_{DMPTC} = \lambda_{T_e}(T^*_e - T_e(k+1))^2$ $+\lambda_i(\mathbf{i}^*_g - \mathbf{i}^*_g(k+1))^2 + \lambda_{max}(T^{max}_e - T_e(k+1))$ $+\lambda_v(v_o(k+1))^2$	$v_o(k+1)$ is the predicted voltage difference between multi-level DC-link capacitors ($v_o(k+1)$ is set to constant zero if $N_L = 2$).
Dual-fed induction generator (DFIG) WECS	$J_{MPDPC} = \lambda_P(P^*_s - P_s(k+1))^2$ $+\lambda_Q(Q^*_s - Q_s(k+1))^2 + \lambda_v(v_o(k+1))^2$	$(x)^*$ is the reference value of $x\,\forall\, x \in \{P_s, Q_s\}$; the stator active and reactive power are defined by $P_s = \mathrm{Re}(\mathbf{S})$, $Q_s = \mathrm{Im}(\mathbf{S})$, respectively; $v_o(k+1)$ is the predicted voltage difference between multi-level DC-link capacitors ($v_o(k+1)$ is set to constant zero if $N_L = 2$).
Energy Storage	$J_{ESS} = (i^*_b - i_b(k+1))^2$ s.t. $SOC_{min} \le SOC(k) \le SOC_{max}$, $i_b \le \lvert i_{max}\rvert$	i^*_b is the reference for battery current i_b, and SOC represents state of charge.
Fuel cell	$J_{FC} = (i^*_L - i_L(k+1))^2$	i_L is the filter inductor current with reference i^*_L.
Solar PV	$J_{PV} = \lambda_i(i^*_L - i_L(k+1))^2 + \lambda_v(v^*_{PV} - v_{PV}(k+1))^2$	i_L is the converter filter inductor current with reference i^*_L. (v_{PV}) is the instantaneous PV voltage with reference (v^*_{PV}). References i^*_L and v^*_{PV} are determined by MPPT algorithms (perturb and observer or incremental conductance).

WECS = wind energy conversion system, DMPTC = direct model predictive torque control.

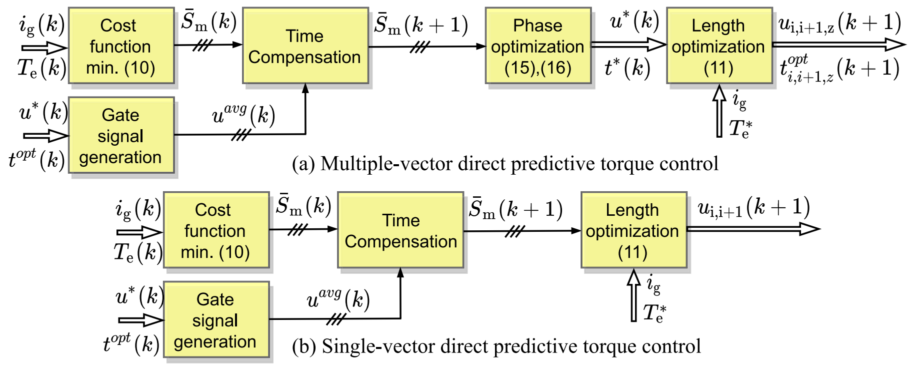


Fig. 5. Direct predictive torque control techniques for PMSG WECS [116].

s.t. (i) $t_q + \partial t_r = T_s$, (ii) $t_q, t_r \in [0, T_s]$, where t_x is the optimal time to apply $\mathbf{u}_x \; \forall \; x \in \{q, r\}$. After pairs of $(\mathbf{u}_x, t_x)$ have been enumerated, the applied pair is derived by optimization.

$$(\mathbf{u}_q, t_q, \mathbf{u}_r, t_r) := \arg\min J(\mathbf{u}_i)(\mathbf{i}_m(k+1), T_e(k+1)). \tag{8}$$

Multiple-vectors DMPTC: This method applies an additional step to the dual-vector DMPTC. After utilizing active vectors to obtain $(\mathbf{u}_q, \mathbf{u}_r)$, if they do not satisfy system constraints, they are combined with a voltage vector $\mathbf{u}_z$. First, $(\mathbf{u}_q, \mathbf{u}_r)$ are synthesized to become $\mathbf{u}_{opt}$ [68,116,119]:

$$\mathbf{u}_{opt} = \frac{t_q}{T_s}\mathbf{u}_q + \frac{t_r}{T_s}\mathbf{u}_r. \tag{9}$$

Hence, the optimal times for $(\mathbf{u}_{opt}, \mathbf{u}_z)$, i.e., (t_{opt}, t_z), respectively, are computed by [119]

$$\frac{\partial J(\mathbf{i}_m(k+1), T_e(k+1), (\mathbf{u}_{opt}, \mathbf{u}_z))}{\partial t_{opt}, \partial t_z} = 0 \tag{10}$$

$$\text{s.t. (i) } t_{opt} + t_z = T_s, \text{(ii) } t_{opt}, t_z \in [0, T_s], \tag{11}$$

and (iii) $\mathbf{u}_z \in \{\mathbf{u}_0, \mathbf{u}_7\}$.

Thus, if $n = \frac{t_{opt}}{T_s} \in [0, 1]$, then

$$t_q^{opt} = n t_q,\; t_r^{opt} = n t_r, \text{ and } t_z = T_s - (t_q^{opt} + t_r^{opt}). \tag{12}$$

The afore-discussed variants of DMPTC are shown in Fig. 5.

3.1.2. Doubly-fed induction generator (DFIG)

DFIGs have both rotor and stator windings connected to the external three-phase AC terminal. The rotor winding is designed to operate flexibly with variable wind speeds, and this can supply variable-frequency bidirectional active and reactive power to the grid though interfacing back-to-back converters. The stator supplies power at grid frequency [114].

Model predictive direct power control (MPDPC) of DFIG WECS. First, the classical MPDPC is discussed, and variants of the improved low-computation MPDPC (LC-MPDPC) are introduced afterwards.

Control objectives and cost function: Let us consider a generic voltage source converter with N_L voltage levels (where N_L is a positive integer greater than or equal to 2). The control objectives for the MPDPC of the N_L-level converter include: (i) the tracking of the active power reference; (ii) the tracking of the reactive power references, (iii) balancing of the DC-link capacitor voltages (in the case when $N_L > 2$). The MPDPC scheme will be regulated by cost function J_{MPDPC} in Table 2, where each term represents objectives (i)-(iii) respectively.

The conventional MPDPC predicts active and reactive power from the discretized form of the derivative of negative complex apparent power $(-\frac{d}{dt}\mathbf{S})$. Nonetheless, this procedure is not efficient in the selection of optimal voltage vectors and increases computational resources. Hence, a seminal low-complexity MPDPC (LC-MPDPC) introduced by [123] will be described.

Low-Complexity MPDPC (LC-MPDPC): MPDPC selects an optimal voltage vector that minimizes the power error [124], and produces better accuracy and lower power ripples than linear control e.g., direct power control with look-up table [125,126]. Nonetheless, classical MPDPC requires a rigorous evaluation of all candidate voltage vectors in the optimization procedure, and may require several prediction horizons for accuracy. Thus, [123] proposed an effective LC-MPDPC within a single prediction horizon.

LC-MPDPC applies the principles of direct current control [127] to select the most optimal voltage vector within one prediction horizon. LC-MPDPC reduces the procedure in conventional MPDPC from computations for eight voltage vectors (case of two-level converter) to only two vectors — an active vector and a zero vector. The following steps describe the MPDPC algorithm:

(1) Calculate $\mathbf{S}$ with instantaneous power theory [128].
(2) Predict the complex power $\mathbf{S}_0(k+1)$ that is due to zero vector $\mathbf{u}(000)$. The predicted power is the discretized derivative of the negative complex apparent power $(-\frac{d}{dt}\mathbf{S})$.
(3) Obtain the error due to the zero vector, i.e., $\mathbf{S}_0^{error}(k+1) = -\overline{(\mathbf{S}^* - \mathbf{S}_0(k+1))}$, where $\overline{(.)}$ is the complex conjugate operator.
(4) Compute the actual angle of $\mathbf{S}_0^{error}(k+1)$, i.e., $\angle\mathbf{S}_0^{error}$, by adding the angle of the grid voltage $\angle\mathbf{e}_g$. (It is assumed that steps 1 to 3 were done in the $d-q$ reference frame.) Based on $\angle\mathbf{S}_0^{error}$, determine the active voltage vector $\mathbf{u}_{opt}$ closest to $\mathbf{S}_0^{error}(k+1)$.
(5) Compute the error vector $\mathbf{S}_u^{error}(k+1) = -\overline{(\mathbf{S}^* - \mathbf{S}_u(k+1))}$, due to $\mathbf{u}_{opt}$.
(6) Compare $\mathbf{S}_0^{error}(k+1)$ and $\mathbf{S}_u^{error}(k+1)$; the optimal voltage vector between them has the smallest angle. E.g. the optimal vector is $\mathbf{u}_0(000)$ if $\angle\mathbf{S}_0^{error} < \angle\mathbf{S}_u^{error} <$, and $\mathbf{u}_{opt}$ otherwise.

Dual- and Multiple-Vector LC-MPDPC: The dual-vectors LC-MPDPC improves the steady-state performance reported in [123] by applying the duty-cycle optimization concept [129] to select optimal active and zero vectors. In order to achieve error-free steady-state performance, the multiple-vector LC-MPDPC which applies three optimal vectors (two adjacent active and one zero vector) was reported by authors in [130]. Nonetheless the high-fidelity of steady-state performance was at the expense of higher switching losses. A control scheme which applies four voltage vectors per sampling period was reported in [70]. This method improves the other MPDPC schemes by effective operation under both balanced and unbalanced conditions, and constant switching frequency. However, it is more complex to implement. The afore-discussed variants of MPDPC are illustrated in Fig. 6.

Performance Comparison: Using switching losses (which are directly proportional to average switching frequency [131]) and power ripples, the comparative performances of the above techniques can be quantitatively assessed. Ref. [130] showed that power ripples decrease as the applied voltage vectors per control period increases. However, there is a loss-trade-off because the switching frequency (hence, switching losses) increases as the number applied vectors per control period increases.

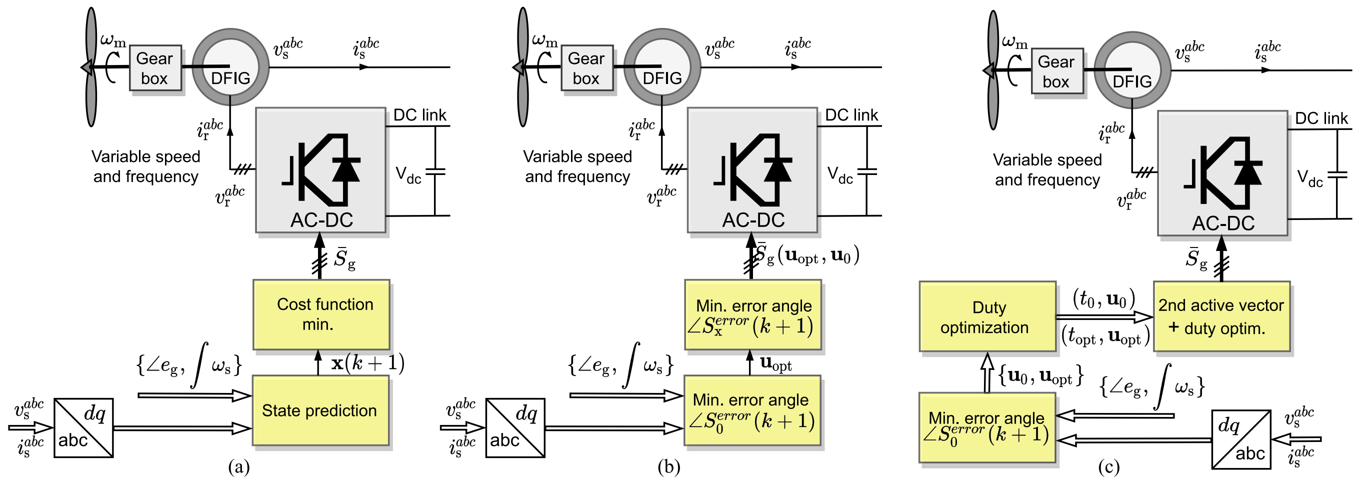


Fig. 6. Predictive direct power control techniques for DFIG WECS. (a) Classical model predictive direct power control (MPDPC), (b) Single-vector low-complexity MPDPC, (c) Multiple-vector low-complexity MPDPC.

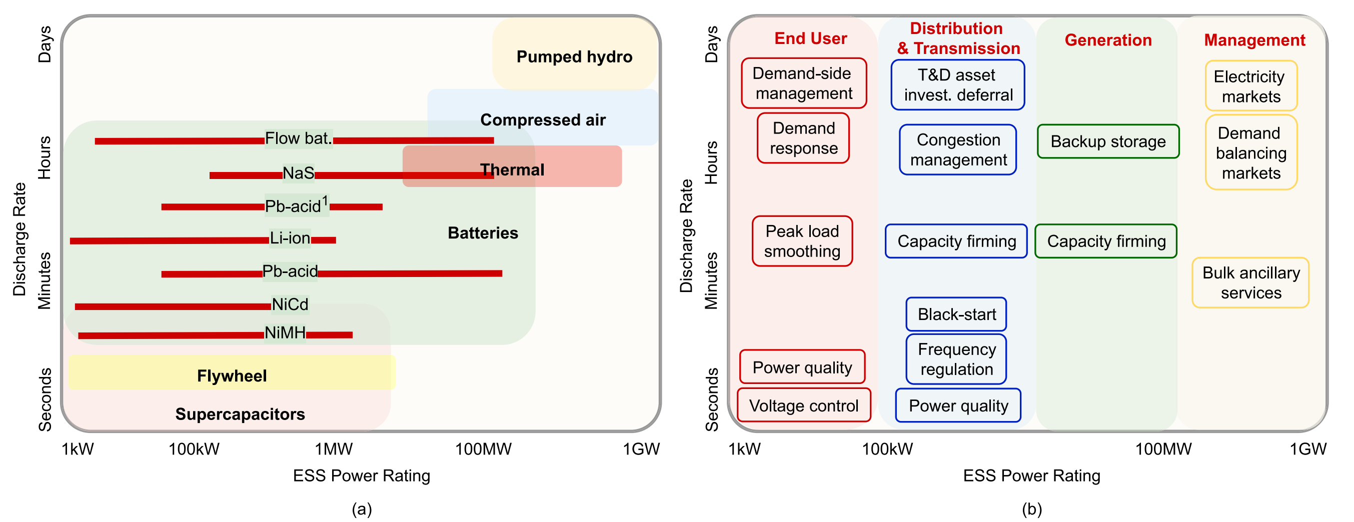


Fig. 7. Energy storage technologies and their functionalities in the smart grid. (a) Energy storage technologies and their application contexts. (b) Functionalities of ESS in the smart grid. Acronyms: Flow battery (flow bat.), Sodium sulphide battery (NaS), Advanced lead acid battery (Pb-acid[1]), Lead acid battery (Pb-acid), Lithium ion battery (Li-ion), Nickel Cadmium battery (NiCd), Nickel-metal hydride battery (NiMH), Thermal energy storage (Thermal), Compressed air energy storage (Compressed air), Pumped hydro storage (Pumped hydro).

3.2. Predictive control of bidirectional DC/DC converters for ESS

This section covers the predictive control of power converters for energy storage systems (ESS). It starts with a description of microgrid ESS technologies and converters. Next it discusses MPC for bidirectional DC/DC converters for ESS. Finally, MPC solutions to constant power load (CPL) and pulsed power load challenges with DC/DC converters are discussed.

3.2.1. Smart grid ESS technologies and converters

ESS consist of several mature and developing technologies which operate on electro-chemical, electro-thermal and electro-mechanical principles. Batteries energy storage and supercapacitors are electro-chemical devices; flywheels and compressed air energy storage (CAES) are electro-mechanical; and thermal energy storage systems are electro-thermal in nature [132,133]. Fig. 7(a) shows that the ESS with higher power density have shorter discharge rate of seconds, while ESS with higher energy densities discharge over minutes to several days. Fig. 7(b) shows how these energy technologies are matched to the parts of the grid: ESS with lower power rating and lower discharge time are applied by end users and in the distribution network; ESS with higher rating and higher discharge time are applied for transmission, generation and system management.

In order to maximize the diversity of electro-chemical characteristics of ESS types, hybrid ESS are common. A supervisory controller regulated by MPC can assign optimal power references to the DC/DC controller of each storage type based on state of charge, power/energy density matching [134–136]. Solutions for hybrid ESS including battery [137,138], ultra/super-capacitors [139,140] and flywheel [141] have been reported. In addition, optimal hybrid ESS-based frequency response for grid-support facilitates extended ESS lifetime and lower life-cycle costs [142]. A battery (with lower power density) will only be required to provide energy for small changes in active power (and frequency), while the ultracapacitor (with large power density) regulates large changes in active power [142].

ESS require bidirectional power flow through DC/DC converters for charging and discharging. These converters are grouped as isolated and non-isolated; the isolated converters have galvanic isolation to physically decouple the input circuit from the output, while non-isolated ones have physical continuity between the input and output. The common non-isolated DC-DC converters include half-bridge, inverting buck-boost, cascaded buck-boost, Cuk, SEPIC/Zeta, and switched capacitor converters [143,144]. MPC was applied to interleaved converters with robust control of uncertainties [145,146], and matrix converter for renewable generation [147]. Common isolated converters have a high frequency transformer, and include dual-active bridge (DAB), and flyback converters. Although the afore-mentioned converters are suitable for low-voltage applications, in medium to high voltage applications, DAB are preferred for their higher efficiency and relatively lower cost than modular multi-level DC/DC converters [148]. MPC-based DAB regulation with superior dynamics was reported in [149–151]. Table 1 shows the applications of MPC to bidirectional DC/DC converters for battery energy storage, and supercapacitor [95].

A predictive control scheme for a buck-boost bidirectional DC/DC converter for ESS has the cost function J_{ESS} (see Table 2) for regulating battery charging/discharging.

3.2.2. Predictive control solutions to constant power load and pulse power load issues

A constant power load (CPL) is a tightly regulated electronic load that absorbs constant power, and so, manifests negative impedance characteristics [152]. This results in reduced damping and instability challenges. A composite offset-free continuous MPC solution was proposed for a buck converter in [153]. Explicit MPC was applied to a boost converter, with fuzzy-control of nonlinearities [154]. Stability of a DC-bus via ESS injection current was studied in [102,103].

Pulsed power loads are associated with applications that draw high power within a brief moment as in electric vehicles, electric ships and electric aircraft [101]. To prevent instability, ESS with high power density, e.g., supercapacitors and flywheels, are necessary [100]. MPC techniques, including continuous MPC [155], and explicit MPC [156], which have fast dynamic responses are effective for pulsed power control of DC/DC boost converter.

3.3. Predictive control of converters for fuel cells

Fuel cells have a high potential in the renewable energy transition due to their ability to convert hydrogen gas to electricity with very little greenhouse gases emissions (water being the main by-product). Also, they have an efficiency of $40-60\%$, making them up to three times more efficient than solar PV and two times more efficient than wind turbines [157]. What is more, they have almost ten times more energy density than batteries [158]. They are classified into six types based on the type of fuel and electrolyte: (i) Proton exchange membrane fuel cell (PEMFC), (ii) alkaline fuel cell, (iii) phosphoric acid fuel cell, (iv) molten carbonate fuel cell (v) solid oxide fuel cell, and (vi) direct methanol fuel cell.

Fuel cells are electronically conditioned by unidirectional DC/DC power converters to regulate their electrical power outflow [159]. As earlier mentioned, non-isolated converters are common. However, when galvanic isolation and higher voltage conversion rations are needed, isolated converters with integrated high-frequency transformers are utilized.

Studies on MPC applications to fuel cells are reported in [45,104,105,160]. In the maximum power/efficiency tracking operation of a PEMC, artificial neural network (ANN) was used to predict states of optimally controlled variables. MPC can also prolong device lifespan: The optimal power tracking performance of a PEMFC, without sacrificing the longevity of the cell stacks, can be achieved by multi-objectively controlling cathode and anode pressures, and hydrogen/oxygen supply to the cells [104]. The cost function to optimally track the reference current is J_{FC} in Table 2.

3.4. Predictive control of solar PV converters

Electricity generated from solar PV in 2020 was 577 TWh, representing 18.9-fold increase from 2010 [111]. This can be attributed to 85% drop in costs of utility-scale PV systems between 2010 to 2020 [112]. Relative to other renewable systems, PV cells have a low conversion efficiency. Hence, maximum power tracking (MPPT) controllers are usually required to extract maximum power from them at all operating conditions, especially during low insolation [161]. The common MPPT algorithms include the perturb and observe [162], and incremental conductance [163] techniques. However, their most common limitations are: (i) non-convergence to the true maximum power point during rapidly changing atmospheric conditions, and (ii) higher oscillations around the maximum power point [46].

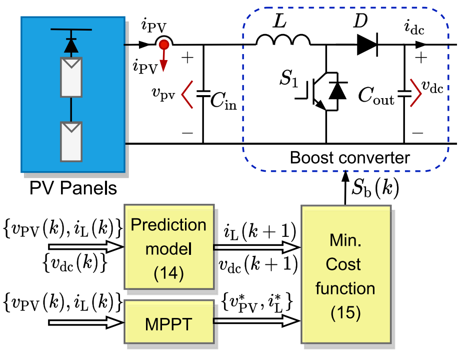


Fig. 8. FCS-MPC-MPPT control of DC/DC boost converter for PV system.

MPC solutions have been applied to address non-convergence and instability issues of linear MPPT algorithms for boost converter [161], buck converter [79], and buck-boost converter [90]. MPC-based MPPT methods are grouped into continuous control set-MPC-MPPT (CCS-MPC-MPPT) [86,87] and discrete-MPC-MPPT (DMPC-MPPT). DMPC-MPPT comprises two subgroups: finite control set MPC-MPPT (FCS-MPC-MPPT) [79–85], and digital observer-MPC-MPPT (DO-MPC-MPPT) [88–90]. MPC-based methods introduce improved conversion efficiency, fast dynamic response, and negligible oscillations around the maximum power point. DO-MPC-MPPT generally has better performance than FCS-MPC-MPPT (see Fig. 8) under rapidly changing weather conditions (because FCS-MPC-MPPT relies on conventional MPPT calculation methods). An improved method to reduce drift of DO-MPC-MPPT under highly unsteady conditions was reported in [79].

3.4.1. Classical MPC

The cost function J_{PV} (15) in Table 2 is minimized by the classical MPC. This also relies on conventional MPPT techniques, and these reduce its overall dynamic performance.

$$\begin{aligned}\frac{d}{dt}i_{\mathrm{L}} &= \frac{1}{L}(v_{\mathrm{PV}} - (1-S_{\mathrm{n}})v_{\mathrm{dc}}),\\ \frac{d}{dt}v_{\mathrm{dc}} &= \frac{1}{C}(i_{\mathrm{PV}}(1-S_{\mathrm{n}}) - i_{\mathrm{dc}}),\end{aligned} \tag{13}$$

where $S_{\mathrm{n}} = 0$ if S_1 is OFF, and $S_{\mathrm{n}} = 1$ if S_1 is ON. Discretizing (13) by the forward-Euler approximation, with sampling time T_{s}, the state predictions become [46]

$$\begin{aligned}i_{\mathrm{L}}(k+1) &= i_{\mathrm{L}}(k) + \frac{T_{\mathrm{s}}}{L}(v_{\mathrm{PV}}(k) - (1-S_{\mathrm{n}})v_{\mathrm{dc}}(k)),\\ v_{\mathrm{dc}}(k+1) &= v_{\mathrm{dc}}(k) + \frac{T_{\mathrm{s}}}{C}(i_{\mathrm{PV}}(k) - (1-S_{\mathrm{n}})i_{\mathrm{dc}}(k)),\\ v_{\mathrm{PV}}(k+1) &= (1-D)v_{\mathrm{dc}}(k+1),\end{aligned} \tag{14}$$

where D is the duty ratio.

$$J_{PV} = \lambda_i(i_{\mathrm{L}}^* - i_{\mathrm{L}}(k+1))^2 + \lambda_v(v_{\mathrm{PV}}^* - v_{\mathrm{PV}}(k+1))^2, \tag{15}$$

References i_{L}^* and v_{PV}^* are determined by MPPT algorithms (perturb and observer or incremental conductance).

3.4.2. Digital-observer MPC MPPT

The preceding method calculates PV voltage and current references with conventional MPPT algorithms. However, these are non-robust. Hence, the digital-observer MPPT was introduced [89] for improved robustness under dynamic atmospheric conditions. It utilizes present and historical measurements to model the PV source as an equivalent voltage v_{eq} and resistance R_{eq} in (17) [89]. These are used to compute references for the converter control.

$$R_{eq} = -\frac{v_{PV}(k) - v_{PV}(k-1)}{i_{PV}(k) - i_{PV}(k-1)} \tag{16}$$

$$\begin{aligned} R_{eq}(k) &= -\frac{v_{PV}(k) - v_{PV}(k-1)}{i_{PV}(k) - i_{PV}(k-1)}, \\ v_{eq}(k) &= v_{PV}(k) + R_{eq} i_{PV}(k). \end{aligned} \tag{17}$$

So, the predicted operating point tracks the maximum power point on the PV I–V curve by the cost function J_{MPPT} (18).

$$\begin{aligned} v_{PV}(k+1) &= v_{PV}(k) \pm \Delta v_{PV}(k), \\ i_{PV}(k+1) &= (v_{eq}(k) - v_{PV}(k+1))/R_{eq}, \\ P_{PV}(k+1) &= v_{PV}(k+1) i_{PV}(k+1), \\ J_{MPPT} &= P_{PV}(k+1) - P_{PV}(k), \end{aligned} \tag{18}$$

Δv_{PV} is an adaptive step-size which ensures that the maximum power point is closely tracked, and J_{MPPT} is the cost function.

The afore-discussed DERs can also be combined in hybrid format. For instance, MPC can be applied to provide optimal references to control hybrid combinations of PV–wind–battery [106], PV–wind–hydrogen fuel cell [107], and PV-ESS [109].

4. Predictive control of grid-connected converters

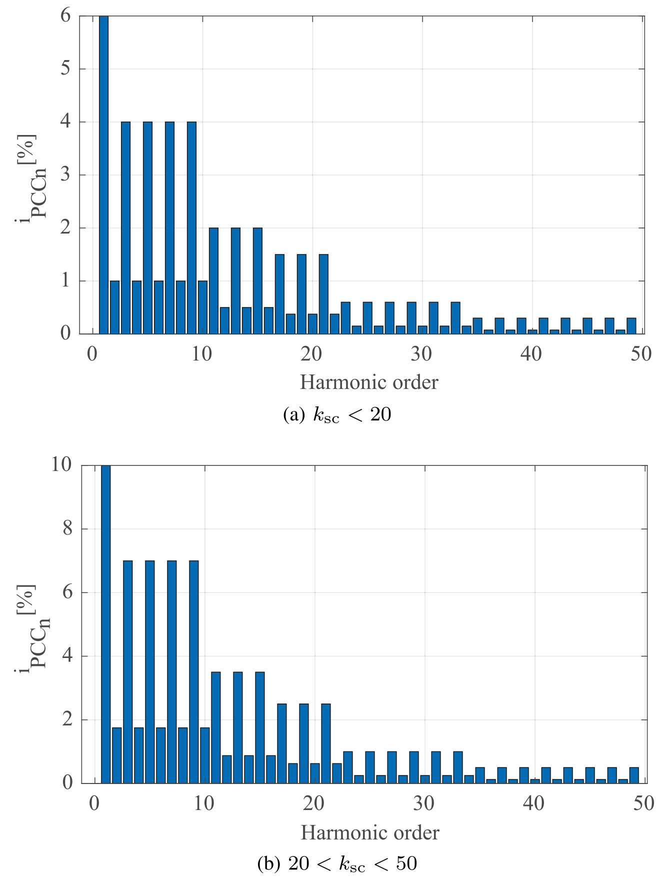
In this section, the predictive control of grid-connected converters will be discussed. First, the recent regulatory control requirements for grid-connected converters will be highlighted. Second, the recent research advances which meet those requirements through fixed switching frequency MPC solutions will be covered.

4.1. Control requirements

Finite control set MPC (FCS-MPC) is the more popular type of predictive control applied to DER converters. This is mainly due to the absence of a modulator, which improves its speed of dynamic response. One recurring challenge with FCS-MPC is that it has variable switching frequency, which results in non-deterministic harmonic spectra. This poses a challenge for grid-connected converters which must meet regulatory harmonic specifications, e.g., as specified by IEEE 519 Standard (see Fig. 9). Thus, for a short circuit ratio k_{sc} < 20, the maximum current harmonic at the point of common coupling (i_{PCCn}) to the grid, for any harmonic order, is 4.0%. This implies that conventional FCS-MPC will be unsuitable for grid-connected systems if the harmonic components are not regulated. Several studies report solutions in this regard, and they will be discussed below. It should be clarified that among them, only [164] confirms that both fixed switching frequency and harmonic spectrum identical to PWM or SVM (with lower switching frequency) are guaranteed. It achieves this desirable result by specifically controlling the switching symmetry in each sampling period.

4.2. Solutions with fixed switching frequency

Fixed switching frequency in MPC for grid-connected power converters can be realized with continuous control-set MPC (CCS-MPC), and finite control-set MPC (FCS-MPC). CCS-MPC requires a separate modulator apart from the optimizer. On the other hand, FSC-MPC combines both the optimization and modulation within the same scheme, requiring no separate modulator.



(a) $k_{sc} < 20$

(b) $20 < k_{sc} < 50$

Fig. 9. Current harmonic limits at the point of common coupling for systems rated 120 V through 69 kV (IEEE 519 – 2014 standard) [165]. (k_{sc} is the short circuit ratio.)

Since CCS-MPC schemes have their fixed switching frequency guaranteed by the modulator, the literature focuses on innovating the optimal control of objectives for VSC, modular multilevel converters (MMC), neutral-point clamped (NPC) converters, cascaded H-bridge, and inductor–inductor–capacitor (LLC) resonant converters for solar PV systems. The VSC applications feature embedded integrator and Kalman filter [166], full and reduced-order models with closed-form expressions [167]. Authors in [168] report on virtual voltage vectors with space-vector PWM. A modulation-based MPC technique was reported in [169] for normal and unbalanced grid conditions. Renewable systems like solar PV require MPPT control, thus fixed-switching frequency predictive phase shift MPPT [170] and MPPT with space vector modulation [170] are beneficial.

FCS-MPC comprises two variants: optimal switching vector MPC (OSV-MPC), and optimal switching sequence MPC (OSS-MPC). The former being more commonly reported in the literature. As earlier mentioned, FCS-MPC has an inherent variable switching frequency — in particular, OSV-MPC. Therefore, a little more intricacy is necessary to achieve fixed switching frequency. The literature reports the following successful implementations with constant switching frequency: multiple vector FCS-MPC [172], floating virtual voltage vectors [171] and virtual vectors in a reshaped and compacted solution space [173]. Detailed methods and features of the above categories are presented in Table 3.

A predictive control technique based on floating virtual voltage-vector is shown in Fig. 10 [171]. The algorithm divides the total vector area into 30 virtual vectors, instead of the 8 conventional ones

Table 3
MPC for grid-connected converters with fixed switching frequency.

Category	Application	Feature
Continuous control-set MPC (CCS-MPC)	VSC with L(CL) filter	✓Embedded integrator and Kalman filter [166]. ✓Full and reduced-order models with closed-form expressions [167]. ✓Virtual voltage vectors and space-vector PWM [168]. ✓Minimizes AC line and circulating current ripples [174]. ✓Effective for unbalanced grid [169].
	Modular multilevel converter	✓Optimal modulation Refs. [175]. ✓Sliding-discrete-control-set modulated MPC [176].
	3L neutral-point-clamped converter	✓Advanced switching sequences [177]. ✓Modulated MPC for grid current and dc-link capacitor voltages [178]. ✓MPPT and space vector modulation [170].
	Cascaded H-bridge converter	✓Separation of voltage balancing control from the cost function [179]. ✓Modulated integral action MPC [180].
	Switched-boost common-ground 5L inverter	✓Single-step MPC [169].
	LLC resonant converter for PV	✓Fixed frequency predictive phase shift MPPT technique [170].
Finite control-set MPC (FCS-MPC)	VSC with L(CL) filter	✓Multiple vector FCS-MPC [172]. ✓Floating virtual voltage vectors [171]. ✓Virtual vectors in a reshaped and compacted solution space [173]. ✓Fixed modulation cycle similar to discontinuous pulsewidth modulation [164].
	H-bridge neutral-point-clamped converter	✓Eliminates high-frequency common-mode voltage components. [181]. ✓Weighting factor only affects the peak current during transients [182].
	3L neutral-point clamped converter	✓Cascaded optimal switching sequence MPC without weighting factor [183]. ✓Optimal switching sequence with modulator in its formulation [184].

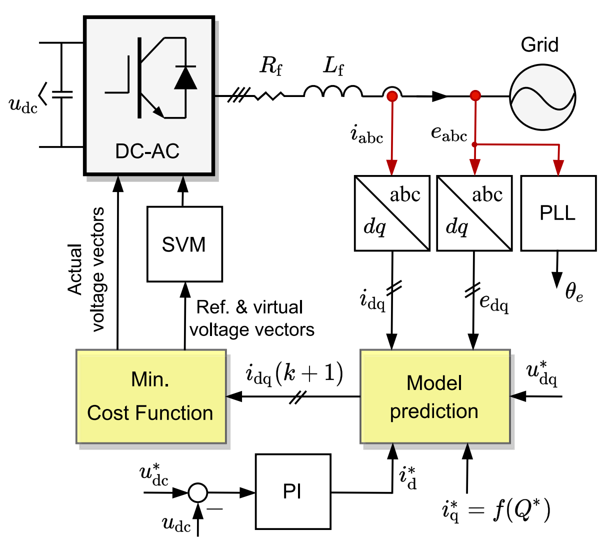


Fig. 10. Predictive control of grid-connected converters with fixed switching frequency: Floating virtual voltage-vector-based predictive control [171].

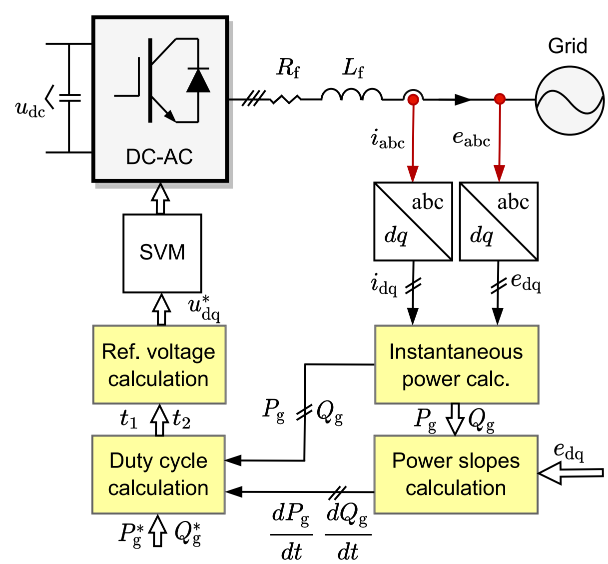


Fig. 11. Predictive control of grid-connected converters with fixed switching frequency: multiple-vector-based predictive power control [172].

(for a two-level converter). Thus, adjacent virtual voltage vectors have smaller spacing between them, giving much lower current ripples. This method also has lower computational requirements than conventional MPC.

Fig. 11 illustrates the multiple-vector-based predictive power control of a grid-connected converter [172]. It utilizes the computation of instantaneous power for active and reactive power slopes within each sampling cycle. These provide inputs for the determination of the reference voltage vectors and their corresponding on and off time durations (duty cycles). Space vector modulation (SVM) is finally applied for the pulse-width modulation of the converter.

Fig. 12 shows the direct predictive power control of a three-level neutral-point clamped converter based on optimal switching sequence. It comprises a cascade of outer MPC for power control, and inner MPC for DC-link capacitor control. First, a relaxed solution of voltage vectors is obtained within specified constraints. Next, an optimal sector search is done to determined the optimal sector (comprising three voltage vectors in [183]). A reduced region is delimited within the optimal sector, and then optimal duty cycle is calculated for application to the converter with optimal switching sequence.

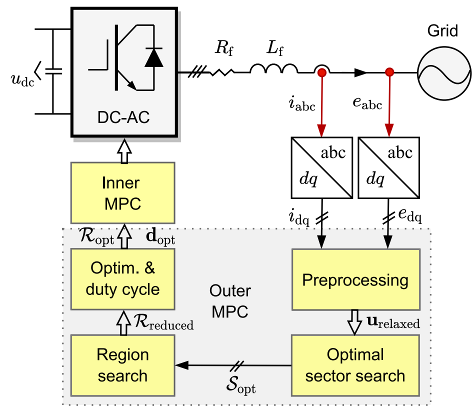


Fig. 12. Direct predictive power control based on optimal switching sequence [183].

4.3. Mode transition for microgrid-based DERs

The functions of a microgrid require it to operate in both standalone and grid-connected modes. Thus, it is essential to regulate its transition from standalone to grid-connected operation and vice-versa. Poor control in this period can result in loss of synchronism, voltage/current overshoots, and even instability. Universal controllers are utilized to achieve this goal to ensure seamless switching between different operational modes. A unified control scheme is presented in [185] which facilitates mode-transitions without an islanding detection algorithm. It also allows fault ride-through operation with protection from excessive fault currents. An improved MPC-based mode-transition scheme is reported in [186] with a unified predictive voltage and current cost function. This improves the smoothness of transition from voltage control (when the converter is functioning as a grid-forming converter) to current control (when functioning as a grid-following converter).

5. Artificial intelligence-based predictive control

Data-based methods are facilitated by the plethora of data that is generated by sensors, IoT, edge computing, digital twin and big data analytics. These data serve as inputs for artificial-intelligence (AI) design optimization, control, and real-time condition monitoring of power electronics [187]. AI-based MPC methods emerged from the necessity to enhance the performance of MPC in three main areas: easier optimal tuning of weighting factors (and prediction horizon), reduction of the computational burden, and parametric estimation. Two broad classifications of these techniques are shown in Fig. 13, namely, AI-type-based classification and purpose-based classification. Considering the type of AI-method involved, there are six methods: artificial neural network (ANN), fuzzy logic, deep learning, reinforcement learning, particle swarm optimization and neuro-fuzzy logic. ANN is the most popular among these methods for 30 total papers reviewed (Table 4).

The purpose-based classification identifies twelve purposes (or objectives) associated with AI-MPC methods. The most recurrent in the literature include (in decreasing popularity) online weighting factor tuning, emulation of MPC algorithm, offline weighting factor design and condition monitoring (see Table 4). AI methods which emulate MPC's optimal control find application in two-level voltage source converters [188,189], MMC [190–192], and resonant power converter [193]. These solutions involve the offline training of an ANN model (and deep learning) to achieve identical transient and steady-state performance as MPC. They have the advantage of lower memory computational burden, and faster implementation time than the comparable MPC which they emulate. ANN-based offline weighting factor design involves training a surrogate model of the system from simulation or experimental data. Then, a user-defined fitness function gives a multi-objective

Table 4
Popularity of AI-based MPC methods.

	Method/Purpose	Frequency (%)
AI-Type	Artificial neural network	56.7
	Fuzzy logic	26.7
	Deep learning	3.3
	Reinforcement learning	3.3
	Regression-based learning	3.3
	Neuro-fuzzy logic	3.3
	Particle swarm optimization	3.3
	Total*	100.0
Control purpose	Online weighting factor tuning	40.0
	Emulation of MPC	16.7
	Offline weighting factor design	10.0
	Condition monitoring	6.7
	Others[b]	26.6
	Total[a]	100.0

[a]Sum may not equal 100% due to rounding errors.

[b]Others include model-parameter-free intelligent control, cyber-attack detection and mitigation, event-triggered MPC, online parameter estimation, blackbox data-driven controller, load modeling, converter impedance estimation, online optimization of prediction horizon.

optimization of weighting factor — more accurate than heuristic tuning. Applications include VSCs [194,195], dual active-bridge (DAB) converter for aircraft microgrid [195], and induction motor [196]. AI-based online weighting factor tuning involves a real-time dynamic update of optimal weighting factors in the cost function. This results in improved reference tracking accuracy under varying operational conditions for VSCs [197,198], three-level NPC converter [199], and PMSM [200].

Several other control objectives are reported in the literature. These include: model-parameter-free control [201], false-data injection cyber-attack detection and mitigation [202], event-triggered MPC [203], online parameter estimation [204], blackbox data-driven control [205], load modeling [206], converter terminal impedance estimation [207], and online optimization of prediction horizon [208]. Further details on the control objectives are provided in Table 5.

6. Virtual power plants and grid ancillary services

In this section, the predictive control of grid ancillary services and virtual power plants will be discussed.

6.1. Virtual power plants

A virtual power plant (VPP) is an aggregator of spatially distributed energy resources for present or future grid (or microgrid) management [219]. The energy sources in a VPP are physically located at/within [220] DERs, microgrids, buildings, and PEVs. The virtual coordination is carried out through cyber–physical interaction between the flexible sources and optimal controllers, and is facilitated by electricity market stakeholders [221].

Studies on MPC-based VPP energy management and price arbitrage indicate promising opportunities. Energy-arbitrage was actualized in [222], by centralized MPC, for a VPP from battery storage, PC and diesel generators. Authors in [223] implemented optimal energy-price arbitrate with distributed MPC for multiple sources and thermal management. Optimal day-ahead scheduling is computed with MPC for a VPP with several grid support services [224], as shown in Fig. 14. Other studies consider nonlinear battery aging [225], frequency regulation [226], and real-time operations [227,228].

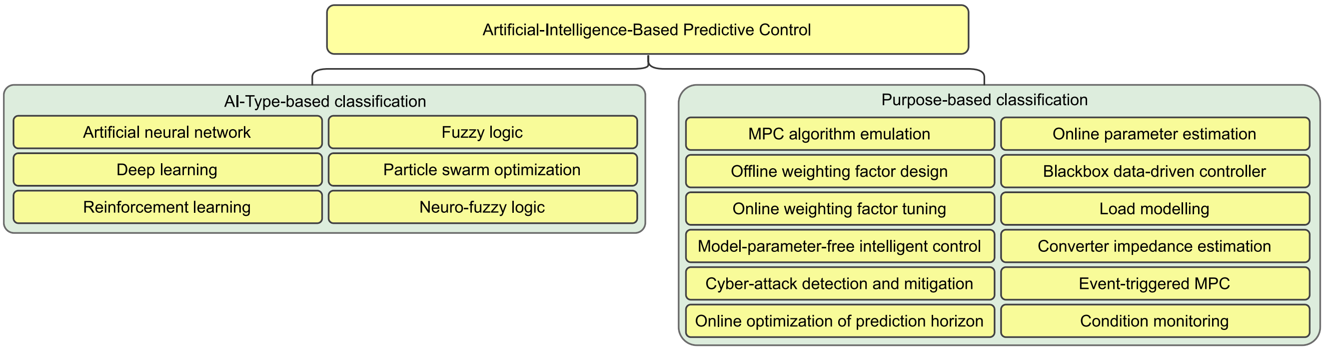


Fig. 13. Broad classifications of AI-MPC-based control methods.

Table 5
Overview of AI-based predictive control applications to power converters.

Purpose	Method	Feature	Advantage	Application
Emulation of MPC	✓ANN ✓Deep learning	✓ANN-based emulation of MPC algorithm. ✓Identical transient and steady-state performance as MPC. ✓Offline-trained emulator.	✓Lower computational burden.	✓2L VSC [188,189] ✓MMC [190–192] ✓resonant power converter [193]
Offline weighting factor design	✓ANN	✓Trains offline surrogate model of the system from model data. ✓User-defined fitness function gives multi-objective optimization of weighting factor.	✓More accurate weighting factor is derived than heuristic tuning. ✓Improved dynamic performance of system.	✓VSC [194,195] ✓DAB converter aircraft microgrid [195] ✓induction motor [196]
Online weighting factor tuning	✓Reinforcement learning ✓ANN ✓PSO ✓Fuzzy logic	✓Automated online training. ✓Online dynamic update of optimal weighting factor.	✓Improves reference tracking accuracy under varying operational conditions. ✓Easier weighting factor tuning.	✓VSC [197,198] ✓3L NPC converter [199,209] ✓direct matrix converter [210] ✓machine drives [200,211–216]
Model-parameter-free control	✓ANN	✓Cascaded predictor-based neural network for system identification.	✓Model-free weighting factor-free control. ✓Improved robustness to parametric uncertainties.	✓MMC [201]
False data injection cyber-attack detection and mitigation	✓ANN	✓ANN controller for cyber-attack detection and mitigation.	✓Impact of cyber-attack on the microgrid is mitigated.	✓DC Microgrids [202]
Event triggered MPC	✓ANN	✓NN controller trained to emulate event-triggered MPC.	✓Robustness to uncertainties and energy loss minimization. ✓Low switching frequency control for MMC.	✓MMC [203]
Online parameter estimation	✓Neuro-fuzzy logic	✓Neuro-fuzzy logic-based online model parameter estimation.	✓Improved reference tracking accuracy. ✓Improved robustness to parametric variations.	✓2L VSC [204]
Blackbox data-driven control	✓Regression-based learning	✓Calculation of conditional entropy for input–output mapping. ✓Erroneous data detection and processing.	✓Improved classification accuracy. ✓Ill-impact of corrupted data in training is eliminated.	✓VSC [205]
Load modeling	✓ANN	✓Data-based surrogate model of load.	✓Improved prediction accuracy.	✓Matrix converter [206]
Converter terminal impedance estimation	✓ANN	✓Converter parameter (impedance) identification through ANN. ✓Learned impedance factor added to MPC cost function.	✓Improved reference tracking accuracy.	✓VSC [207]
Online optimization of prediction horizon	✓ANN	✓Online calculation of optimal prediction horizon. ✓Prediction horizon adapts to the operational states of the converter.	✓Improved reference tracking accuracy. ✓Improved robustness to parametric variations.	✓Boost converter [208]
Condition monitoring	✓ANN	✓Fault detection by wavelet transform and neural network-based islanding classifier. ✓LVRT during voltage sags. ✓Open-circuit fault diagnosis.	✓Improved accuracy of fault detection. ✓Accurate fault identification.	✓Grid-connected PV system [217] ✓3L NPC converter [218]

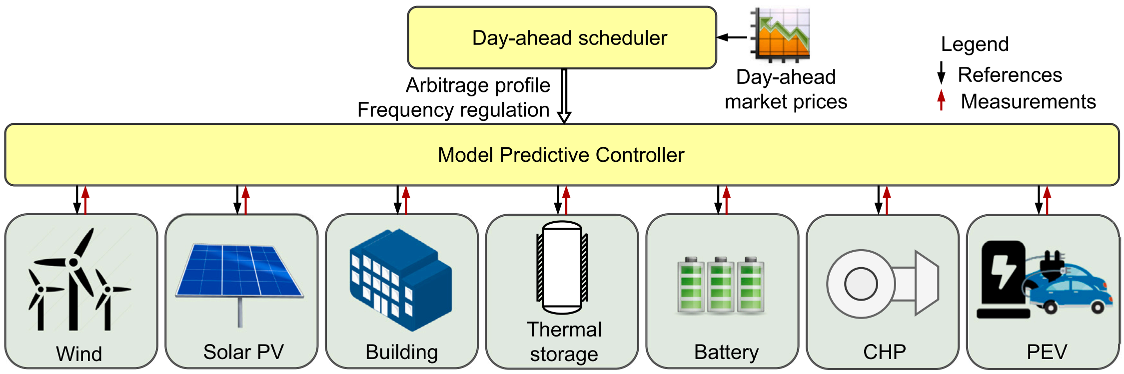


Fig. 14. Model predictive control of virtual power plants [224].

6.2. Grid ancillary services

Ancillary services are specialty services that facilitate reliable power supply in the grid. They are supplied by specialty providers to the system operator [27], and include frequency control, voltage and reactive power control, black start capability, oscillation damping, congestion management and loss compensation (see Fig. 15). Among these, the most commonly required are frequency and voltage control services. Frequency control involves maintaining the frequency at regulatory levels by ensuring a balance between active power generated and consumed [27]. The deployment of positive and negative frequency control reserves helps to achieve this goal. Voltage control service regulates participating devices which generate or absorb reactive power as a means to control voltage levels [28–30]. As the smart grid accommodates an increasing number of converter-interfaced DERs, MPC becomes beneficial to implement optimal frequency [31,32] and voltage control [33,34]. The predictive control of several heterogeneous thermostatically-controlled loads to provide ancillary service was validated in [35]. It was shown in [8] that by engaging ancillary services within an MPC framework, the microgrid operating expenses can be reduced by almost 25%.

As modern power grids become more renewable and environment-friendly, they also require inertia support. In particular, replacing fossil-powered synchronous generators with converter-interfaced renewable sources comes at a price of reduced system inertia. The virtual synchronous generator (VSG) has become beneficial to support grid frequency response and control. MPC-based VSG control is reported in [229], and it is adaptive to electrical load conditions. Fault ride-through and over-current protection for VSG was studied in [230]. The application of VSG with MPC-based converter in [231,232] gives better rate of change of frequency (within regulatory levels) and system stability than conventional droop control. In addition, ESS-supported fast frequency response for networked microgrids is also achievable through MPC and multi-agent control theory [233]. Practical projects have been implemented that deployed grid-scale battery storage for frequency regulation ancillary services; an example was reported by East Penn, USA [234]. Energy storage optimization is essential to maximize financial returns from such capital intensive projects.

Congestion management in transmission [235] and distribution [236] networks can be achieved by optimal control of ESS and partial curtailment of renewable sources. The study in [237] proposed a distributed model predictive control solution for economic dispatch of DER. The method utilizes both forecast data and stochastic variables in the prediction model. A similar problem was solved in [238] for DER in a microgrid.

Voltage support in a microgrid was investigated in [239,240]. Similarly, bus voltages in a DC-microgrid can be supported with controlled rate of change of voltage [241]. Voltage control can be achieved in centralized [16], decentralized [242], and distributed [232] topologies. Centralized topology requires more sophisticated communication resources than distributed methods. Distributed control is more effective for wide area electrical networks [18,232].

7. Open issues and future trends

This section will review open issues and future perspectives on the development of predictive control of DERs.

7.1. Open research issues

Despite the highly promising characteristics of predictive control for distributed generation, it has several limitations, and two key issues will be discussed here. First, MPC's performance is strongly determined by the accuracy of system's mathematical model. Therefore, external disturbances e.g., stochastic parametric variations can deteriorate the control performance. Recent research solutions to this challenge include: adaptive MPC with revised prediction model [69,245], and model-free predictive control [246]. Second, MPC's ability to control multiple objectives is enhanced through weighting factors. Nonetheless, calculation of optimal weighting factors can be laborious. Some solutions to this include optimization techniques for offline or online weighting factor computation, and MPC without weighting factors [247].

7.2. Future trends

The proliferation of DERs creates a need for innovative planning, and optimal real-time operation of multi-energy systems. Multi-energy systems are characterized by spatial distribution, multi-fuel inputs, and multi-service applications [248]. Whereas energy systems were historically controlled as independent agents, more recent requirements of economical minimization of environmental impacts demand their synergistic manipulation. This implies a more intricate simultaneous optimization of multiple energy vectors (e.g., electricity and heat) in an interactive manner. A few ground-breaking studies that adopt this philosophy show that the MPC-based multi-energy approach can improve the economic operation of DERs [224,249].

Interconnected multi-microgrids have the potential to enhance the reliability of power supply through the sharing of energy resources among nearby microgrids. Therefore, when a microgrid has a critical shortage in power supply, a better alternative to load-shedding will be power-sharing by a neighbor-microgrid (which has excess power). MPC can help in this regard to optimize power sharing subject to multiple objectives, and operational constraints. This will reduce energy losses, and extend the lifespan of energy storage systems. In addition, MPC-based methods can also provide other ancillary services like frequency and voltage control to microgrids within a common cluster.

Data-science and artificial intelligence techniques are expected to improve the cost-effective operation of large numbers of DERs in the smart grid. Thus, data-based methods are expected to further simplify, and improve the industrial applicability of predictive control. For instance, low-computational-resource intelligent algorithms that emulate advanced MPC with long prediction horizons, and model-free data-driven methods.

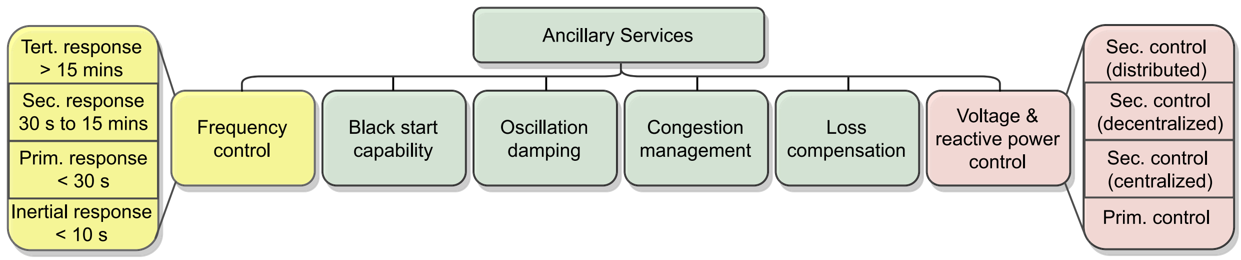


Fig. 15. Ancillary services for the smart grid [243,244].

8. Conclusion

The stringent grid-code requirements for grid-connected distributed energy resources (DERs) necessitate high performance, multi-objective control methods for power electronic converters. In this article, the applications of MPC to the smart grid were introduced. Furthermore, a comprehensive review was done on power converters for wind energy conversion systems (WECS), solar photovoltaic, fuel cell, and energy storage systems. Complementing MPC with artificial intelligence offers benefits including: lower computational burden, easier and more accurate weighting factor tuning, improved reference tracking accuracy, and improved robustness to parametric uncertainties. The future trends of MPC show its good potential to support emerging technologies, viz., multi-energy systems, multi-microgrids, and virtual power plants.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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