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Model Predictive Control of Microgrids – An Overview

Jiefeng Hu[a,*], Yinghao Shan[b,**], Josep M. Guerrero[c], Adrian Ioinovici[d], Ka Wing Chan[b] and Jose Rodriguez[e]

[a] *School of Engineering, IT and Physical Sciences, Federation University Australia, Mt Helen, Australia*

[b] *Department of Electrical Engineering, The Hong Kong Polytechnic University, Hong Kong*

[c] *Department of Energy Technology, Aalborg University, Aalborg, Denmark*

[d] *Holon Institute of Technology, Holon 5810201, Israel*

[e] *Faculty of Engineering, Universidad Andres Bello, Santiago, Chile*

***Abstract*—The development of microgrids is an advantageous option for integrating rapidly growing renewable energies. However, the stochastic nature of renewable energies and variable power demand have created many challenges like unstable voltage/frequency and complicated power management and interaction with the utility grid. Recently, predictive control with its fast transient response and flexibility to accommodate different constraints has presented huge potentials in microgrid applications. This paper provides a comprehensive review of model predictive control (MPC) in individual and interconnected microgrids, including both converter-level and grid-level control strategies applied to three layers of the hierarchical control architecture. This survey shows that MPC is at the beginning of the application in microgrids and that it emerges as a competitive alternative to conventional methods in voltage regulation, frequency control, power flow management and economic operation optimization. Also, some of the most important trends in MPC development have been highlighted and discussed as future perspectives.**

***Keywords* —Model predictive control, microgrid, primary control, secondary control, tertiary control, hierarchical control**

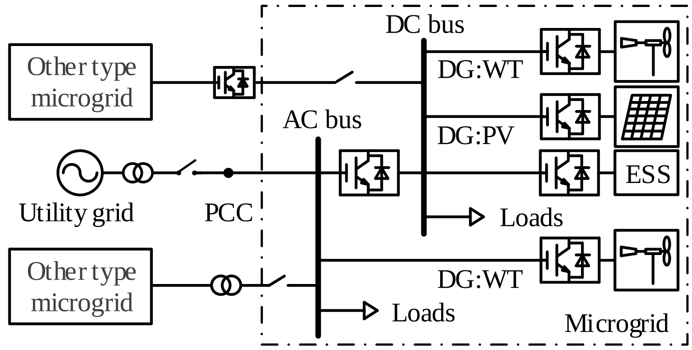
[*] Corresponding author.
[**] Corresponding author.
E-mail addresses: j.hu@federation.edu.au (J. Hu), yh.shan@connect.polyu.hk (Y. Shan)

1. Introduction

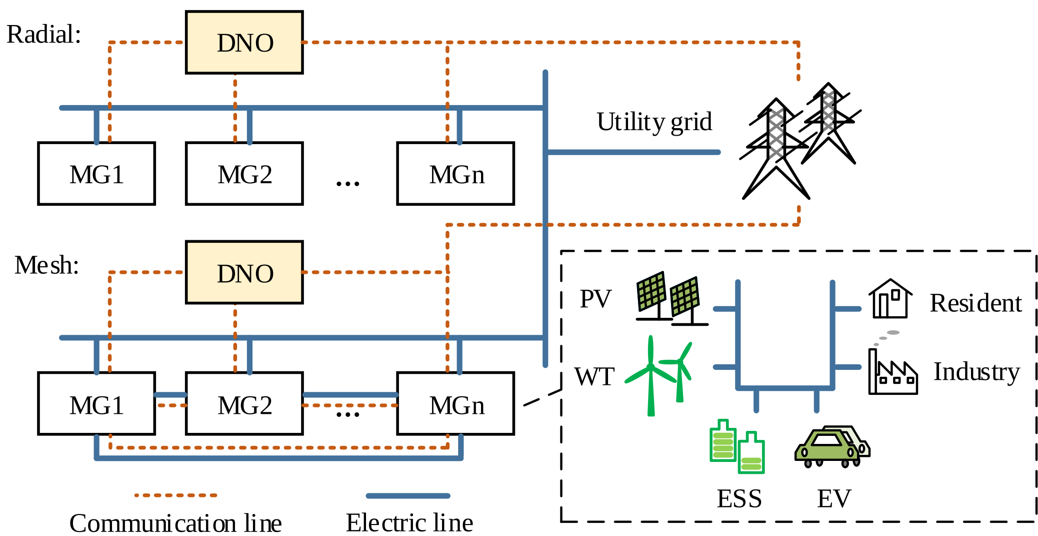
Over the past decades, renewable energy systems (RESs) have been rapidly developed due to ecological, social, economic and political forces and interests, such as the widely installed photovoltaic systems (PVs) and wind turbine systems (WTs) [1-3]. In order to better integrate distributed generations (DGs) into the utility grid, microgrids have emerged as a promising solution to interconnect RESs, energy storage systems (ESSs) and loads through various power electronics interfaces [4-8].

For the sake of interaction with the utility grid, the microgrid has the capacity to operate in grid-tied mode acting as a controllable single unit or in an islanded mode as a self-sufficient autonomous system. Microgrids can be classified, according to the main common buses, into dc, ac, and hybrid types. Fig. 1 (a) shows the configuration of converter-interfaced microgrids with distributed RESs and ESSs. As shown, a microgrid can be connected with other types of microgrids through various converters. Also, it can link to the upstream grid via the point of common coupling (PCC). Fig. 1 (b) depicts the diagram of interconnected microgrids. It shows that microgrids can be interconnected in radial or mesh topology, using distribution network operator (DNO) to govern the power flow. In each microgrid, PV, WT, ESS, electric vehicle (EV), resident and industry systems can be accommodated.

Currently, droop control methods are widely researched and adopted for the power sharing inside a microgrid, endowing an ability to eliminate critical communication links among DGs [9-11]. However, conventional droop control suffers from poor transient performance, inherent conflict between the precision of power sharing and the deviations of frequency/voltage, etc. Recently, hierarchical control of microgrids is foreseen to play a particularly important role [6][10][12][13]. Hierarchical control has the advantages of maintaining the strength of droop control, wiping out frequency&voltage deviations and guiding the power flows to/from the utility grid. Generally, hierarchical control consists of three levels, namely primary control, secondary control and tertiary control. These layers are distinguished by different communication bandwidths and time responses. Primary control is the fundamental layer that stabilizes system frequency and voltage, and shares loads with the fast response. Secondary control offsets the deviations of frequency/voltage derived from the primary control, aiming to recover the voltage/frequency to the rated values in steady state and to achieve utility grid connection. Tertiary control concerns the power flow among microgrid clusters, or between microgrids and upstream grid with additional functions like power planning and economic optimal scheduling.



(a) Configuration of converter-interfaced microgrids.



(b) Diagram of interconnected microgrids

Fig. 1. Microgrids

In the primary control, the power sharing methods, together with cascaded inner current and outer voltage feedback loops, are frequently used [6]. Nevertheless, this kind of cascade linear control (CLC) has main drawbacks such as [14-16]: 1) system performance is highly dependent on control parameters; 2) system status is sensitive to external noises and load changes; 3) trial-and-error based iterative tuning procedure results in a less effective application; 4) an additional step with the pulse-width modulation (PWM) regulator is needed. Consequently, the design of more advanced control strategies has gained great attention in global academic and research communities to address the high penetration of RESs. Besides, the conventional CLC methods still show less intelligence and flexibility to address the complexities and uncertainties from the high penetration of RESs, leading to power quality reductions and stability concerns [14][17-19].

For secondary control, it mainly has centralized and distributed/decentralized categories [7][13][20]. The centralized one requires a central controller to densely collect, process and deliver signals, causing the possible single point of failure. In contrast, the distributed type based on local controller collecting local information can avoid such failure and enables scalability. With the rapid development of DGs and microgrids, secondary control tends to be implemented in the distributed manner. As for tertiary control, power flow management and relevant economic optimization of the microgrid interacting with other microgrids or the utility grid are the main objectives [21-23].

Recently, a promising method named model predictive control (MPC) or receding horizon control, clearly distinguished from conventional CLC principles, has been widely used in either DG systems equipped with power converters [24-27] or microgrids with multiple RESs [21][22][28-30]. In this context, the optimal control behaviors or scheduled commands are determined according to predefined cost functions or objective targets under different constraints. To sum up, MPC has many advantageous features [31][32]: 1) multiple constraints from control and physical perspectives can be explicitly and intuitively involved; 2) excellent dynamic performance with robust control system; 3) control signals can be produced directly giving a straightforward simplicity; 4) an open access is enabled to interface various solving algorithms, making complex optimization problem solvable and convenient. While these techniques have already been reported in existing literature, they are seldom summarized from the perspective of hierarchical microgrids. Besides, in microgrids, researchers need to face new challenges in the development of MPC with the consideration of RES intermittency, load sharing accuracy, circulating currents, grid stability, etc.

The purpose of this paper is to offer a thorough systematic review of the state-of-the-art MPC strategies applied to microgrids. The major contributions are listed below. 1) A comprehensive review of MPC used in microgrids has been conducted, covering two categories, converter-level MPC and grid-level MPC. 2) The two-level MPC strategies applied to the three layers of microgrid’s hierarchical control architecture have been discussed. 3) The most important trends in MPC development have been highlighted and discussed, illustrating MPC is at the pilot stage in microgrid applications and it is foreseen to be a very competitive alternative to conventional methods.

The remainder of the paper is structured as follows. First, the basic principles of MPC on converter level and grid level are summarized. Then, a comprehensive investigation into recent MPC approaches in three layers of the hierarchical control architecture, including power converter control, frequency/voltage restoration and power flow management/economic optimization is conducted. Next, some of the challenges and limitations are discussed. Last but not least, possible future trends are pointed out.

2. Basic Principle of Model Predictive Control

Actually, MPC does not refer to a particular control approach, but rather to a set of control approaches that take full advantage of the system model under specific constraints to gain the control signals or commands through minimizing predefined cost functions or objective targets [33]. As for the MPC applied in microgrids, it can be apparently different in terms of converter level and grid level. In general, the former produces switching signals to drive the power converters while the latter determines the dispatching commands for DGs and controllable loads. However, these two levels have a similar control structure and design procedure based on the common MPC architecture. On this point, it can be said there is no clear boundary between these two control levels.

Regarding the common control structure, predictive model, cost function and solving algorithm are three key ingredients of MPC [27][34]. While for the common design procedure, generally, developing the predictive model is the first step, followed by designing the cost function, and lastly setting the solving algorithm. Among them, constraints are usually formulated inside the cost function. In this section, converter-level and grid-level MPC methods are respectively investigated and studied.

2.1 Converter-level MPC

Existing MPC methods for converters can be classified into two sets: continuous control set MPC (CCS-MPC) and finite control set model predictive control (FCS-MPC) [25][35]. CCS-MPC generates continuous signals for the PWM regulator to drive converters, while FCS-MPC is built on the discrete behavior of converters and thus avoids the usage of PWM regulators. During these years, FCS-MPC has been extensively used in many applications [24][26].

As stated above, FCS-MPC is an important branch of the MPC family. Taking the one-horizon prediction, for instance, Fig. 2 shows the general principle of converter-level MPC. The predictive model is obtained from the discretization of *RLC* circuit dynamics through state variable acquirement that can be achieved by either measurement or estimation of voltage/current/power.

The predictive model can be represented by the following equation, through which the state variables at next k+1 instant $\hat{\mathbf{x}}(k+1)$ can be acquired.

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

where $\mathbf{x}(k)$ refers to RLC circuit dynamics at k instant; $\mathbf{u}(i)$ refers to the converter switching states in a finite number; f(,) is the function which follows Kirchhoff's voltage/current law.

The cost function considering the Euclidean distance between the predicted and the rated values is usually expressed as

$$g = \sum \left(w_j \left| \mathbf{x}^* - \hat{\mathbf{x}}(k+1) \right| \right) \tag{2}$$

where x^* is the control reference, i.e. the desired values of voltage, current, power, etc.; w_j is the weighting coefficients.

Since FCS-MPC considers limited switching states, solving the algorithm can be simple. Usually, exhaustive search algorithms are fully competent [36]. This is different from undermentioned grid-level MPC which usually employs a specific toolbox to help solve a more complex algorithm. It is worth mentioning that various converter topologies can be applicable in Fig. 2, including but not limited to dc-dc [37-39], dc-ac [40-42], ac-dc [43-45], ac-ac [46][47], multi-level converters [48-50], or the converters with complex topology [51-53].

During these years, converter-level MPC has been actively developed. Since a constant switching frequency is generated, the most used derivatives of CCS-MPC are generalized predictive control (GPC) and explicit MPC. In Refs. [54] and [55], GPC was both used with LCL filter for solving harmonic issues. In Ref. [56], a neutral network core to build the input-output model was embedded in an explicit MPC for dc-dc converters. As for FCS-MPC, those considering control time sequence are an important emerging branch. In Ref. [57], a deadbeat technique was adopted to regulate currents during one control period, thus to better govern control time sequence. Besides, in Ref. [58], a steady switching frequency and an improved steady-state performance were simultaneously obtained by improving the FCS-MPC.

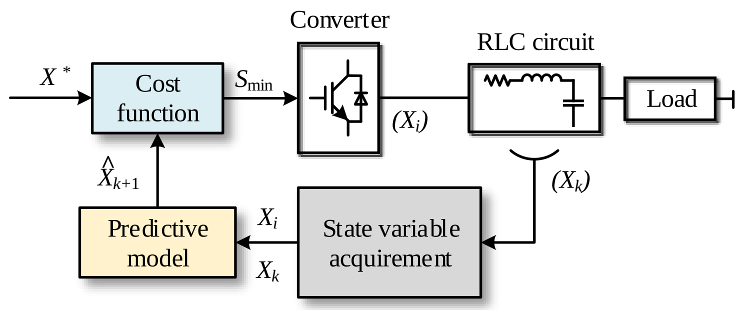


Fig. 2. Diagram of converter-level MPC.

2.2 MPC for Grid Level

Similar to converter-level MPC, the grid-level MPC also consists of predictive model, cost function and solving algorithm. However, grid-level MPC aims to control system-level operating statuses (e.g. ESS capacity, power flows within a microgrid or among networked microgrids). Grid-level MPC serves as an optimization algorithm that is suitable to optimize the performance of constrained systems with multiple objectives. Fig. 3 illustrates the general diagram of grid-level MPC. As shown, the predictive model is built upon the system states with possible forecasts, which formulates an expression for the future state prediction usually on the basis of current/past states. More concretely, the forecasts/predictions of the predictive model can be various state variables on a certain time-interval basis, like load demands, electricity prices, PV/WT generations, etc.

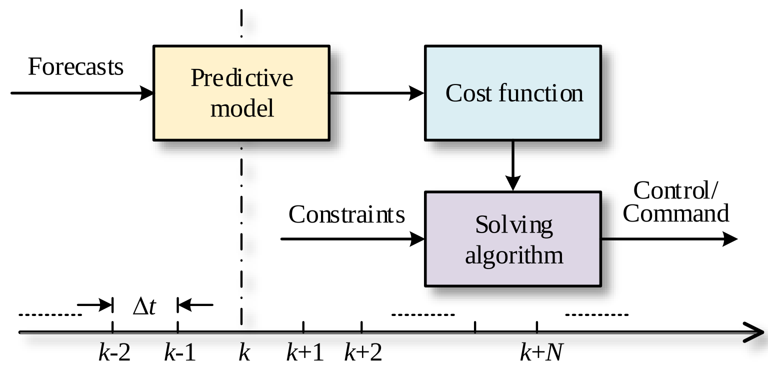


Fig. 3. Diagram of grid-level MPC.

Cost function design should reflect the concerns of the control objectives. Generally, the items in a cost function are in line with the multiple control or optimization targets. The predictions generated from the predictive model and possible desired targets are formulated into this cost function. During each sampling period, the optimal control/command sequence over a certain time horizon is computed for all the concerned parts of the whole system. Then, a group of system states is refreshed, resulting in an updated cost function, waiting for a further round of calculation to move the horizon one step forward. Grid-level MPC can provide a receding prediction horizon with a feedback mechanism that effectively reduces the impacts of uncertainties, thus making it more robust to disturbances.

Constraints should be considered in all involved DGs, power converters, power components, power lines, and the utility grid. Once the constraints are well formulated, the system performance can be improved with an ability to operate inside or near the constraint boundaries safely. The optimization problems taking constraints into account will then be solved by moving the time horizon window forward with the optimization problems being recalculated and solved again once new predictions are available.

The sampling interval Δt of a grid-level MPC can be ranged from several seconds to several hours and often larger than that of converter-level MPC. The time horizon is often determined according to multiple factors. For example, if the PV power output is recorded on a 1-min period basis, while the PV generation is predicted in every 30 minutes. In this case, the final sampling interval for the MPC is expected to be multiples of 30 minutes for a better match and precision.

The following steps can be summarized to implement the grid-level MPC: 1) first, system states and targets are utilized to form a receding model; 2) for a certain control horizon, an optimal control/command sequence is figured out for the next prediction period based on the data predictions; 3) implement the first step of the MPC considering all variables and constraints; 4) update all available states for the next period while moving one step ahead and repeating the optimization.

3. Microgrid Primary Control

The hierarchical control of microgrids stems from the three-layer control structure of large-scale power systems. In the hierarchy of microgrids, the fundamental level is the primary control which aims at maintaining the basic operation of the microgrid, thus providing a stable frequency/voltage supply and sharing the load demand properly. The followings are the brief descriptions of primary control and the associated MPC controllers that are mainly adopted for converter levels.

3.1 *Power Sharing Method*

A brief overview of the widely used power sharing method, i.e. droop control, is discussed here. Equation (3) illustrates the mathematical droop characteristic in an ac microgrid.

$$\begin{cases} f = f^* - mP \\ E = E^* - nQ \end{cases} \tag{3}$$

where f^* and E^* are the rated values of ac bus frequency and voltage, P and Q the active and reactive powers, m and n the P-f and Q-E droop coefficients, respectively.

Since reactive power and frequency do not exist in dc microgrids, the droop control in dc microgrids is formulated in a way that dc voltage reference will be linearly reduced with the increase of output current, which is expressed as

$$E_{dc} = E_{dc}^* - i_{dc}R_d \tag{4}$$

where E_{dc}^* is the dc voltage reference, i_{dc} the converter output current, R_d the virtual resistance used to match the real line resistances.

3.2 *Virtual Impedance Method*

Virtual impedance design is an effective way to reconstruct the system control output impedance, thus seeking a suitable application environment of droop methods and avoiding the use of real impedors. The design principle is described as

$$v_o^* = v_{ref} - Z_D(s) \cdot i_o \tag{5}$$

where v_{ref} is from droop equation (3) after a voltage synthesis (usually also after using a coordinate transformation), $Z_D(s)$ the transfer function of virtual output impedance in S domain, i_o the output current.

In practice, the output impedance is usually modified to either inductive, or resistive, or capacitive, depending on the nature of the power feeder, the filter and the control strategy [9]. For instance, the conventional droop method, i.e. equation (3), is supposed to have an inductive output impedance thus to meet the assumption in its formula derivation. Actually, virtual impedance can be endowed with a wide range of functions. For example, it can be set to a required harmonic impedance at a certain frequency to enable harmonic sharing and damping [59].

3.3 *MPC in Primary Control*

For the MPC applied in primary control, most of the existing work focuses on replacing the cascaded voltage and current loops with MPC controllers. As for the islanded microgrids, the essential task is to provide a stable voltage supply, which leads to a voltage formulation in the cost function using MPC methods. In this case, v_o^* in (5) can be selected as the cost function reference for the MPC. For example, the schematic diagram of the MPC used in the primary control of an islanded ac microgrid is illustrated in Fig. 4 in which the CLC method is also depicted. As shown, the measurement or the estimation from the circuit is used both for power calculation and MPC/CLC controllers. Then these controllers need the virtual impedance obtained from the droop control with the calculated powers. The main benefit of using MPC in a microgrid is the fast transient response to deal with the fluctuating power outputs from the renewable energies [17][60-63]. Moreover, the simplification of removing the PWM modulator is also achieved.

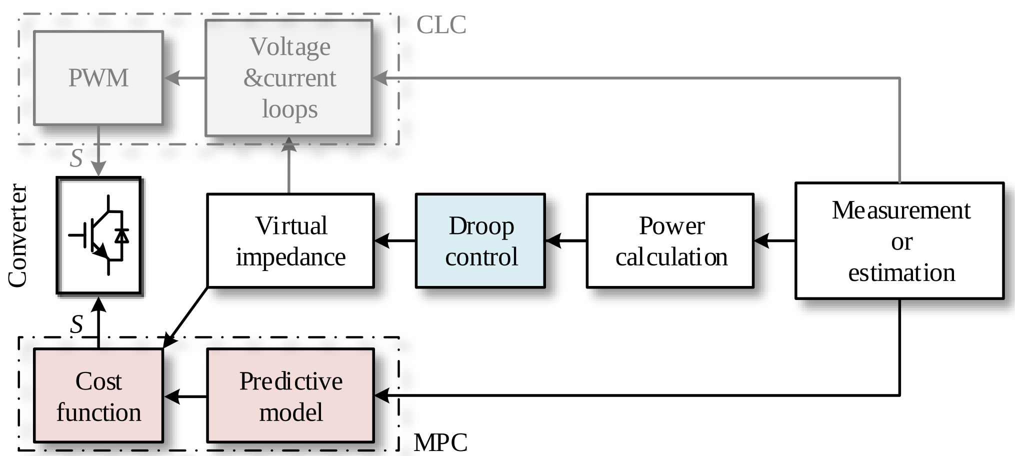


Fig. 4. MPC used in the primary control of an islanded ac microgrid.

When a microgrid works in grid-tied mode, the control target is changed to the regulation of power flow since the frequency and voltage are strongly fixed by the stiff utility grid. In this scenario, the converter-level MPC can incorporate the power flow into the cost function to replace the conventional power&current loops in CLC method, as depicted in Fig. 5. Also, it is straightforward for cost functions to formulate the rated active and reactive power values.

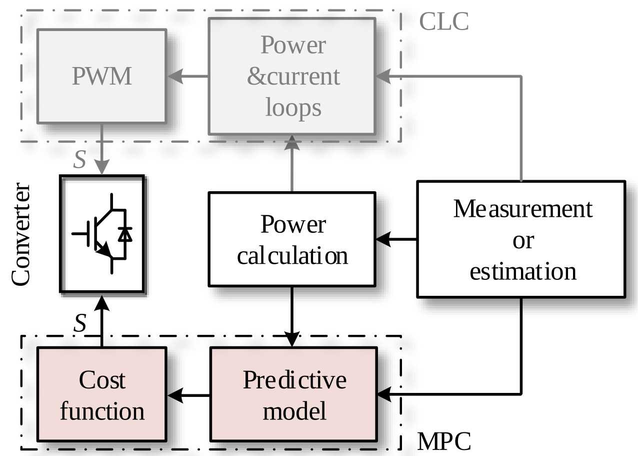


Fig. 5. MPC used in a grid-connected ac microgrid.

3.4 *Predictive Model with Longer-Horizon Prediction*

The converter-level MPC based on Euler forward approximation only has one step predictive horizon. For a longer-horizon prediction, the following steps are mostly adopted.

1) In k+1 instant, we assume all predictive models can be denoted as (in state-space form)

$$\mathbf{x}(k+1) = A\mathbf{x}(k) + B\mathbf{u}(k) \tag{6}$$

where A and B are coefficients.

2) When one more step prediction is considered, it yields [64]

$$\mathbf{x}(k+2) = A\mathbf{x}(k+1) + B\mathbf{u}(k+1) \tag{7}$$

It should be noted that the above equation is also an effective way to compensate the one-step delay for a real digital implementation.

3) Then, to achieve a further prediction horizon N (integer and >2), a linear extrapolation method can be employed [65]

$$\mathbf{x}(k+N) = \mathbf{x}(k+1) + (N-1)[\mathbf{x}(k+2) - \mathbf{x}(k+1)] \tag{8}$$

With this procedure, a longer-horizon prediction can be done to obtain additional merits such as system stabilization and reduced switching frequencies. However, it is noted that a longer-horizon prediction does not always ensure a better performance, which subjects to the accuracy of the predictive model [66].

3.5 *Cost Function Optimization*

The cost function reflects the control objectives and provides a criterion for selecting the optimal control set. In general, when the number of terms formulated in the cost function is not less than one, i.e. multiple targets are considered. Therefore, the weighting coefficients of each term need to be designed carefully. Different coefficient ratios generate different system performances. Normally, for different units and different values of the cost function terms, the coefficients are set to be divided by their references respectively to reach a normalized value if each term is equally treated. Otherwise, if one term needs to be treated with high priority, its coefficient will be set to a larger value to prioritize this objective. This kind of compensation along with the coefficients adjustment turns out to be a trial-and-error process which heavily relies on expert and experiential knowledge of the control target. As one advantageous way to optimize the weighting coefficients, intelligent algorithms can be employed. For instance, fuzzy logic control can be adopted to make the decision of selecting weighting coefficients, thus to obtain a better system performance [67-70].

With regard to the control references in cost functions, they are usually set to constant or ideal values. However, sometimes the approximations of past-instant variables which change little will be chosen as the references, as expressed in (9). This can be seen in a converter-level MPC with a small sampling time (around tens of microseconds). For instance, the ac bus voltage in a grid-connected ac microgrid can be assumed unchanged during successive time instants since the bus is strongly fixed by the stiff grid.

$$\mathbf{x}(k+1) \approx \mathbf{x}(k) \tag{9}$$

One way to make this approximation more precise for the above example of the ac bus voltage is to modify the k+1 instant variable with a voltage compensation by using [71]

$$v(k+1) = v(k)e^{j\omega T_s} \tag{10}$$

where ωT_s means the one-interval ahead angle.

3.6 *Circulating Current Suppression*

The circulating current caused by the parallel operation of converters also exists in the system regulated by converter-level MPC methods. Although fast dynamic response and high robustness can be achieved when using converter-level FCS-MPC, owing to the variable switching frequency, circulating current cannot be completely neglected. Unnecessary circulating current will increase the converter power loss, reduce system efficiency and damage electronic device. Recently, some studies have investigated the alleviation of circulating current on converter level through improving the MPC algorithms. An approach to suppress the circulating current through adjusting the weighting coefficients of the cost function was proposed in Ref. [72], where the coefficients are set according to the circulating current based on a preset switching table. Also, the MPC switching states are grouped according to the contribution of alternative switching states to the circulating current magnitude. Thus, the cost function is solved by only selecting those current-suppressed voltage vectors to restrain the circulating current. In addition, since the variable switching frequency can cause circulating current, as mentioned previously, fixing the switching frequency can also mitigate the circulating current. For example, in Ref. [73], virtual state vectors were added to achieve a constant switching frequency for this purpose.

4. Microgrid Secondary Control

Currently, droop control is extensively used as an effective method for power sharing in primary control. However, it unavoidably results in frequency/voltage deviations in steady state due to its inherent control limitations. To mitigate this problem, secondary control has been developed to eliminate deviations with the purpose of improving voltage quality and being connected to the utility grid safely. In this section, MPC-based secondary control is investigated and discussed.

4.1 Secondary Control Principle

The basic principle of secondary control is to provide additional compensation with the ability to correct the primary control reference, in other words, to shift the droop control characteristic curve to reach a new set point. This process can be performed by

$$\begin{cases} f = f^* - mP + \Delta f \\ E = E^* - nQ + \Delta E \end{cases} \tag{11}$$

where Δf and ΔE are the compensation signals.

Centralized and distributed methods are the two main categories of secondary control, which are compared in Fig. 6. As depicted, centralized secondary control is mainly based on PI methods, which requires centralized and complex communication networks to detect the PCC voltage and frequency, suffering from the possible single point of failure and inferior reliability. Besides, centralized control is more sensitive to communication delay and data loss, posing a risk to the system stability if the compensation signals delivered to primary control deviate from required values. Distributed secondary control, in contrast, attracts more interests owing to its high reliability and high stability. A sparse communication network with multiple agents is adequate to provide local and neighboring information to implement the distributed secondary control. The diagram of distributed secondary control using MPC is shown in Fig. 6. In comparison with centralized type, the buses information in the DG and its neighbor DGs will be measured. In addition, distributed secondary control facilitates the plug-and-play operation.

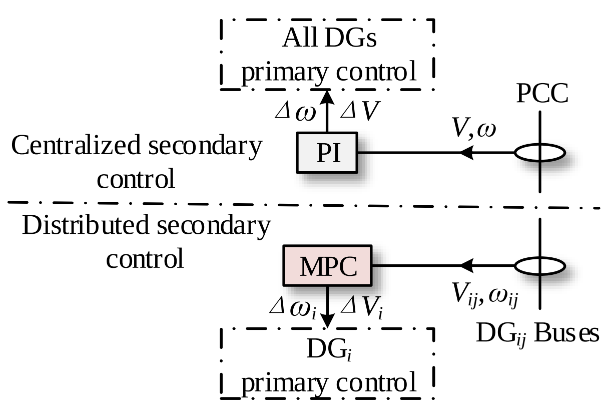


Fig. 6. Diagram of centralized and distributed secondary control.

4.2 MPC-Based Secondary Frequency/Voltage Control

For MPC-based secondary control, as previously mentioned, the aim is to produce the required compensation signals Δf and ΔE for the droop-based primary control. In line with grid-level MPC architecture, here three key components should be defined: 1) Predictive model is built on the mathematical relationship between future states and past/current states basically from local and/or neighboring systems; 2) The elements of frequency/voltage should be included in cost function; 3) Using specific toolbox to simplify the programming and solving.

In Ref. [20], a MPC method was used for restoring the system frequency. Compared to PI methods, namely conventional PI method and an enhanced PI controller with Smith predictor (SP), it is proved that frequency can reach nominal values with a faster speed but fewer oscillations during load variations. In Ref. [74], a distributed MPC secondary control for both frequency and voltage regulation was developed. Local and neighboring information are required to form predictive models while YALMIP toolbox and Gurobj optimizer are applied as solvers. It is found that the grid-level MPC is robust to various disturbances and perturbations. Similarly, in Ref. [75], MPC was utilized in a distributed manner to realize secondary voltage control.

It is worth mentioning that, different from the voltage which varies along distribution line due to the effect of line impedances, the frequency is a global variable in an ac autonomous system. For isolated microgrids, they may present different operating frequencies. Secondary control for frequency compensation is therefore needed to further interconnect multiple microgrids into a microgrid cluster. In Ref. [76], a method using MPC was presented to control the frequency among multiple microgrids. It demonstrates that MPC is better than traditional PI controller when dealing with various disturbances and communication delays. In Ref. [77], a distributed secondary frequency control based on MPC method was proposed, where MPC is used to regulate the frequency by adjusting the voltages of voltage-sensitive loads with the consideration of bus voltage constraints.

4.3 Communication Delays

The frequency/voltage compensation signals are produced and delivered through data communication network with diverse bandwidths, capacities and rates. Thus, the network is prone to time delays, which impacts the information integrity and signal update as well as control effectiveness. As a result, the resilience and resistance of the system to communication delays should be considered as a design criterion. Otherwise, the microgrid performance could be compromised with secondary control. Usually, communication delays are time-varying, which increases regulation difficulty. A gain scheduling approach can be used to relieve the delay effect on system dynamic performance [78]. The fast transient response by using MPC in secondary control can also be influenced by the communication delays when the delay is close to a certain boundary, but the robustness can usually be guaranteed [20]. This phenomenon indicates that MPC can be effectively applied to systems as a secondary control even under a severe condition where the communication delays are unknown and complex.

5. Microgrid Tertiary Control

Tertiary control plays a crucial role in achieving flexible interaction among interconnected/networked microgrids or between the microgrid and utility grid. Addressing power flow and optimizing economic operations are the main focuses for this highest control level. In this context, grid-level MPC is mostly applied to solve the optimization problems with various constraints. Fig. 7 illustrates the main objectives of tertiary control, where four elements are overlapped with each other meaning that they all have common areas (see following subsections).

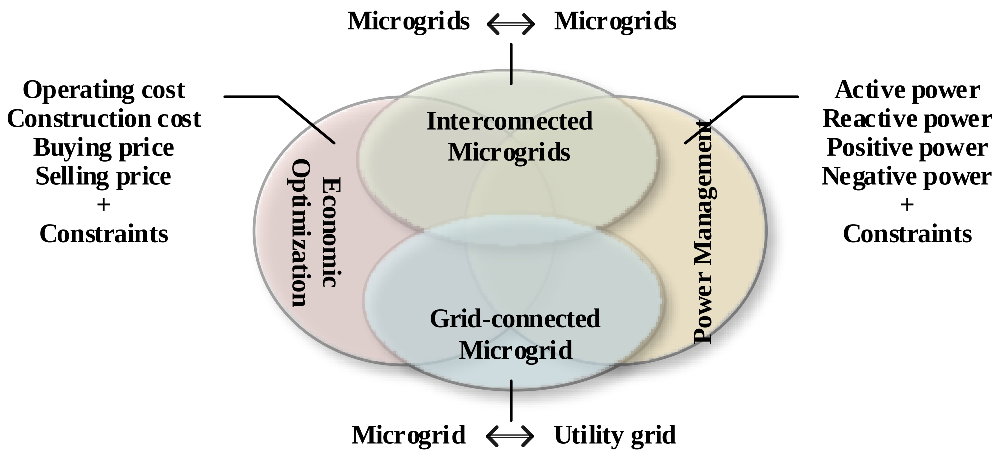


Fig. 7. Main objectives of tertiary control.

5.1 *Tertiary Control Principle*

In order to implement MPC control at a grid level, an integrated mathematical representation of all concerned parts inside or outside a microgrid is necessary. This is the first step to construct the predictive model with the consideration of various uncertainties and constraints. Next, a time series based method is used to formulate a future-value receding equation, which indicates the predicted states based on existing current states. Generally, forecasting information about DG outputs, electricity prices, and load demands will be involved. Key factors and emphasized components will be formulated in the cost function aiming to achieve power flow optimization, operating cost minimization and DG output efficiency maximization. The power flow management and optimization are the questions as to how the load demands should be shared among various power sources and/or energy storages, simultaneously giving full consideration to power loss minimization, power generation maximization and power storage optimization. The algorithm is usually solved by using a specific solver toolbox, which is similar to the secondary control.

The benefits of utilizing MPC for tertiary control in microgrids can be summarized as 1) multiple objectives can be involved in an intuitive and a direct way into the cost function with a straightforward quadratic summation; 2) various constraints can be comprehensively considered with suitably limited ranges; 3) an effective specific toolbox with a powerful solver is available to facilitate the algorithm solving process, which is particularly useful in tertiary-level control with complex formulations and various constraints.

5.2 MPC-Based Power Management & Economic Optimization

In a practical schedule of power flows inside or outside microgrids, specific conditions must be met. Among them, pursuing economic interests is a prominent example. This economic optimization relevant to power management is common in the interaction between the microgrid and the power system. For instance, in Ref. [21], MPC was adopted for the power flow optimization of a grid-connected microgrid. Five cost-related parts are considered in the cost function, as expressed in (12), i.e. buying and selling prices of electricity (1st and 2nd terms), fuel consumption cost (3rd term), and generator start-up cost (4th term). Additionally, one more term regarding battery energy was also involved (5th term).

$$\begin{aligned}
&J^*(\zeta(k), \bar{\boldsymbol{P}}_{PV}(k), \bar{\boldsymbol{P}}_{L}(k), \bar{\boldsymbol{c}}_{Imp}(k), \bar{\boldsymbol{c}}_{Exp}(k)) = \\
&\min \sum_{i=0}^{N-1} [\underbrace{\Delta T\, \bar{c}_{Imp,i}\, P_{eImp}(k+i)}_{\text{1st}} - \underbrace{\Delta T\, \bar{c}_{Exp,i}\, P_{eExp}(k+i)}_{\text{2nd}} \\
&+ \underbrace{\Delta T c_G \boldsymbol{F}^{\boldsymbol{T}} \boldsymbol{k}_{\boldsymbol{G}}(k+i)}_{\text{3rd}} + \underbrace{c_s c_G k_s(k+i)}_{\text{4th}}] - \underbrace{c_B V_{nom} Q \zeta(k+N)}_{\text{5th}}
\end{aligned} \tag{12}$$

In (12), $\zeta(k)$ is the state of charge (SOC) of the battery, $\bar{\boldsymbol{P}}_{PV}(k)$ the PV generation forecasts, $\bar{\boldsymbol{P}}_{L}(k)$ the load demand forecasts, $\bar{\boldsymbol{c}}_{Imp}(k)$ the import price forecasts, $\bar{\boldsymbol{c}}_{Exp}(k)$ the export price forecasts, N the number of samples, ΔT the sampling time, P_{eImp} the import power from the grid, P_{eExp} the export power to the grid, c_G the cost of generator fuel, c_s the penalty of start-up fuel, c_B the stored energy value of the battery, V_{nom} the nominal voltage of the battery and Q the capacity of the battery.

To better dispatch the power energy, a whole microgrid considering power storages and power demands was modeled in Ref. [79] to build the MPC predictive model. A distributed MPC for microgrid power management was proposed in Ref. [80], which takes both economic and environmental impacts into the cost function. In Ref. [81], a distributed MPC considering the cost/benefit of energy sources, the cost from the imbalance between power supply and load demand, the cost of the power exchange with the main grid, and operation cost/benefit of batteries was developed to achieve an economic optimization. In Ref. [82], a novel distributed economic MPC approach was proposed to optimize microgrid users' benefits, where the cost of buying energies from or selling energies to the microgrid was formulated into the cost functions. In Ref. [83], a stochastic MPC method balancing microgrid power and predefining exchange power was developed to calculate the optimal power references for wind generators and electric vehicles.

5.3 Grid-level MPC for Islanded Microgrids

The operational optimization of an islanded microgrid is highly crucial due to not only the difficulty of internal regulation of uncertain and intermittent renewable energies but also the concern of operating cost and economic benefit. Therefore, a grid-level optimization for islanded microgrids is also needed.

In Ref. [84], a two-layer MPC was presented for the optimization of an islanded microgrid, where seasonal auto regression integrated moving average model (SARIMA) and exponential smoothing are used to form the predictive model, and discrete dynamic programming is adopted to execute the algorithm. In Ref. [85], MPC was used for the power flow optimization with a cost function considering the load consumption, power line loss, and battery discharge/charge. The algorithm is solved by using YALMIP toolbox with CPLEX solver. A two-layer distributed MPC scheme was proposed in Ref. [86] to regulate an islanded dc microgrid. The upper-layer MPC coordinates parallel dc-dc converters, while the lower-layer MPC manipulates wind generator controllers. Similarly in Ref. [87], MPC was utilized to control power flows coordinating with the ESS in an islanded microgrid. The power losses from line resistances, filter resistances and batteries are taken into account, the solving algorithms are using CPLEX solver and YALMIP toolbox.

5.4 Grid-level MPC for Networked Microgrids

Networked microgrids, which are a cluster of electrically interconnected microgrids to accommodate more RESs and loads, now have become a growing concern. This networked architecture enables mutual peer power support among small ac/dc microgrids and promotes the usage of renewable energies [88]. To facilitate this interaction, DNO and distribution energy management system (DEMS) are usually necessary for generating/transmitting control commands and regulating power flows. In contrast to individual microgrids, the power coordination of networked microgrids becomes more complex, resulting in a higher demand for more efficient power optimization.

In Ref. [89], a centralized MPC was applied to coordinate the power flow among a microgrid network. The predictive model is constrained with an upper and a lower limits. The cost function has two parts, both related to the energy sold or purchased, the first one is about adjacent microgrids while the second one about the utility grid. In Refs. [90] and [91], MPC was used to minimize the operating expense and keep the power balance simultaneously under the uncertainties from both the supply and demand sides. The dynamic receding-horizon procedure of the MPC enables appropriate actions to address various constraints. A distributed MPC was proposed in Ref. [22] to maximize the economic benefit and simultaneously minimize the degradation of storage systems subjected to diverse constraints. These are solved by using TOMLAB/CPLEX solver.

For a better visualization and understanding, the above major MPC methods adopted in microgrids are summarized in Table 1, which are categorized in terms of control levels, control layers, predictive models, cost functions and solving algorithms.

Table 1 Summary of MPC methods in Microgrid Applications.

Control levels	Control layers	Predictive models	Objectives in cost functions	Solving algorithms	Relevant references (e.g.)
Converter-level	Primary control	Dynamics of converters and *RLC* circuits	Converter outputs: voltage, current, active power, reactive power, circulating currents	Exhaustive search (FCS-MPC, CCS-MPC)	Refs. [14], [17], [60-62]

Grid-level	Secondary control	Topology features, forecast and dynamics of DGs, ESSs, and load demand	Compensation of frequency and voltage, grid synchronization	Specific toolbox & solver (e.g. TOMLAB, CPLEX, YALMIP)	Ref. [74]
	Tertiary control		Power flows, operational cost, economic benefit, power loss, etc.		Refs. [22], [85], [87]

Besides, the highlights of reviewed representative MPC methods are compared in Table 2 where the applications, advantages and disadvantages are involved.

Table 2 Advantages and disadvantages of reviewed MPC methods.

MPC methods	Applications	Advantages	Disadvantages	Relevant references
Converter-level MPC voltage & power control	Interlinking converter	Enable stable operation of microgrids, flexible power regulation and grid support	Coordinated control under different cases is challenging	Ref.[14]
Converter-level MPC voltage & power control	dc-dc & dc-ac converters	dc-bus voltage shows less oscillation; inverters' power sharing is faster and smoother	Need more additional measurements	Ref.[17]
Converter-level MPC with virtual space vectors	Three-level neutral-point clamped inverters	Dynamic response is fast, controller design is simple and harmonic distortion is reduced	Increased cost of switching losses	Ref.[18]
Grid-level MPC considering communication delays	Restoring microgrid system frequency	Faster speed with fewer oscillations	Possible slightly slower dynamic performance	Ref.[20]
Grid-level distributed MPC with day-ahead operation	Maximize economic benefit and minimize storage system degradation	Improved economical benefits and maximized storage system lifetime	Different system constraints should be fulfilled	Ref.[22]
Grid-level distributed economic MPC	Coordinated stochastic multi-microgrids energy management	Successfully reduce the system operating cost with supply-demand balance	System-wide operating cost will be slightly higher than centralized scheme	Ref.[29]
Converter-level MPC current control	Bidirectional three-level dc/dc converter	Significantly reduced power switch and inductor ratings, significantly reduced inductor current ripple	Small dc-bus voltage-level fluctuations	Ref.[37]
Converter-level MPC with current and SOC constraints	Bidirectional single-inductor multiple-port converter	It has smaller size, less component and lower cost. It presents better performance when integrating into dc microgrids	Need a move-blocking technique and enumeration method	Ref.[51]
Converter-level MPC with improved cost function	Voltage source converter	Transient response is superior, system is robust to parameter variation and voltage supply is significantly improved	Lack of theoretical analysis of MPC stability	Ref.[62]
Grid-level distributed MPC	Secondary frequency and voltage regulation	Robust to various disturbances and perturbations	Specific solution algorithm is used which may limit the application	Ref.[74]
Grid-level distributed economic MPC	Economic optimization of the wind-photovoltaic-battery microgrid	System economic benefit and system stability are improved with less computation time	Dual-mode MPC method is used, which will be more complicated than the traditional method	Ref. [81]

Grid-level centralized MPC	Coordinate the power flow inside microgrid networks	Minimizing the exchange between microgrids and maximizing the utilization of renewable energy	Need the forecasting information about energy prices, production power, and loads	Ref. [89]

6. Current challenges in Predictive Control in Microgrids

Although MPC presents many benefits in the hierarchical control of microgrids, it also has challenges and limitations that could degrade its control performance and limit its scalability. The following aspects about MPC predictive model, sampling interval, stability, and cost function design are covered. Besides, the possible solution for each challenge is provided.

6.1 Predictive Model

The modeling quality and accuracy of the predictive model directly impact control performances, in this sense, the development of predictive model is always fundamental and crucial [92]. Predictive model needs to build the connection between future output variables and current/past input variables. There are many ways to design predictive models, among them, discretization process is often used to discretize the model for a better controller application. Commonly, for converter-level MPC, Euler approximation (like Euler forward approximation) and Taylor series expansion are adopted. However, in either discretizing situation, there is always a tradeoff between the model accuracy and calculation complexity [93][94]. Thus, how to effectively balance this tradeoff is a challenge. This problem can be effectively solved by using a powerful processor. In such case, accurate model and fast algorithm solution can be both satisfied.

6.2 Sampling Interval

The design of the sampling interval is another issue if the predictive model is executed in a discretization manner, which is suitable for not only converter-level MPC but also grid-level MPC. For converter-level MPC, usually, zero-order holders and observers are utilized for the sampling [74][76]. For the implementation, observers have more flexibility and can possess more functionalities. In general, a better performance will be achieved when a smaller sampling time is set, however, which results in a heavier computational burden and a possible lower economic efficiency. While for grid-level MPC, as aforementioned, forecasts are generally needed. In terms of data acquisition, the precision of forecasts along with the errors between forecasts and actual values will impact the optimization accuracy. In order to reduce these effects, more accurate short-term predictions can be carried out to achieve better updates [95].

6.3 Stability

Stability is highly important for microgrids, especially operating in autonomous operation. So far, the stability analysis about the combination of droop control and CLC has been more mature and comprehensive than the combination of droop control and converter-level MPC. On the other hand, until now, converter-level MPC itself has still lacked a standard theoretical mode for the stability analysis. Even though Lyapunov concept has been applied to the analysis of converter-level MPC, extensive verification is still needed [27][96]. Currently, in order to evaluate the robustness and stability of converter-level MPC, the essential factors of RLC behaviors formulated in predictive models are tested. In these trials, the control parameters are continuously altered in the processor settings while maintaining the real components unvaried [62][71].

6.4 Cost Function Design

As previously mentioned, usually, for an exhaustive control target, many items will be covered in the cost function. The items might be the active power and reactive power controls for a converter-level MPC under a microgrid grid-connected operation; and multi-factors like operational cost, voltage quality, power loss and economic benefit for a grid-level MPC. All these control objectives along with diverse constraints must be reflected in the cost function. In this case, the design, arrangement and allocation of these items become a real challenge.

In addition, how to effectively set the weighting factors of the polynomial cost function is still under development. For example, as stated in Ref. [97], just heuristically tuning the weighting coefficients, or simply setting the same value to the two objectives in the cost function is a questionable practice. Generally, this will deteriorate the current total harmonic distortion (THD) and the closed-loop performance. As aforementioned in Subsection 3.5, intelligent algorithms such as fuzzy logic control can be used to optimize the weighting coefficients.

7. Future Trends

With the rapid increasing penetration level of RESs in the low voltage distribution network, the existing power system is in the transformation from centralized-control bulky systems to decentralized smart systems with the microgrids as building blocks. These new development trends and directions indicate the new requirements for superior control schemes. In this context, as previously stated, MPC will be competitive and promising to meet the urgent need of future grid. And the following areas will likely be the research focuses in the following years.

7.1 New Mathematical Formulation

In fact, the mathematical model of MPC can be represented in either impulse response form, or transfer function form, or state-space form [98]. At present, predictive models are usually described in state-space forms. Actually, there exist other alternatives to rewrite the model state, like Laguerre functions used in Ref. [99]. The results show that this alternative method drastically reduces the number of optimizing variables without any degradation of transient response. On the other hand, for the grid-level MPC, the future-value receding model can be adopted for the predictive model like the controlled autoregressive moving average (CARMA) model in Ref. [100] which can produce steps-ahead prediction for multiple-input multiple-output systems, and the input-output feedback linearization (IOFL) in Ref. [101] which facilitates the predictive model design without considering the prior steady-state operating point, as well as the SSARX model establishing an adaptive scheme to eliminate steady-state offsets in Ref. [94]. In addition, more complicated but more accurate MPC types like the nonlinear MPC which can better simulate the nonlinear and hybrid target can be considered for future applications[102][103].

7.2 Holistic and Intelligent MPC Approaches

Currently, there is still a gap in MPC of microgrids between the research of power electronics and power systems. The existing research, on the one hand, focuses on the regulation of power converters, but the effect of the grid is seldom considered. On the other hand, system-level power flow control of the network with high PV penetration has been investigated, however, the details of converter topologies and their switching methods are not taken into account. There is a need to develop holistic MPC approaches that can deal with power converter control at the bottom and the power flow on the top. Meanwhile, MPC will incorporate with other methods such as fuzzy logic control and multi-agent system control to gain more control flexibility and intelligence.

7.3 MPC in dc Microgrids

After losing the battle with ac distribution for centuries, now dc distribution is likely to win back with the fast development of power electronic converter technologies and proliferation of dc generation and dc loads. DC microgrids offer many advantages including higher efficiency and reliability [85][86]. Also, dc microgrids facilitate plug and play features and enable simpler integration of RESs. Therefore, dc microgrids and the associated MPC methods tend to be one of the major research areas in the next decades. For example, in a PV-dominant microgrid, in order to better manage power flows, an ESS system with bidirectional dc-dc conversion is also usually equipped. PV and ESS systems are interconnected via dc bus. Their associated dc-type converters can be regulated by using converter-level MPC control, while using grid-level MPC on top to coordinate their interactions.

7.4 MPC in Networked Microgrids

Converter-level MPC techniques are relatively mature as they have been widely studied and applied in the primary control layer. However, grid-level MPC in the tertiary control layer dealing with power flow and economic operation still needs further development. In the future, islanded microgrids that are geographically adjacent to each other are more likely to be networked to constitute microgrid clusters with additional flexibility for resilient operations. Each microgrid in the network is able to choose when and how to be interconnected and to exchange power with others. Under this new grid architecture, new MPC strategies are highly desired to optimize the power flows within the microgrid cluster to achieve overall optimal economic power dispatch with general stability of load frequency and voltage.

8. Conclusion

In this paper, the state-of-the-art studies on the predictive control in microgrids have been reviewed. First, the basic principle of predictive control is presented. After that, recent converter-level and grid-level technologies are investigated. These predictive control approaches have been applied in three different control layers of the hierarchical control of microgrids. Major benefits, such as faster dynamic responses in lower control level and flexible integration of various objectives in higher control level, have been discussed. Also, the current challenges and limitations of predictive control have been analyzed. Finally, future perspectives of this emerging area have been pointed out. With the on-going development of power electronic techniques and the increasing penetration level of distributed renewable energies into the existing power network, the authors believe more advanced predictive control with new mathematical formulation and holistic intelligent scheme tends to play a significant role in microgrids, particularly in promising areas such as dc microgrids and networked microgrids.

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