Robust Model Predictive Control of Converter-Based Microgrids

Oluleke Babayomi, *Senior Member, IEEE*, Rafal Madonski, *Senior Member, IEEE*, Zhenbin Zhang, *Senior Member, IEEE*, Jose Rodriguez, *Life Fellow, IEEE*, Innocent Davidson, *Senior Member, IEEE*, and Dong-Seong Kim, *Senior Member, IEEE*

***Abstract*—Converter-based microgrids are modern decentralized energy systems that integrate distributed energy resources, communication networks, and control systems. They manage energy generation, distribution, and utilization to enhance resilience and operational efficiency in modern power networks. Fourth industrial revolution technologies, such as automation, Internet-of-Things, artificial intelligence, and energy storage are integrated to create resilient, efficient, and sustainable energy systems. Model predictive control (MPC) is a promising technique for optimizing microgrid operations by considering system constraints and forecasting disturbances. However, standard MPC implementations struggle with robustness against internal and external uncertainties such as model uncertainties, measurement noise, and cyber threats, making them less effective for real-world microgrid applications. This article provides a comprehensive review of robust MPC techniques designed to enhance the reliability and security of cyber-physical microgrids. The study explores various robust MPC methodologies, including adaptive MPC, observer-based MPC, tube-based MPC, stochastic MPC, and data-driven approaches. The application of these techniques to mitigate uncertainties across different hierarchical levels of microgrid control, in particular, converter and system levels. In addition, this article examines cyber-resilient MPC approaches to mitigate cyber-attacks, including false data injection and denial-of-service attacks. Finally, emerging trends, such as AI-enhanced MPC, digital twin-based testing, and event-driven control, are outlined to support the development of next-generation robust MPC strategies for power converter-based microgrids.**

***Index Terms*—Artificial intelligence, cybersecurity, disturbance, grid-forming (GFM), measurement noise, microgrids, model predictive control (MPC), observer-based MPC, power converters, robust MPC.**

Received 10 April 2025; revised 25 June 2025; accepted 1 July 2025. Date of publication 7 July 2025; date of current version 27 August 2025. This work was supported in part in part by the Institute of Information & Communications Technology Planning & Evaluation (IITP)-Innovative Human Resource Development for Local Intellectualization program grant funded by the Korea government (MSIT) under Grant IITP-2025-RS-2020-II201612, in part by the Priority Research Centers Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education, Science and Technology under Grant 2018R1A6A1A03024003, and in part by the Institute of Information and Communications Technology Planning and Evaluation(IITP)-ITRC(Information Technology Research Center) grant funded by the Korea government(MSIT) under Grant IITP-2025-RS-2024-00438430. Recommended for publication by Associate Editor S. K. Mazumder. *(Corresponding author: Dong-Seong Kim.)*

Oluleke Babayomi is with the ICT-Convergence Research Center, Kumoh National Institute of Technology, Gumi 39177, South Korea (e-mail: babayomi@ieee.org).

Rafal Madonski is with the Faculty of Automatic Control, Electronics and Computer Science, Silesian University of Technology, 44-100 Gliwice, Poland (e-mail: rmadonski@polsl.pl).

Zhenbin Zhang is with the School of Electrical Engineering, Shandong University, Jinan 250061, China (e-mail: zbz@sdu.edu.cn).

Jose Rodriguez is with the Faculty of Engineering, Universidad San Sebastian Santiago, Santiago 8420524, Chile (e-mail: jose.rodriguezp@uss.cl).

Innocent Davidson is with the French South African Institute of Technology (F'SATI), and the African Space Innovation Center (ASIC), Cape Peninsula University of Technology (CPUT), Bellville 7535, South Africa (e-mail: davidsoni@cput.ac.za).

Dong-Seong Kim is with the Department of IT Convergence Engineering, Kumoh National Institute of Technology, Gumi 39177, South Korea (e-mail: dskim@kumoh.ac.kr).

Color versions of one or more figures in this article are available at https://doi.org/10.1109/TPEL.2025.3586709.

Digital Object Identifier 10.1109/TPEL.2025.3586709

NOMENCLATURE

CCS-MPC	Continuous control-set MPC.
CESO	Cascade extended-state observer.
CP-ESO	Cascade-parallel extended-state observer.
EMPC	Economic MPC.
ESO	Extended-state observer.
FCS-MPC	Finite control-set MPC.
GFM	Grid-forming.
GFL	Grid-following.
MMG	Multimicrogrid.
MPC	Model predictive control.
MF-ESO	Multifrequency extended-state observer.
PC-ESO	Parallel-cascade extended-state observer.
SAESO	Structurally adaptive ESO.
VSC	Voltage-source converter.

I. INTRODUCTION

THE increasing grid penetration of distributed energy resources (DERs), such as solar photovoltaics, wind turbines, and energy storage systems has led to the proliferation of microgrids—localized energy systems capable of operating autonomously or in connection with the main electric power grid [1]. Unlike traditional power systems, modern microgrids rely on advanced controllers (with or without communication networks) to coordinate energy generation, storage, and consumption. Nonetheless, as the spatial distribution of microgrid physical elements expand, and these elements proliferate, communication networks are increasingly being applied to coordinate their control. The resulting cyber-physical microgrids introduce new opportunities for enhancing energy efficiency, reliability, and sustainability. However, they also face major challenges, such as renewable energy intermittency, communication delays, cyber-security threats, and physical component uncertainties [2]. To address these challenges requires advanced control strategies capable of enhancing system stability and optimal performance amidst these unpredictable disturbances.

Linear control techniques are well established for conventional power systems, but rely on linearized system models that are reliable over a defined operational range [3]. This is limiting for multihierarchical, multitimescale systems like microgrids, which in more recent times aggregate a large number of power converters with nonlinear characteristics. Therefore, nonlinear control schemes that allow a reliable representation of the dynamics of nonlinear systems over wider operational range have become necessary [4]. A recent related study compared several leading advanced control methods (including data-driven control, MPC, direct power control, sliding-mode control, passivity-based control, and H_∞ control) for converter-based microgrids and showed that MPC has the added advantage of optimally handling constraints for the safe and reliable operation of microgrids [5].

MPC has emerged as a powerful control technique for microgrid applications due to its ability to handle multivariable systems, constraints, and prediction of future events. Unlike conventional control methods, which rely on predefined rules or simple feedback mechanisms, MPC incorporates system dynamic models and disturbances into an optimization framework. By solving a constrained optimization problem at each control interval, MPC generates a sequence of optimal control inputs while respecting system constraints such as voltage limits, power flow constraints, and power converter limitations. This predictive capability makes MPC particularly suitable for microgrid applications, where proactive decision-making is essential to maintain system stability under varying conditions [5]. Two kinds of MPC schemes are applied in converter-based systems: FCS-MPC and CCS-MPC. FCS-MPC is simpler and does not require a dedicated pulsewidth modulator, while CCS-MPC requires a modulator for its operation. This article focuses on FCS-MPC for converter control, unless otherwise stated.

Despite its advantages, conventional MPC for microgrid converters [6] is highly sensitive to system uncertainties. In microgrids, uncertainties arise from both internal and external factors, such as unmodeled dynamics, sensor inaccuracies load variations, and grid disturbances. These introduce prediction errors, which can degrade the performance of standard MPC and potentially lead to instability [7]. To address these issues, recent robust MPC techniques enhance resilience against disturbances and improve microgrid reliability.

Multistep MPC has been reported to improve MPC's closed-loop stability, steady-state performance, and robustness to measurable disturbances [8]. However, improved performance is associated with a tradeoff in computational complexity. To solve this challenge, improved computational efficiency using the sphere decoding algorithm has been achieved in multilevel converters for high-power, medium-voltage electrical drives [9]. However, microgrids require two-level low-voltage VSCs arranged in parallel, operating at lower power levels [1]. Therefore, MPC techniques that provide high performance and robustness within a single step prediction are preferred for microgrid applications. Further details on multistep MPC are covered in Section II-D2.

Robust MPC extends traditional MPC by incorporating worst-case uncertainty models, adaptive mechanisms, and real-time learning techniques [10]. Various robust MPC methods exist, each tailored to different microgrid control challenges. For example, adaptive MPC continuously updates the control model using real-time data, allowing the system to adjust to changing conditions [11]. Observer-based MPC leverages estimation techniques such as Kalman filters or ESOs to compensate for measurement noise and unmodeled dynamics [5]. Tube-based MPC ensures that all predicted trajectories remain within a bounded uncertainty region, making it effective for handling parameter variations [12]. Data-driven MPC utilizes machine learning to enhance decision-making by learning system behavior from historical data [13].

At the hierarchical level, robust MPC can be applied to both converter-level and system-level control. Converter-level robust MPC focuses on maintaining voltage and frequency stability at the power electronics level, addressing uncertainties in GFM and GFL inverters [14], [15], [16]. However, system-level robust MPC optimizes global energy dispatch, frequency restoration, and economic operation while ensuring stability under fluctuations in renewable generation. Furthermore, the integration of cyber-security measures into MPC frameworks, referred to as cyber-resilient MPC, has become crucial due to the increasing threat of cyber-attacks on microgrid communication networks. Attacks such as false data injection, denial-of-service (DoS), and replay attacks can disrupt microgrid operations, making resilience against such threats a growing research focus [17].

While robust MPC techniques offer improved resilience, they also introduce computational complexity, requiring advanced optimization algorithms and high-speed processors for real-time execution. Balancing robustness and computational efficiency remains a major challenge in implementing robust MPC for microgrids, especially in scenarios with fast control loops, such as power electronic converters [10].

In addition, ensuring scalability in MMG systems presents another hurdle, as robust MPC approaches must efficiently coordinate multiple distributed controllers while maintaining stability across interconnected microgrids [18]. To address these challenges, emerging research trends focus on AI-enhanced MPC [19] and event-driven control architectures that reduce computational overhead while improving robustness. Digital twin-based simulation environments are also being explored to test and refine robust MPC strategies before deployment in real-world microgrid operations [20].

Several studies have surveyed MPC applications in microgrids. Hu et al. [21] studied MPC for converter and grid applications in microgrids. A comprehensive review of MPC for hierarchical ac and dc microgrids was reported in [22] and [23]. Meanwhile, Torres et al. [24] surveyed the design for microgrid functionalities with MPC. However, to the best of the authors' knowledge, no comprehensive and systematic

SEC. II. BACKGROUND AND FUNDAMENTALS
A. System Description
B. Control Uncertainties in Converter-Based Microgrids
C. Modeling of AC Microgrid Converters
D. Conventional MPC for Microgrid VSCs
1) Cost Function 2) Multistep MPC
3) Impact of Uncertainties

SEC. V. ROBUST MPC FOR SYSTEM-LEVEL CONTROL
A. Distributed Secondary Control
B. Economic MPC for Energy Management

SEC. III. ROBUST MPC TECHNIQUES FOR MICROGRIDS
A. Adaptive MPC
B. Tube-based MPC
C. Observer-based MPC
D. Multivariable feedback MPC
E. State-gradient-based MPC
F. Stochastic MPC
G. Data-driven MPC

SEC. VI. CYBER-RESILIENT MPC FOR MICROGRIDS
A. Cyber-Attacks and Mitigation Principles
B. State of the Art on Cyber-Resilient MPC

SEC. IV. ROBUST MPC FOR CONVERTER-LEVEL CONTROL
A. Grid-Forming Power Converters
B. Grid-Following Power Converters
C. Multi-Observers for Enhanced Robust Control

SEC. VII. CHALLENGES AND FUTURE TRENDS
A. Challenges
1) Complexity 2) Robustness vs. Optimality 3) Scalability
B. Future Trends
1) Distributed control 2) Multi-timescale, multi-spatial
3) Event-driven control 4) Data-driven MPC
5) Digital-twin testing 6) Security and autonomy

Fig. 1. Organization of this article.

review specifically addresses recent advances in robust MPC for microgrids. In addition, key challenges and research trends in cyber-resilient MPC for cyber-physical area remain unclear. To bridge this gap, this article provides an in-depth review of robust MPC techniques for converter-based ac microgrids, covering their theoretical foundations, practical applications, and future research directions. The key contributions of this work include the following:

1) A detailed classification of robust MPC techniques, highlighting their applicability to ac microgrids' converter- and system-level control hierarchies.
2) At the converter level of control, robust MPC solutions are covered for GFM and GFL power converters in microgrids.
3) A systematic review of robust EMPC schemes for the energy management of microgrids is presented. It covers schemes for ensuring optimal operational cost in the face of uncertainties in renewable energy, electricity prices and communication networks.
4) A review of cyber-resilient MPC strategies, addressing security threats in cyber-physical microgrid environments.
5) A comprehensive analysis of emerging research trends in robust MPC for microgrids.

The rest of this article is organized as follows (see Fig. 1). Section II introduces the mathematical model of microgrids and discusses key uncertainties affecting control performance. Section III reviews robust MPC techniques, including adaptive, tube-based, observer-based, and data-driven approaches. Section IV focuses on converter-level robust MPC strategies, while Section V discusses system-level control applications. Section VI examines cyber-resilient MPC methods for mitigating security threats. Section VII highlights challenges and future research directions, including industry trends. Finally, Section VIII concludes this article with key takeaways and potential research opportunities in robust MPC for converter-based microgrids.

II. Background and Fundamentals

This section briefly introduces the dynamical system, control uncertainties in converter-based microgrids, foundational models for ac microgrids, conventional MPC for VSCs, and the impact of uncertainties on the prediction models of VSCs.

A. System Description

A microgrid comprises hierarchical subsystems operating at different timescales, as shown in Fig. 2. The primary level (milliseconds) controls fast-switching power converters, using droop control for frequency and voltage regulation, while virtual impedance enhances active and reactive power decoupling [1]. The secondary level (seconds to minutes) corrects voltage and frequency deviations. The tertiary level (minutes to hours) integrates market dynamics, energy pricing, and weather uncertainties to optimize power dispatch across control hierarchies.

A timescale-based decoupling of the primary, secondary, and tertiary hierarchies is usually invoked based on the assumption that the converter's transient response is stable and several orders faster than the higher secondary and tertiary levels' [25], [26]. Without loss of generality, consider a discrete-time linear system, which represents any hierarchical level at a given time, with additive disturbances $d(k)$ and measurement noise $v(k)$, described by

$$\begin{cases} x(k+1) = Ax(k) + Bu(k) + d(k) \\ y(k) = Cx(k) + v(k) \end{cases} \tag{1}$$

where $x(k)$ is the system state at time step k, u is the control input, A, B, C are system matrices, $d \in \mathcal{D}$ is the bounded disturbance, $\mathcal{W}$ is the disturbance set, $v \in \mathcal{V}$ is the bounded measurement noise, and $\mathcal{V}$ is the noise set. At each hierarchical level of the microgrid, the states represent different physical quantities. For example, at the converter level, the states represent current, voltage and power, while at the grid-system level, they could be the power references for distributed generation.

In this article, the control objectives of a microgrid will be divided into two groups: *converter-level* and *system-level* objectives. The converter-level control focuses on primary objectives at the local power electronic converter, including voltage/frequency control, virtual impedance, power sharing, etc. Conversely, the system-level objectives encompass secondary and tertiary control hierarchies of the microgrid, as shown in Fig. 2, including grid-system-wide control and coordination: optimal power flow, market participation, etc.

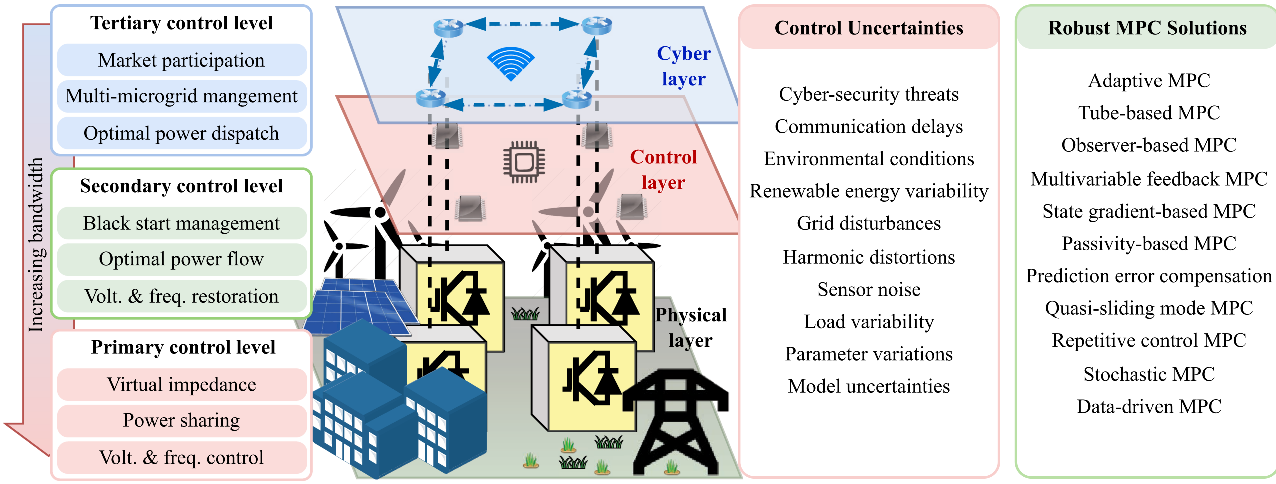


Fig. 2. Control uncertainties and robust MPC techniques for cyber-physical microgrids.

B. Control Uncertainties in Converter-Based Microgrids

The uncertainties in microgrids are broadly categorized into internal and external types.

1) Internal Uncertainties: Internal uncertainties originate from within the microgrid system and are related to its components and control mechanisms. Parameter variations (e.g., line impedances and filter characteristics) are due to aging, temperature changes, or manufacturing tolerances, and degrade control performance. Component failures or degradation of power electronic devices, sensors, and controllers impact the reliability and continuity of microgrid operations. Modeling inaccuracies cause discrepancies between mathematical models and actual system dynamics and could degrade the control performance. Load uncertainty, i.e., fluctuations in local demand due to varying consumption patterns introduce uncertainty in power requirements. Internal faults like sensor malfunctions, communication failures, or converter faults can compromise control performance. Sensor measurement noise due to environmental conditions, electromagnetic interference, or hardware limitations cause measurement errors, and can lead to incorrect control actions and degraded system performance.

2) External Uncertainties: External uncertainties are introduced by factors, which are outside the microgrid system but influence its operation. Renewable energy intermittency of renewable energy sources, such as solar and wind, cause unpredictable power fluctuations. Grid disturbances including voltage sags, frequency deviations, etc., can affect grid-tied microgrid stability. Harmonic distortions from nonlinear loads and external grid conditions can impact power quality. Communication challenges of distributed control schemes make the communication networks susceptible to delays, packet losses, and synchronization challenges. Cyber-security threats due to malicious activities or vulnerabilities in communication networks, control systems, and data infrastructure and compromise the integrity, availability, and confidentiality of the microgrid. Environmental conditions like changes in temperature and humidity can impact the performance of passive and active electrical components in the microgrid.

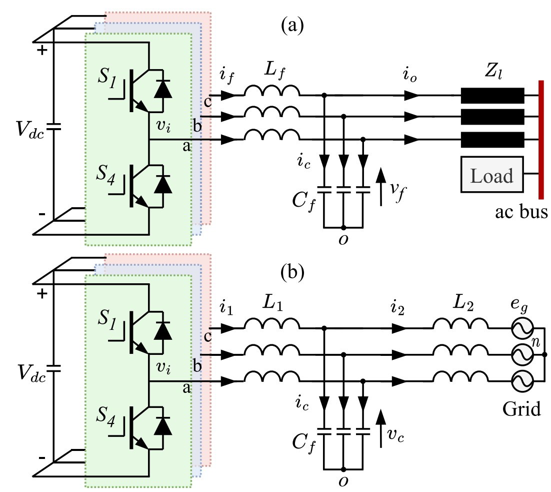


Fig. 3. Topologies of three-phase, (a) GFM power converter with LC filter and (b) GFL converter with LCL filter.

C. Modeling of AC Microgrid Converters

This section will succinctly review the modeling, discretization, and conventional MPC for microgrid VSCs.

1) Continuous-Time Model: Assuming the GFM VSC in Fig. 3(a) has identical filter parameter values in all three phases, Kirchoff's current and voltage laws, give the LC filter dynamic model in continuous-time state-space as

$$\frac{d}{dt}\begin{pmatrix} i_{\mathrm{f}} \\ v_{\mathrm{f}} \end{pmatrix} = \mathbf{A}\begin{pmatrix} i_{\mathrm{f}} \\ v_{\mathrm{f}} \end{pmatrix} + \mathbf{B}\begin{pmatrix} v_{\mathrm{i}} \\ i_{\mathrm{o}} \end{pmatrix} \tag{2}$$

where $\mathbf{A} = \begin{bmatrix} -\frac{R_{\mathrm{f}}}{L_{\mathrm{f}}} & -\frac{1}{L_{\mathrm{f}}} \\ \frac{1}{C_{\mathrm{f}}} & 0 \end{bmatrix}$; $\mathbf{B} = \begin{bmatrix} \frac{1}{L_{\mathrm{f}}} & 0 \\ 0 & -\frac{1}{C_{\mathrm{f}}} \end{bmatrix}$. The variables $R_{\mathrm{f}}, L_{\mathrm{f}},$ and C_{f} represent the (inductor) filter resistance, inductance and capacitance, respectively. The filter current is $i_{\mathrm{f}} = i_{\mathrm{f}\alpha} + ji_{\mathrm{f}\beta}$; the filter voltage is $v_{\mathrm{f}} = v_{\mathrm{f}\alpha} + jv_{\mathrm{f}\beta}$; the VSC output voltage is $v_{\mathrm{i}} = v_{\mathrm{i}\alpha} + jv_{\mathrm{i}\beta}$; load current is $i_{\mathrm{o}} = i_{\mathrm{o}\alpha} + ji_{\mathrm{o}\beta}$; $\alpha\beta$ is

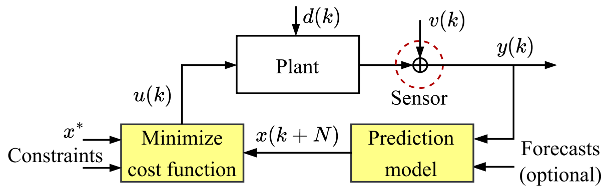


Fig. 4. MPC for a system with uncertainties and measurement noise.

the stationary reference frame derived by invoking the Clarke's transform on *abc* signals.

2) Discrete-Time Model: The discrete-time state-space model of (2) is achieved using zero-order-hold with a sampling period T_s as[1]

$$\underbrace{\begin{pmatrix} i_{\mathrm{f}}^{\mathrm{p}}(k+1) \\ v_{\mathrm{f}}^{\mathrm{p}}(k+1) \end{pmatrix}}_{:=\mathbf{x}^p(k+1)} = \mathbf{A_d} \underbrace{\begin{pmatrix} i_{\mathrm{f}}(k) \\ v_{\mathrm{f}}(k) \end{pmatrix}}_{:=\mathbf{x}(k)} + \mathbf{B_d} \underbrace{\begin{pmatrix} v_{\mathrm{i}}(k+1) \\ i_{\mathrm{o}}(k+1) \end{pmatrix}}_{:=\mathbf{u}(k)} \quad (3)$$

where $\mathbf{A_d} = e^{\mathbf{A}T_s}$ and $\mathbf{B_d} = \int_0^{T_s} e^{\mathbf{A}\tau}\mathbf{B}d\tau$. In practice, the load current i_{o} is of slow dynamics (grid frequency); thus, it can be assumed constant within two samples ($i_{\mathrm{o}}(k+1) \approx i_{\mathrm{o}}(k)$), without any loss of accuracy.

3) Droop-Based Power Sharing in Multiple VSCs: The droop curve dictates how power drawn by the common load is shared between parallel-connected VSCs; it is given by the following equations:

$$\omega = \omega^* - k_{\mathrm{p}}(\tilde{P} - P^*) \quad (4)$$

$$V = V^* - k_{\mathrm{q}}(\tilde{Q} - Q^*) \quad (5)$$

where k_{p} and k_{q} are droop coefficients for frequency-active-power and voltage-reactive-power, respectively; $[\tilde{P}, \tilde{Q}]$ are the low-pass filtered active and reactive power, respectively. A virtual impedance can be introduced to improve decoupling between active and reactive power [1].

D. Conventional MPC for Microgrid VSCs

MPC utilizes measured (or estimated) outputs of the system along with forecasts of the inputs (where available) to compute a prediction model of the plant. This is used in an optimization over a prediction horizon N with the aid of a cost function J_n along with control input and state constraints to generate a sequence of optimal control inputs. However, only the first input $u \in \mathcal{U}$ of the sequence is utilized in a receding horizon manner (see Fig. 4).

1) Cost Function: The objective in this case is to minimize the Euclidean distance error of tracking v_{f}, and the single-step cost function is

$$J_{\mathrm{c}} = \|v_{\mathrm{f}}^* - v_{\mathrm{f}}(k+1)\|^2 + \chi_{\mathrm{u}} u_{\mathrm{sw}}^2(k+1) + \psi_{\mathrm{lim}}(k+1) \quad (6)$$

where χ_{u} penalizes the switching effort $u_{\mathrm{sw}}(k) = \sum |u(k) - u(k-1)|$, and the last term accounts for the physical current limits on the device as

$$\psi_{\mathrm{lim}}(k) = \begin{cases} 0 & \text{if } |i_{\mathrm{f}}(k)| \leq i_{\mathrm{max}} \\ \infty & \text{if } |i_{\mathrm{f}}(k)| > i_{\mathrm{max}}. \end{cases} \quad (7)$$

The reference voltage is (where V_{ref}, ω_{ref} are the reference voltage amplitude and angular frequency, respectively)

$$v_{\mathrm{f}}^* = V_{\mathrm{ref}}\cos(\omega_{\mathrm{ref}}t) + jV_{\mathrm{ref}}\sin(\omega_{\mathrm{ref}}t). \quad (8)$$

The above model is for a standalone GFM VSC. A similar procedure can be carried out for GFL mode of operation as described in [28].

2) Multistep MPC: Long prediction horizons can improve the closed-loop stability, steady-state performance and robustness to measurable disturbances of MPC [8]. However, this might not hold true if the cost function is poorly formulated by the exclusion of the penalized control input as in [29]. Since the standard approach enumerates all the possible voltage vectors, this process increases the computational burden exponentially over the prediction horizon N, increasing the risk of computational infeasibility. Thus, high performance can be associated with a tradeoff of high computational complexity. Solutions with improved efficiency have been demonstrated in multilevel converters (three steps and above) for medium-voltage high-power electrical drives, which operate at low-switching frequencies. Notably, the sphere decoding algorithm enables an efficient solution to the optimization problem [9]. Similarly, the benefits of multistep FCS-MPC have been demonstrated for LC-filtered medium-voltage drives [30].

However, microgrids have different requirements from industrial drives because the VSCs are usually low-voltage multiple paralleled two-level converters, each operating at lower power levels [1] and, thus, can accommodate higher switching frequencies without exceeding switching loss limits. Therefore, MPC techniques that provide high performance and robustness without the high computational requirements of multistep MPC are increasingly reported in microgrid-related studies. The order of the microgrid systems also informs the impact of prediction horizon. First-order systems, e.g., L-filtered grid-tied power converters, do not have significant improvement in performance for long prediction horizons. Hence, one-step prediction horizons are justifiable for this case [8]. However, higher order systems with LC- and LCL-filters introduce higher order dynamic interactions that need to be suppressed by advanced control method. Therefore, this study focuses on MPC techniques that aim to achieve robust control of microgrid VSCs within a single-step horizon.

Note: 1) For system-level control, since the computational requirement is more relaxed, long prediction horizons are common [31], [32]. 2) Although multistep MPC enhances robustness against measurable disturbances and transient uncertainties, it is limited in mitigating parameter uncertainties, measurement noise and unmodeled dynamics [33], [34].

[1] During implementation, the computational delay is compensated as: $\mathbf{x}^p(k+2) = \mathbf{A_d}\mathbf{x}(k+1) + \mathbf{B_d}\mathbf{u}(k+1)$ [27].

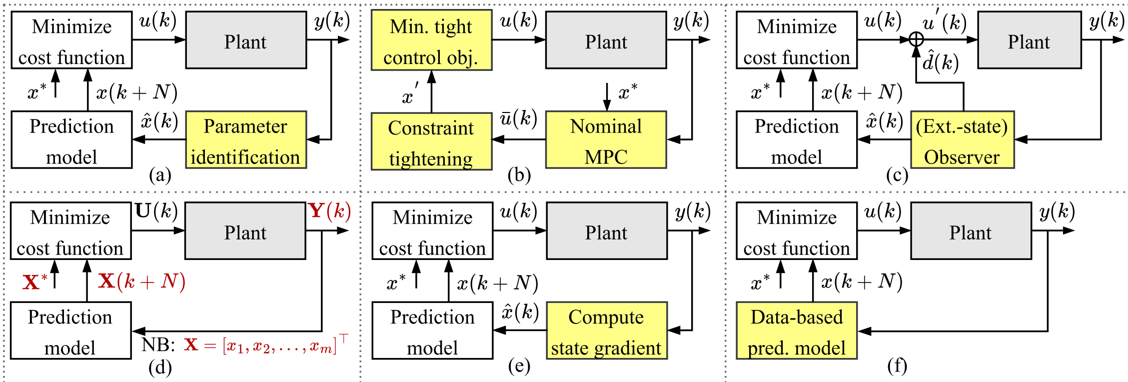


Fig. 5. Robust MPC techniques for microgrids. (a) Adaptive MPC. (b) Tube-based MPC. (c) Observer-based MPC. (d) Multivariable feedback MPC. (e) State gradient-based MPC. (f) Data-driven MPC.

3) Impact of Uncertainties: The uncertainties introduce prediction errors into the state prediction x^p

$$x^p(k+1) = \underbrace{\bar{x}^p(k+1)}_{:=\text{Nominal prediction}} \underbrace{+\Delta x^p_d(k+1) + \sum_{v=1}^{\infty} \Delta x^p_v(k+1)}_{:=\Delta x^p(k+1)=\text{Total prediction error}} \tag{9}$$

where $\Delta x^p_d(k+1)$ is the prediction error, over one prediction horizon, due to the total disturbances including unmodeled dynamics and parameter mismatch. The second term of the total prediction error is due to the measurement noise harmonics. Hence, the objective of robust MPC methods, to be discussed in the following, is to ensure that $\Delta x^p(k+1) \to 0$ within a reasonable control interval.

III. Robust MPC Techniques for Microgrids

In this section, popular robust MPC methods are introduced, namely, adaptive MPC, tube-based MPC, observer-based MPC, multivariable feedback MPC, state-gradient-based MPC, stochastic MPC, and data-driven MPC.

The min–max MPC is one of the most popular robust MPC solutions in control systems, but its significant computational burden [35] makes it unpopular for microgrid control and inspired several other solutions that are more compatible with the low sample-time of microgrid applications. These schemes are discussed in the following sections.

A. Adaptive MPC

Adaptive MPC schemes [see Fig. 5(a)] aim to mitigate the control degradation arising from changes to the system's parameters. The focus is on identifying the uncertain parameters and, therefore, updating the system's dynamic model to improve model prediction accuracy. In this case, system (1) can be described with respect to model uncertainties as

$$x(k+1) = \underbrace{(\bar{A} + \Delta A)}_{:=\hat{A}} x(k) + \underbrace{(\bar{B} + \Delta B)}_{:=\hat{B}} u(k) + d(k) \tag{10}$$

where $\bar{(.)}$ represents a nominal term, $\{\Delta A, \Delta B\}$ are the bounded model uncertainties, and $\hat{(.)}$ is the estimated term. Parameters can be estimated online or offline, but the latter method increases computational cost, while improving real-time model accuracy. Most identification techniques focus on the real-time value of the parameters. So, they estimate the system matrices $\hat{A}$ and $\hat{B}$ directly, from which the parameter uncertainty can be implicitly determined from the known nominal system, e.g., $\Delta A = \hat{A} - \bar{A}$. Some reported identification methods in the literature include recursive least squares autoregressive model with exogenous inputs (ARX) [36], [37], virtual flux [38], extended Kalman filter [39], and singular-value decomposition [40].

B. Tube-Based MPC

Tube-based MPC [see Fig. 5(b)] seeks a control policy u

$$u(k) = \underbrace{\bar{u}(k)}_{:=\text{Nominal}} + \underbrace{\mathcal{K}(x - \bar{x})}_{:=\text{Feedback}} \tag{11}$$

such that the control and state constraints are not violated by disturbance $d(k)$. $\bar{x}$ is the nominal state, x the actual system state, $\mathcal{K}$ is the unconstrained control gain, and $\bar{u}$ is the MPC control input for the nominal system dynamics. The disturbance-free dynamics is utilized with nominal constraints tightened to account for noise, i.e., $\bar{x} \in \mathcal{X} \ominus \mathcal{Z}$, $\bar{u} \in \mathcal{U} - \mathcal{K}\mathcal{Z}$. NB: $\mathcal{Z}$ is the robust invariant set that keeps all state trajectories within a tube [41].

C. Observer-Based MPC

This scheme [see Fig. 5(c)] seeks to achieve robust MPC by dual degrees-of-freedom in the controller: by both state feedback control and disturbance feedforward. The former ensures stable reference tracking, and the latter guarantees rejection of lumped disturbances $\hat{d}$. The methods utilize an ESO to estimate $\hat{d}$, which includes known exogenous disturbances, model uncertainties, and measurement noise. The estimated lumped disturbance is then used for disturbance feedforward control for active disturbance rejection. Thus, improved overall robust control performance can be achieved. It should be noted that some approaches only focus on state observation and exclude disturbance estimation and rejection. Meanwhile these observers could be linear (e.g., Kalman filter) or nonlinear (unscented/extended Kalman filter, nonlinear ESO, sliding-mode observer, etc.), depending on the class of states/disturbances to be estimated.

D. Multivariable Feedback MPC

One of the advantages of MPC is multivariable feedback control. However, higher numbers of variables increase the complexity and computational cost of the control scheme. Some schemes aim to simplify the controller by reducing the number of terms being tracked by the cost function. While this can be accommodated for single-order systems, it makes higher order systems vulnerable to both suboptimal performance and instability. In higher order converter-level systems, for instance, it has been reported that tracking all the states of the dynamic model suppresses resonances and improves stability [54], [55] [see Fig. 5(d)]. Thus, multivariable feedback methods capture the control tracking error of two or more state variables in the primary objective of the cost function.

E. State Gradient-Based Model-Free Method

The continuous-time form of the system model (1) is

$$\dot{x}(t) = f(x, u) + d(t). \tag{12}$$

Given sufficiently small sampling interval T_s, the Euler's forward discrete-time approximation is

$$x(k+1) = x(k) + \underbrace{T_s f(x, u)}_{:=\Delta x(k)=x(k)-x(k-1)} + T_s d(k) \tag{13}$$

where $\Delta x(k)$ is the state *gradient* derived as the difference of preceding consecutive discrete-time samples. Equation (13) is a model-free prediction approach that is parameter-free. Usually, the set of finite control inputs is mapped to gradients in a look-up table, and needs to be refreshed each time a control input is selected [56]. This approach comes with its own challenges: nonuniform refreshing of the gradients (due to nonuniform selection of the control inputs in the set), high approximation errors for higher order systems and need for separate scheme for measurement noise suppression.

F. Data-Driven MPC

Data-driven control refers to a set of techniques used to regulate physical systems without requiring an explicit dynamic model. Among the widely utilized approaches are fuzzy logic, metaheuristic optimization, and machine learning, which includes supervised learning, unsupervised learning, and reinforcement learning (RL). The development of data-driven MPC methods was motivated by the need to improve MPC performance in three key aspects: simplifying the optimal tuning of weighting factors and prediction horizons [61], minimizing computational complexity [59], and enhancing parametric estimation [64].

G. Stochastic MPC

Stochastic MPC is applied to systems with probabilistic disturbance $d(k) \sim \mathcal{D}$, where $d(k)$ could be a known probability distribution. This is different from the bounded system described in (1). In this case, the controller seeks an optimal control input that minimizes the expected cost $\mathbb{E}(J_n)$ over a prediction horizon N. This is subject to deterministic state and input constraints, as well as (probabilistic) chance constraints. Thus, stochastic MPC is more suitable for systems with random variables and risk tolerance, e.g., microgrid system-level optimization with probabilistic market and weather conditions. However, the prior-described deterministic methods are more suitable for safety-critical applications at the power converter level, which have disturbances within a permissible range.

Summary: All the afore-described methods are commonly applied in the literature to converter-level control except stochastic MPC and tube-based MPC. Stochastic MPC and tube-based MPC are seldom applied to power converter-level control because their computational complexity and latency typically exceed the ultra-fast sampling and control requirements of power converters. However, both stochastic MPC and tube-based MPC are common techniques for the system-level where the timescale can be up to several hours, and parallel-computing devices can be applied. Besides the robust MPC techniques discussed, some other methods include: prediction error compensation [7], [65] quasi-sliding-mode MPC [66], passivity-based MPC [57], and repetitive control MPC [67].

IV. Robust MPC for Converter-Level Control

The previous section introduced robust MPC techniques applied generically to all hierarchies of microgrid control. In this section, the schemes that are commonly applied to power converters in microgrids are reviewed, for both GFM and GFL modes of operation. Furthermore, the role of multiobservers in robust converter control is explored. These methods are summarized in Table I.

A. GFM Power Converters

GFM power converters in microgrids are responsible for providing voltage and frequency references to the network—without reliance on grid-synchronization. GFM converters with LC filters [shown in Fig. 3(a)] are usually required for the supply of high-quality power to the loads when the microgrid is operating in islanded mode. Among several uncertainties that cause prediction error in the application of MPC to converters, parameter mismatch was one of the first to be extensively studied.

1) Adaptive MPC: The most intuitive way to correct parameter mismatch is to update the model online. Thus, adaptive MPC includes different methods for real-time parameter identification with online parameter update in the controller. The ARX model, which is a combination of an autoregressive model and an exogenous input model is a data-driven method that models dynamical linear-time-invariant systems. Heydari et al. [36] first employed the ARX model for real-time parameter

TABLE I
ROBUST MPC TECHNIQUES FOR MICROGRIDS: CONVERTER-LEVEL CONTROL

Method	Approach	Advantages	Disadvantages
Adaptive MPC	ARX identification [36], [42] (GFM)	Interpretable; robust to parameter mismatch.	Sensitive to noisy data/disturbances.
	Neuro-fuzzy identification [43] (GFM)	Improved identification over fuzzy methods.	Requires large training dataset.
	ARX identification [37] (GFL)	Low to medium computational burden.	Tuning process can be involving.
	Grid impedance estimator [44] (GFL)	Robust to grid-impedance variations.	Variable switching frequency.
	Extended Kalman filter [39] (GFL)	Effective for nonlinear systems.	Tuning process can be involving.
	Virtual flux-based [38] (GFL)	Online inductance identification.	Poor measurement noise suppression.
	Singular-value decomposition [40] (GFL)	Adaptive weighting factor.	Poor measurement noise suppression.
Tube-based	Two-stage FCS-MPC [12] (GFM)	Robust to parameter mismatches.	Noise robustness not studied.
	Learning-based Gaussian [45] (GFL)	Robust to parameter and noise uncertainties.	Increased computational burden.
Observer-based	Extended-state observer [46] (GFM)	Ultra-local model improves parametric robustness.	Noise attenuation varies with ESO.
	Kalman filter [47], [48] (GFL)	Attenuates Gaussian noise.	Sensitive to nonlinearities.
	Sliding-mode observer [49] (GFL)	Robust to parameter uncertainties.	Not robust to unmodeled dynamics.
	Cascade ESO [50], [51] (GFL)	Good measurement noise attenuation.	Poor disturbance rejection.
	Parallel-cascade ESO [34] (GFL)	Good noise suppression/dynamic performance.	Medium to high complexity.
	Quasi-resonant ESO [52] (GFL)	Robust to fast-varying disturbances.	Tuning requires expert knowledge.
	Generalized ESO [53] (GFL)	Good noise suppression.	Limited disturbance rejection.
Multivariable	LC-filter i, v feedback (GFM) [54]	Improved parametric robustness	Limited noise attenuation.
	LCL-filter 2-/3-state feedback [55] (GFL)	Resonance damping; improved robustness.	Limited noise attenuation.
Gradient-based	Table-based computations [56] (GFM)	Improved parametric robustness	Robustness to noise is not guaranteed.
Compensation	Prediction error compensation [7] (GFL)	Improved parametric robustness.	Poor noise attenuation.
Passivity-based	Passivity-based MPC [57] (GFL)	Robust to uncertainties with stability guarantees.	Increased design complexity.
Data-driven	Kernel methods [13] (GFL)	Good overall robustness.	High computational cost.
	Learning-based tube MPC [45] (GFL)	Online learning reduces conservativeness.	Improved robustness than fixed tube.
	Bayesian network [58] (GFL)	Has probabilistic reasoning; handles uncertainty.	Computationally expensive for large
	ANN emulator [59], [60] (GFM/GFL)	Good at handling non-linear relationships.	Requires large data-sets for training.
	ANN weighting factor tuning [61] (GFL)	Some improvements to parameter robustness.	Limited noise suppression.
	Time-delay NN emulator [62] (GFL)	Better robustness to parameter mismatch.	Limited measurement noise suppression.
	Recurrent neural network [63] (GFL)	Requires sparse data for training.	Higher complexity; more memory usage.

GFM is grid-forming converter, and GFL is GFL

identification, while an analytical method for computing the ARX model parameters was proposed in [42]. Although this approach is simple and interpretable, it is nonrobust to noise in data, model inaccuracies, external disturbances, and nonlinearities. The model parameters also require intricate design procedures to avoid tradeoffs between model accuracy and real-time computational load [42]. The neuro-fuzzy technique was proposed for identification of filter parameters online [43]. This technique requires significant data for training, and can have high computational demands; meanwhile, its online tuning can be challenging. A nonlinear least-square adaptive Gauss–Newton optimization approach in [68] for system identification has good disturbance rejection and robustness to multiple uncertainties. But its design and implementation are involving, requiring large computational requirements.

2) State-Gradient MPC: Table-based state gradient difference method of state prediction is another popular method in the literature. It computes state predictions by differences between consecutive discrete time gradients of state variables [56]. This method has reportedly manifested good robustness to parametric uncertainties When combined with feedforward of disturbance estimation, it can also improve disturbance rejection. Nonetheless, the scheme does not mitigate sensor noise intrinsically.

3) Observer-Based MPC: The disturbance-observer-based MPC is one of the methods that is capable of holistic mitigation of parameter variations, modeling uncertainties, sensor measurement noise, and external disturbance. The common approach as reported in [46] is the use of an ESO to estimate the state within a model-free framework with lumped disturbance estimation. Estimated disturbance feedforward compensates for different disturbances including model/parameter uncertainties, measurement noise, and external disturbances. The limitation of this method lies in the classical linear ESO's high gain, which creates an intrinsic tradeoff between disturbance rejection and measurement noise suppression. Nonetheless, some solutions to this challenge have been proposed, as discussed in Section IV-C.

4) Multivariable Feedback MPC: The second-order LC-filter system has state intercoupling that a single-state feedback control of capacitor voltage v_f described in [6] is unable to account for. To improve the steady-state performance, higher prediction horizons were proposed in [29]. Although this approach can suppress intercoupling harmonics better, it increases the real-time computational requirements. Meanwhile, the model discretization approximations further limit the permissible prediction steps. To alleviate this challenge, *multivariable feedback control* has been introduced by different researchers. In addition

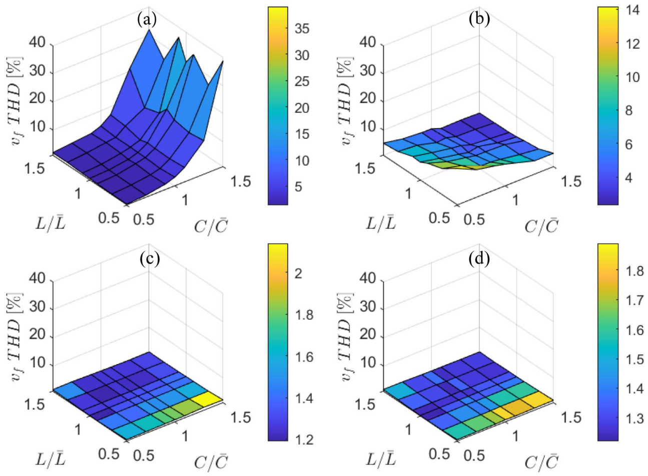


Fig. 6. Steady-state output voltage distortion in GFM converter due to parameter variations. (a) Conventional MPC. (b) Adaptive MPC. (c) Multivariable MPC with capacitor current feedback. (d) Multivariable MPC with inductor current feedback.

to tracking the prediction error of capacitor voltage v_f, inductor current i_f [70], and the derivative of v_f [1] have been proposed as primary control objectives. This approach gives superior steady-state robust performance than the previous approaches (and comparable to carrier-based sinusoidal PWM). Fig. 6 shows the superior performance of multivariable MPC, relative to other techniques, under conditions of parameter mismatches. MPC schemes depicted in Fig. 7, with single-step prediction horizon applied, were simulated with system and control parameters in Appendix A. According to [1], additional secondary objectives like current limiting and switching effort penalization can also be added to the cost function with low computational expense.

5) Data-Driven MPC and Other Methods: Although most of the techniques are model-based, employing all or part of the system's dynamic model, emerging data-driven techniques are accelerating the trend of model-free solutions. For instance, Huang et al. [13] combined robust predictive control and a multistep predictor of nonlinear systems obtained from regularized kernel methods. The method, which maintains the fast dynamic response of MPC, goes directly from data to control, avoiding time-consuming online learning procedures. Nonetheless, the computational cost grows with the size of the dataset and selecting the right kernel and tuning hyperparameters can be complex. Also, guarantee on the actual control performance is not deterministic. Another approach involves using supervised learning to emulate the control actions of MPC. For the same machine learning model, the surrogate controller has relatively lower number of calculations and computational times that do not increase exponentially with prediction horizon [59]. However, this method requires a large training dataset for good accuracy, and might require retraining for different load and operating conditions.

Other methods include the so-called quasi-sliding-mode FCS-MPC [66], which has a cost function that includes the predicted sliding-mode surface. Although the quasi-sliding-mode FCS-MPC improves in robustness over the classical FCS-MPC, it does not account for the intercoupling dynamics of the second-order system, resulting in limited performance. Tube-based MPC, though popular in control theory, is not yet popular in the field of power electronics. The tube-based MPC concept in [12] has two stages of FCS-MPC, where the first stage generates a space of permissible state predictions and control inputs based on a nominal model. Then, a second stage-MPC selects the most optimal predictions and control inputs from the space for the uncertain system under appropriate constraints. Table II shows a summary of the performances and structures of these techniques.

B. GFL Power Converters

GFL power converters are current sources and need to synchronize to the grid voltage phase and frequency using a phase-locked loop or other synchronization methods. LCL- and L-filters are popular choices for attenuating the high-frequency switching harmonics and ensure compliance with the power quality standards of grid codes (e.g., IEEE 1547). GFL converters can be operated either in current control mode or power control mode to provide functions including current injection into the grid, grid frequency/voltage regulation, etc. Many of the robust MPC schemes for GFM converters explained in Section IV-A also apply to GFL converters.

1) Adaptive MPC: Adaptive MPC with ARX parameter identification was proposed in [37]; furthermore, the CCS-MPC technique was applied to achieve nonvariable switching frequency—improving the harmonic spectrum for grid-code compliance. In grid-tied conditions, the grid impedance variations could deteriorate the control performance. Hence, grid impedance algorithm in [44] updates the prediction model real-time, improving robustness to grid impedance variations. Furthermore, virtual flux-based filter inductance estimation [38] was applied to adaptive MPC. Nonetheless, the virtual flux estimator becomes unreliable under distorted grid conditions [5]. Finally, adaptive changes to the weighting factor can be applied to reduce tracking error of control objectives under parameter uncertainties [40]. It should be noted that adaptive MPC techniques generally lack inherent capabilities to mitigate model uncertainties and sensor noise interferences.

2) Observer-Based MPC: Observer-based MPC is also applicable to GFL converters. The sliding-mode observer is well-noted for its robustness, simplicity, and ease practical of implementation [71], [72]. The Kalman filter's strengths with in mitigating noisy and uncertain signals are beneficial to GFL converters, as reported in [47] and [48]. Nonetheless, the Kalman-based method is ineffective with non-Gaussian disturbances and noise. A comparison of the Kalman filter and sliding-mode observer indicates that the former has better noise suppression capabilities, at higher computational cost than the latter [74]. However, these two observers do not account for unmodeled dynamics.

In order to improve robustness to unmodeled dynamics, the ultra-local model approach, supported by the ESO was applied

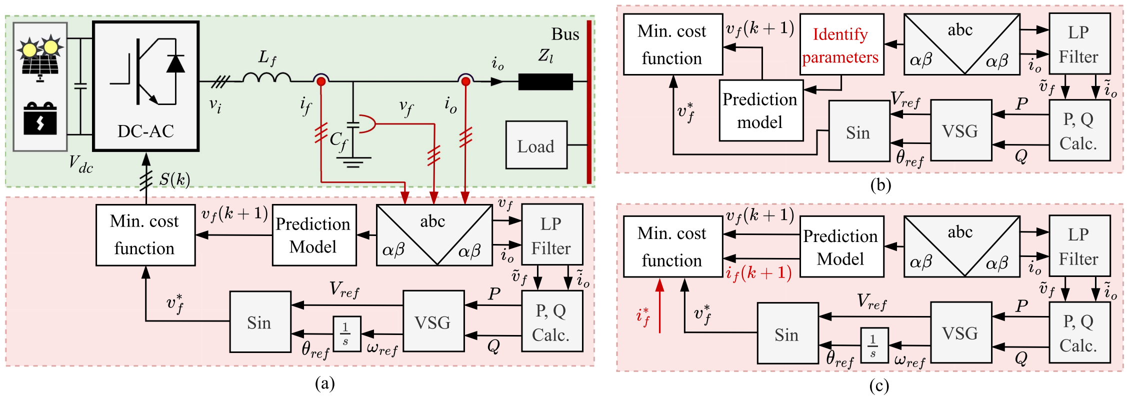


Fig. 7. MPC schemes for GFM power converters, where VSG is the virtual synchronous generator [69], and LP filter is the low-pass filter. (a) Conventional FCS-MPC. (b) Adaptive FCS-MPC. (c) Multivariable feedback FCS-MPC.

TABLE II
ASSESSMENT OF ROBUST MPC SCHEMES FOR GFM/GFL VSCS IN MICROGRIDS

Technique	Cost function†	Design complexity	Computational burden	Dynamic response	Robustness
Conventional MPC [6]	$J = \|y^p(k+1) - y^*(k+1)\|_2^2$	Moderate	Moderate	High	Low
Passivity MPC [57]	$J = \|y^p(k+1) - y^*(k+1)\|_2^2$	High	Moderate	High	High
Data-driven MPC [13], [59]	$J = \|y^p(k+1) - y^*(k+1)\|_2^2$	Moderate to high	Low to moderate	High	High
Multivar. feedback MPC [1]	$\|y_{1\text{err}}(k+1)\|_2^2 + \chi_2\|y_{2\text{err}}(k+1)\|_2^2 + \cdots + \chi_n\|y_{n\text{err}}(k+1)\|_2^2$	Moderate	Moderate to high	Moderate to high	Moderate
Adaptive MPC [36]	$J = \|\hat{y}^p(k+1) - y^*(k+1)\|_2^2$	Moderate to high	Moderate to high	High	Moderate
Observer-based MPC [46], [71]–[73]	$J = \|\hat{\hat{y}}^p(k+1) - y^*(k+1)\|_2^2$	Moderate to high	Moderate to high	Moderate to high	Moderate to high
Tube-based MPC [45]	$J_1 = \|y^p(k+1) - y^*(k+1)\|_2^2$ s.t. tightened constraints $J_2 = \|y^p_{\text{nom}}(k+1) - y_{\text{meas}}(k+1)\|_2^2$ s.t. nominal constraints	High	High	Moderate to high	Moderate to high

†Cost functions show only tracking error objectives. $y_{i\text{err}} = y_i - y_i^*$, where y^p is the predicted value, and y^* is the reference. $\hat{y}$ is derived from identified parameters in the controller. $\hat{\hat{y}}$ is an observed term.

in [75]. This technique is simple to implement, but has limited high-frequency sensor noise suppression. Thus, multifrequency observers (with cascade and parallel features) with superior noise handling were proposed in [34], [50], and [73]. However, the multifrequency observers have slightly higher computational requirements and more tuning parameters.

The subject of estimation and rejection of fast-varying disturbances was addressed with the quasi-resonant generalized ESO [52], which has multiple resonant controllers tuned to the specific frequencies, where high-frequency disturbances are to be estimated. Note that these methods are different from the technique in [53], where a second-order generalized integral observer provides grid-voltage sensorless control, without active disturbance rejection.

Experimental results in Fig. 8 show the overall relative performances of some observer-based methods to the conventional MPC. The results are for tests under nominal conditions, measurement noise (white noise of standard deviation 0.20 added to the measured grid current signal), and parameter mismatches for control schemes in Fig. 9. Details on the experimental system and control parameters are provided in the Appendix B. Note the improved robustness to parameter mismatches of all the observer-based methods, over the conventional MPC. Also, the multiobserver techniques produce better measurement noise suppression than the classical ESO, without significant tradeoff in computational efficiency. The lowest three average computational times (in μs) per sampling period are: ESO1 (5.638), MPC (5.859), and PC-ESO (5.877); while the most computationally intensive is CESO (6.520). Further comparison of multiobservers is discussed in Section IV-C.

3) Multivariable MPC: The robust predictive control of single-order L-filtered grid-connected converters is straightforward. But additional considerations come into play for third-order LCL-filter systems. Panten et al. [76] showed that while single-state current feedback is convenient, it has challenges: tracking only the *converter-side* current cannot suppress grid-side filter resonances, resulting in grid-side current that does not satisfy grid-code distortion requirements. Meanwhile, although

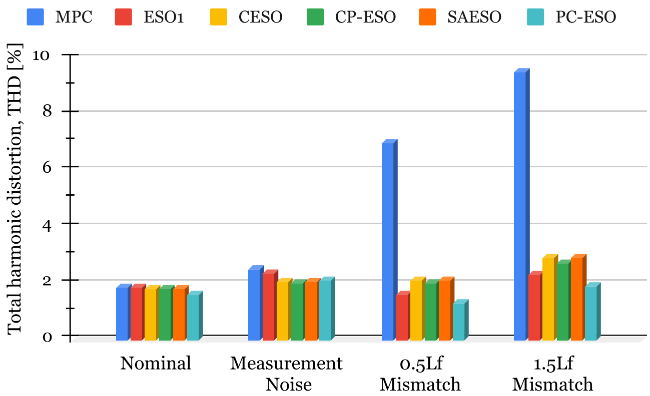


Fig. 8. Experimental results for a GFL converter using different robust MPC methods (from data in [34]). ESO1 represents the conventional ESO, CESO: cascade ESO, CP-ESO: cascade-parallel ESO, SAESO: structurally adaptive ESO, and PC-ESO: parallel-cascade ESO.

tracking only the *grid-side* current produces lower distortion, the approach is more susceptible to resonance-induced instability for short prediction horizons. Feedback control of only the grid-side current (with active damping) also has a lower tracking error, lowest switching losses, and better dynamic performance than two or more-state feedback. However, in order to guarantee stability, a long prediction horizon is required to guarantee stability.

Long et al. [71] tackled this challenge by an ultra-local model with sliding-mode observer-based predictions and error tracking of the converter-side current alone. Its strengths include the nonlinear state and disturbance observer with superior measurement noise suppression. However, its weakness is that it lacks active damping and so is sensitive to harmonics from switching and grid-side voltage distortions. Thus, in general, the feedback control of at least two to three variables is recommended. Nevertheless, the control complexity increases with higher state feedback, i.e., weighting factor design and computational hardware requirements. Falkowski and Sikorski [55] showed that three-state feedback control has lower steady-state distortion and better robustness than single-state feedback with active damping; meanwhile, it also has superior robustness to grid disturbances.

4) Data-Driven MPC: The data-driven methods for robust MPC in microgrids leverage machine learning techniques to improve adaptability and robustness in uncertain environments. Kernel methods [13] provide strong overall robustness by mapping input data into higher dimensional feature spaces, enabling better generalization, but at the cost of high computational complexity. Learning-based tube MPC [45] refines the traditional tube-based approach by incorporating online learning, reducing conservatism, and improving robustness over fixed tube designs. Bayesian networks [58] offer a probabilistic framework for reasoning under uncertainty, making them well-suited for dynamic microgrid conditions, though they become computationally expensive for large-scale applications. Artificial neural network (ANN) emulators [60], [77] effectively capture nonlinear system dynamics, but they require extensive training datasets to achieve reliable performance. ANN-based weighting factor tuning [61] introduces moderate parameter robustness improvements, yet struggles with noise suppression. Time-delay neural networks [62] enhance robustness against parameter mismatches but are less effective in suppressing measurement noise. Recurrent neural networks [63] stand out for their ability to learn from sequential data with sparse training sets; however, their increased complexity and memory requirements pose practical challenges in real-time implementations. Collectively, these methods contribute to more resilient and adaptive MPC strategies, albeit with tradeoffs between computational cost, noise sensitivity, and implementation feasibility.

5) Other Methods: These three robust MPC enhancement methods—prediction error compensation [7], [65], passivity-based MPC [57], and repetitive control-based MPC [67]—each address different aspects of uncertainty and disturbance rejection in microgrid applications. Prediction error compensation focuses on reducing the impact of parameter mismatches and discretization errors. The analytic prediction error correction [7] method provides a more detailed and hierarchical approach to estimating and compensating for prediction errors, while the constant error compensation factor [65] offers a simpler but less precise alternative. Although both approaches effectively mitigate parameter mismatches, they fall short in handling model uncertainties and measurement noise. Passivity-based control [57], on the other hand, ensures system stability by using power shaping and damping injection to counteract disturbances and parameter mismatches. Its ability to guarantee robust performance comes at the cost of increased design complexity, which may pose implementation challenges. Lastly, the repetitive controller [67] enhances MPC robustness by rejecting periodic disturbances and improving resilience to parametric uncertainties and grid voltage variations. However, it introduces multiple tuning parameters, making the design process more intricate, and its sensitivity to measurement noise remains a drawback. Unlike passivity-based MPC, which ensures stability through power-based formulations, and prediction error compensation, which focuses on error mitigation, the repetitive controller prioritizes disturbance rejection but lacks a well-defined approach for measurement noise suppression.

6) Overall Assessment: Table II shows a general trend of tradeoff between robustness, performance and practicality, across most of the techniques. At one end, conventional MPC has high performance but is limited by low robustness. However, the other extreme has methods with high robustness and performance, but characterized by higher computational burden (tube-based MPC) and/or increased complexity (passivity-based MPC and tube-based MPC). Data-driven MPC that emulates the MPC controller can significantly reduce computational burden without trading off performance and robustness. But since it completely relies on data, without the dynamic model, it is not adaptable to different loads and operating conditions. Multivariable feedback MPC is promising, especially if its sensor noise robustness can be mitigated. However, among the techniques, observer-based MPC (especially using adaptive observers or multiobservers) appears to have the strongest balance between performance and practicality. Due to the wide variety of observers applied to this method, the next section will provide further clarity on multiobservers in MPC.

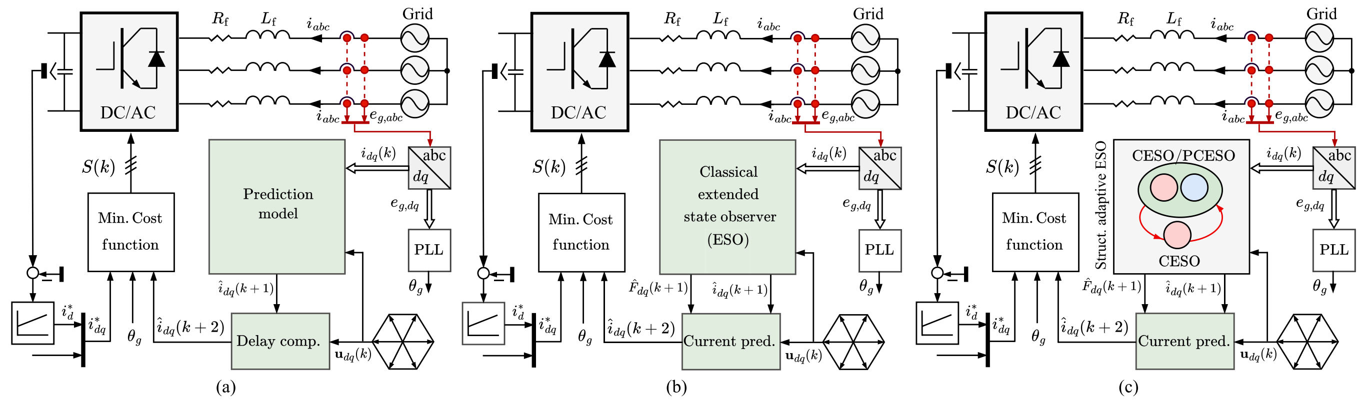


Fig. 9. Control schemes for GFL power converters. (a) Conventional MPC. (b) Observer-based MPC using the classical ESO. (c) Observer-based MPC using the structurally adaptive ESO [34].

C. Multiobservers for Enhanced Robust Control

As earlier discussed in Sections IV-A and IV-B, disturbance-observer-based methods provide robustness with simple structures and moderate computational cost. This informs why they are one of the most popular robust MPC methods in the power electronics research community. These techniques are commonly applied in two ways: a) complete system (full-order) dynamical model with disturbance or state estimation (e.g., grid voltage sensorless control in [85]), b) ultra-local model with state and lumped disturbance estimation using ESOs [71], [86]. The ultra-local model approach utilizes reduced system parameters, providing intrinsic robustness to unmodeled dynamics.

Classical *single* state and disturbance observers (e.g., Kalman filter, Luenberger observer, sliding-mode observer, ESO, etc.) introduce a tradeoff between measurement noise suppression, disturbance rejection, and robustness to model/parameter uncertainties performance [34], [74]. To mitigate this challenge, several multiobservers have been proposed in the literature, namely: linear/nonlinear adaptive ESO, interleaved Kalman filter and ESO, cascade ESO, cascade-parallel ESO, parallel-cascade ESO, structurally adaptive ESOs, switched high-gain observer, and the generalized integrator ESO. Their block diagrams, dynamic structures, and relative (dis)advantages are summarized in Table III.

The linear/nonlinear adaptive ESO [78] has a time-varying gain to vary the active ESO between a linear and nonlinear ESO. This makes the ESO maximize the best characteristics of both linear and nonlinear ESOs, results in improved overall robustness in addition to minimizing the peaking effect during transients. The Kalman filter has optimal performance in state estimation of linear systems with Gaussian noise. However, among its limitations are sensitivity to model and parameter uncertainties. The interleaved Kalman filter and ESO scheme [79] improves the Kalman filter by replacing the filter's traditional disturbance with the ESO's estimated lumped disturbance. Also, the ESO's output comes from the noise-filtered Kalman filter's output. Although this improves the overall robustness, there are more parameters to be tuned for each of the Kalman filter and ESO.

The cascade ESO [50], [80], comprises a compact cascade of sub-ESOs each with its gain tuned over a range from a fraction to full bandwidth of ESO. Noisy measured output is passed into only a low-bandwidth sub-ESO to reduce noise transmission to other sub-ESOs. The ESO can sustain the parametric robustness of conventional ESO, but has weaknesses of traded-off lumped disturbance estimation and poorer disturbance rejection than the classical ESO. Therefore, several other ESOs, derived from the cascade ESO, have been introduced to provide overall improved performance than the cascade ESO: the cascade-parallel-ESO [73], parallel-cascade ESO [34], and structurally adaptive ESO [34], [81]. Notably, the latter has better overall robustness than both the conventional and cascade ESOs.

Switching multiobservers with varying gains [82], [87], [88], depending on the operating conditions is another approach to mitigate the compromise between measurement noise suppression and disturbance rejection. Also, in order to track both low-frequency and high-frequency disturbances, the generalized integrator ESO [83], [84] was proposed by combining parallel resonant filters with the ESO. However, this multiobserver has reduced phase-margin which needs to be compensated by an appropriately designed gain.

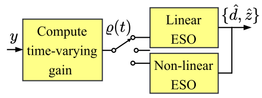
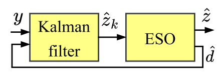
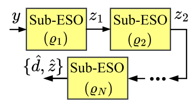
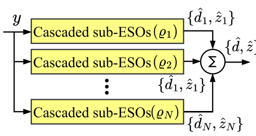
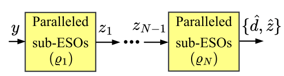
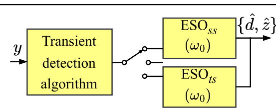
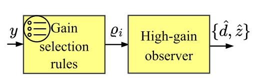
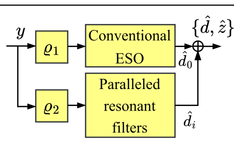
V. Robust MPC for System-Level Control

This section covers techniques for system-level objectives within the robust MPC framework: distributed secondary MPC and EMPC for the energy management of microgrids.

A. Distributed Secondary Control

Secondary control aims to restore voltage and frequency deviations at the converter level. This can be done by centralized MPC [23], decentralized MPC [98], and distributed MPC techniques [23]. Although distributed MPC is easier to scale for larger microgrids, it requires communication networks, which are associated with uncertainties, such as communication delay, packet losses, and environmental disturbances. Therefore, Mottaghizadeh et al. [95] proposed a distributed MPC with robustness to time-varying communication delay, additive

TABLE III
MULTIOBSERVERS FOR ROBUST PREDICTIVE CONTROL

Multi-observer	Block Diagram	Dynamic Structure	Pros and Cons
Linear/nonlinear adaptive ESO [78]		$\begin{cases} \dot{\hat{z}} = \hat{d} + \alpha u - \varrho_1(t)(\hat{z} - y) \\ \dot{\hat{d}} = -\varrho_2(t)(\hat{z} - y) \end{cases}$	**Pro**: Better measurement noise suppression than conventional ESO. **Con**: Complicated tuning for the adaptive gain.
Interleaved Kalman filter and ESO [79]		$\begin{cases} \dot{\hat{\mathbf{z}}}_k = \mathbf{A}\hat{\mathbf{z}}_k + \mathbf{B}_u\mathbf{u} + \mathbf{B}_d\hat{\mathbf{d}} \\ \quad - \varrho_{\mathrm{k}}(\hat{\mathbf{z}}_{\mathrm{k}} - \mathbf{y}) \\ \dot{\hat{z}} = \hat{d} + \alpha u - \varrho_1(\hat{z} - \hat{z}_k) \\ \dot{\hat{d}} = -\varrho_2(\hat{z} - \hat{z}_k) \end{cases}$	**Pro**: Improved overall robustness. **Con**: More parameters to be tuned for both the Kalman filter and ESO independently.
Cascade ESO [50], [80]		$\begin{cases} \dot{\hat{z}}_1 = \hat{d}_1 + \alpha u - \varrho_{11}(\hat{z}_1 - y) \\ \dot{\hat{d}}_1 = -\varrho_{21}(\hat{z}_1 - y) \\ \dot{\hat{z}}_2 = \hat{d}_2 + \alpha u - \varrho_{12}(\hat{z}_2 - \hat{z}_1) \\ \dot{\hat{d}}_2 = -\varrho_{22}(\hat{z}_2 - \hat{z}_1) \end{cases}$	**Pro**: Better measurement noise suppression than conventional ESO. **Con**: Disturbance rejection trade-off.
Cascade-parallel ESO [73]		$\begin{cases} \dot{\hat{z}}_1 = \hat{d}_1 + \alpha u - \varrho_{11}(\hat{z}_1 - y) \\ \dot{\hat{d}}_1 = -\varrho_{21}(\hat{z}_1 - y) \\ \dot{\hat{z}}_2 = \hat{d}_2 + \alpha u - \varrho_{12}(\hat{z}_2 - \hat{z}_1) \\ \dot{\hat{d}}_2 = -\varrho_{22}(\hat{z}_2 - \hat{z}_1) \\ \dot{\hat{z}}_3 = \hat{d}_3 + \alpha u - \varrho_{13}(\hat{z}_3 - \hat{z}_1) \\ \dot{\hat{d}}_3 = -\varrho_{23}(\hat{z}_3 - \hat{z}_1) \end{cases}$	**Pros**: Better measurement noise suppression than conventional ESO. Better disturbance rejection than cascade ESO. **Con**: Disturbance rejection performance is traded off. Multiple gains to be tuned.
Parallel-cascade ESO [34]		$\begin{cases} \dot{\hat{z}}_1 = \hat{d}_1 + \alpha u - \varrho_{11}(\hat{z}_1 - y) \\ \dot{\hat{d}}_1 = -\varrho_{21}(\hat{z}_1 - y) \\ \dot{\hat{z}}_2 = \hat{d}_2 + \alpha u - \varrho_{12}(\hat{z}_2 - y) \\ \dot{\hat{d}}_2 = -\varrho_{22}(\hat{z}_2 - y) \\ \dot{\hat{z}}_3 = \hat{d}_3 + \alpha u - \varrho_{13}(\hat{z}_3 - \hat{z}_2) \\ \dot{\hat{d}}_3 = -\varrho_{23}(\hat{z}_3 - \hat{z}_2) \end{cases}$	**Pros**: Better measurement noise suppression than conventional ESO and better disturbance rejection than cascade ESO. **Con**: Multiple gains to be tuned.
Structurally-adaptive ESOs [34], [81]		ESO_{ss} can be cascade ESO or cascade-parallel ESO. ESO_{ts} can be parallel-cascade ESO.	**Pros**: Good parametric/model robustness, measurement noise suppression, and transient disturbance rejection. **Con**: Multiple gains to be tuned.
Switched high-gain observer [82]		$\begin{cases} \dot{\hat{z}} = \hat{d} + \alpha u - \varrho_1(\hat{z} - y) \\ \dot{\hat{d}} = -\varrho_2(\hat{z} - y), \end{cases}$ where $\begin{cases} \varrho_{12} = \varrho_{12a} \text{ if } \lVert\hat{z} - y\rVert > \epsilon \\ \varrho_{12} = \varrho_{12b} \text{ otherwise} \end{cases}$	**Pro**: Improved overall robustness. **Con**: Multiple gains to be tuned.
Generalized Integrator ESO [83], [84]		$\begin{cases} \dot{\hat{z}} = \hat{d} + \alpha u - \varrho_1(\hat{z} - y) \\ \dot{\hat{d}} = -\varrho_2 \sum_{i=0}^{h} \frac{sk_i}{s^2+\omega_i}(\hat{z} - y) \end{cases}$	**Pro**: Good robustness to fast-varying disturbances. **Con**: Phase margin is reduced and needs to be compensated by an appropriately designed gain.

disturbances, and data packet losses. It relies on Lyapunov–Razumikhin stability analysis for determining of linear matrix inequalities to guarantee a stable terminal constraint set. However, it relies on the min–max MPC [35], which has high computational requirements.

B. EMPC for Energy Management

Energy management systems in microgrids aim to balance the power supply and demand, in a manner that simultaneously optimizes several competing objectives, such as operational, economic, and reliability goals. At the same time, the constraints of the system (generation limits, energy storage capacity, charging/discharging rate, grid codes, etc.) must not be violated. Achieving all these goals can be challenging in the face of uncertainties in renewable energy, electricity prices, and communication links. For example, Fig. 10(a) shows a microgrid that requires robust economic management. It features intermittent renewable supply, electricity price uncertainties, critical, and controllable loads. Fig. 10(b) also shows a possible robust strategy implemented across multitimescales.

1) Optimization Objectives:

a) Operational objectives: Include real-time dispatch of available resources, optimal power flow management, and seamless transitions between grid-connected and islanded modes.

b) Economic objectives: Reducing electricity procurement costs, minimizing operational expenses of local generators, optimizing the utilization of energy storage systems, revenue

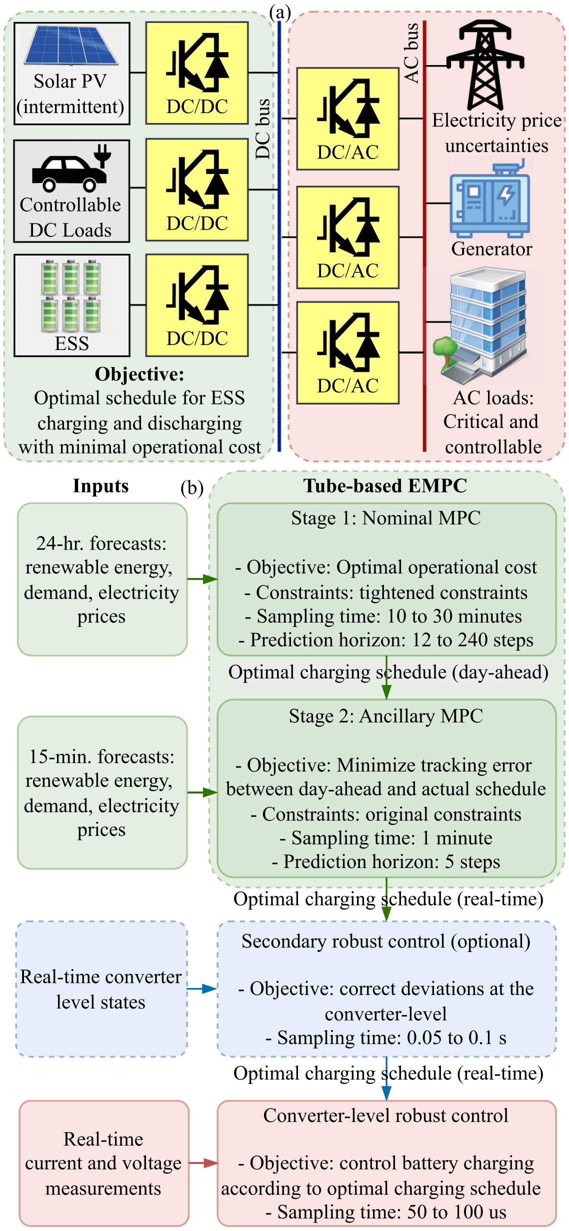


Fig. 10. Robust EMPC for microgrids. (a) Microgrid and its components. (b) Robust EMPC scheme using tube-based EMPC: Derived by authors from combined solutions in [31], [96], [99], [100], and [101].

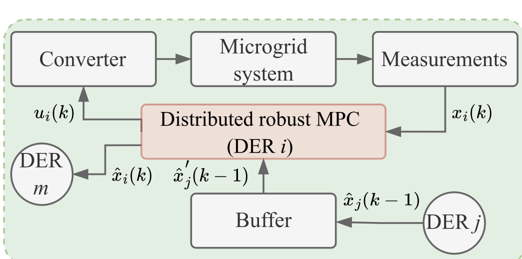


Fig. 11. Distributed robust MPC for cyber-resilient microgrids [109].

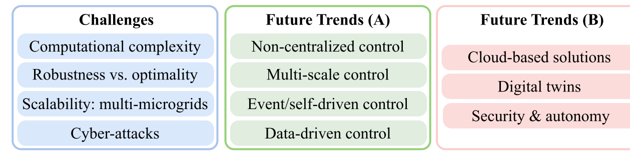


Fig. 12. Challenges and trends in robust MPC for converter-based microgrids.

maximization through participation in ancillary service markets and demand response programs.

c) Reliability and environmental objectives: Optimal scheduling of energy storage to accommodate renewable intermittency and load variations.

2) EMPC Formulation: EMPC is different from classical MPC formulations that employ quadratic cost functions for setpoint tracking. Instead, EMPC directly optimizes the actual economic performance of the system without requiring separate economic optimization layers or steady-state target calculations. The cost function for a microgrid's economic operation is given by

$$J_e = \sum_{k=0}^{N_p-1} (C_g(k)P_{\text{grid}}(k) + C_{fg}(k)P_{\text{fgen}}(k) + C_b(k)P_{\text{bess}}(k) + C_L(k)P_L(k))$$

s.t. constraints on: power balance, grid power, fuel generator operational limits and ramp rate, energy storage state of charge, power constraints, and load curtailment (14)

where C_g is time-varying electricity price, P_{grid} is grid power, C_{fg} is generator fuel costs, P_{fgen} is generator power, C_b is energy storage degradation cost, P_{bess} is energy storage power, C_L is the penalty for load curtailment, and P_L is the curtailed load.

3) Robust EMPC Formulation: This can be formulated as min–max EMPC [102], tube-based EMPC [99], distributed EMPC [91], stochastic EMPC [32], [90], scenario-based EMPC [103], as summarized in Table V. The following is an example of the cost function for robust tube-based EMPC to mitigate uncertainties

$$J_e = \sum_{k=0}^{N_p-1} \left(C_g(k)\bar{P}_{\text{grid}}(k) + C_{\text{fg}}(k)\bar{P}_{\text{fgen}}(k) + C_b(k)\bar{P}_{\text{bess}}(k) + C_L(k)\bar{P}_L(k)\right) + \alpha\|e(k)\|$$

s.t. nominal and tube constraints (15)

where $\bar{P}$ is the nominal power and $\alpha\|e(k)\|$ is the tube constraint violation penalty, and other variables are as defined for (14). This approach was employed in [104]: Robust multitime scale coordination operation is achieved through a two-stage structure where a nominal MPC controller generates robust reference trajectories in the long time scale, which are then tracked by an ancillary

TABLE IV
ROBUST MPC TECHNIQUES FOR MICROGRIDS: SYSTEM-LEVEL CONTROL

Key Focus	Solution Approach	Advantage	Limitation
Multi-Microgrid Coordination	Distributed robust MPC for islanded multi-microgrids [2]	Enhances economic efficiency through energy trading, reduces uncertainty effects.	Complexity in managing energy trading and multi-microgrid coordination.
	Distributed MPC with consensus strategy for isolated microgrids [31]	Operates without knowledge of microgrid topology, robust to load variations.	Sensitivity to communication issues.
Uncertainty Management	Robust Data Predictive Control for multi-microgrid electricity price forecasting [89]	Significant cost reduction and improved prediction accuracy.	High complexity in forecasting models and computational demands.
	Chance-Constrained Model Predictive Control for congestion management in networked microgrids [90]	Effectively handles uncertainty and optimizes congestion management.	Computational burden due to stochastic optimization.
	Distributionally robust MPC for multi-area dynamic optimal power flow [91]	Addresses distributed generation uncertainty and energy-reserve co-optimization.	Complex optimization model, requires decomposition for scalability.
Load and Congestion Management	Adaptive MPC for power management in isolated PV-battery microgrids [92]	Robust to intermittent generation and load conditions, scalable.	Sensitive to communication disruptions and latency.
	Predictive voltage hierarchical controller for voltage and power sharing in microgrids [93]	Ensures voltage stability and reduces data integrity issues under communication loss.	Relies on accurate predictions for compensation.
Cybersecurity and Resilience	Virtual inertia control under DoS attacks [94]	Protects against DoS attacks, improves virtual inertia and frequency control.	Complex attack detection and estimator optimization.
	Distributed robust secondary control for voltage and frequency restoration [95]	Handles communication network disruptions, ensures resilient operation.	Time-varying delays and packet losses can impact performance.
Data-Driven MPC	Online learning-based MPC for microgrid energy management [19]	Adaptable, real-time decision-making capability.	High computational cost due to model complexity.
Stochastic MPC for electric vehicles	Stochastic MPC for electric vehicle (EV) charging in microgrids [32]	Minimizes cost with low computational burden.	Difficulty in managing diverse scenarios and uncertainties.
	Multi-time-scale stochastic MPC for EV charging dispatch [96]	Achieves near-optimal real-time performance, reduces operational costs.	Requires frequent recalculations of scenarios.
Hybrid MPC Approach	Affine arithmetic in isolated microgrids for uncertainty handling [97]	Provides robust performance with minimal recalculations.	Requires predefined uncertainty bounds.

TABLE V
COMPREHENSIVE COMPARISON OF ECONOMIC MPC VARIANTS

EMPC Type	Robustness	Eonomic Performance	Complexity	Best for System Characteristics	Advantages	Limitations
Standard EMPC [108]	Low	High	Moderate	Low uncertainty, reliable forecasts	• Direct economic optimization	• No uncertainty handling
Min-Max EMPC [102]	Very High	Low-Moderate	Very High	High uncertainty, safety-critical systems, guaranteed performance	• Worst-case guarantees • Suitable for critical applications	• Overly conservative • High computational burden, high complexity
Tube-based EMPC [99]	High	Moderate-High	High	Moderate uncertainty, balanced robustness-performance	• Reduced conservatism vs min-max • Good stability properties	• Complex tube design • Requires linear error dynamics
Scenario-based EMPC [103]	Moderate-High	Moderate-High	Moderate	Well-characterized uncertainty, moderate robustness needs	• Computationally tractable Good performance-robustness trade-off	• Limited robustness guarantees • May miss worst-case scenarios
Stochastic EMPC [32], [90]	Moderate	High	High	Known probability distributions, expected performance focus	• Optimal expected performance • Intrinsic uncertainty handling	• Requires accurate distributions • Computationally intensive
Distributed robust EMPC [91]	Moderate	Moderate-High	Moderate-High	Large-scale systems, communication limitations, scalability	• Scalable architecture • Lower communication • Privacy preservation	• Coordination complexity • Convergence time

MPC controller in the short time scale that incorporates real-time renewable correction information. Similarly, Xie et al. [99] developed a tube MPC-based multicriteria energy management framework that provides robustness against system uncertainties while maintaining economic performance and computational efficiency. In addition, they devised a novel compound alternating direction method of multipliers to preserve individual nanogrid privacy and ensure convergence for the mixed-integer nonlinear optimization problem. Further details on EMPC for microgrids can be found in a dedicated study on the topic [105].

4) Decentralized and Distributed Energy Management: Isolated microgrids require stable energy dispatch while ensuring frequency and voltage restoration amid variable loads and generation. Navas F. et al. [31] proposed a distributed MPC strategy that eliminates central coordination, reducing communication overhead, and enhancing robustness to load variations. Meanwhile, the multiobjective capability of robust MPC is deployed to ensure both frequency regulation and optimal dispatch within the same timescale. Similarly, Tavakoli et al. [106] introduced a decentralized MPC approach with a sliding-mode controller for voltage and current stabilization in islanded microgrids. This method provides fast tracking and transient recovery, though its complexity limits large-scale applications. Ingalalli et al. [107] employed an online identification method using a Kalman filter, improving robustness against noise.

5) Energy Management in Multimicrogrids: One of the significant challenges in MMGs is managing the uncertainty of renewable energy sources across interconnected systems. Zhao et al. [104] proposed a distributed dynamic tube MPC framework, using cooperative MPC controllers to reduce computational complexity and improve energy efficiency. A game-theory-based energy trading mechanism ensures a balance between robustness and economic performance. Similarly, distributed robust MPC strategy, which integrates robust optimization with dynamic energy trading to mitigate renewable generation uncertainty is reported to produce effective results [2]. Despite economic benefits, computational complexity remains a challenge.

Huang et al. [91] addressed MMG uncertainties using distributionally robust MPC in a multiarea dynamic optimal power flow model. By co-optimizing energy reserves, the approach improves operational security while maintaining independence among microgrids. This method ensures resilience but requires significant computational resources for multiarea implementation. Omrani et al. [90] proposed a chance-constrained MPC framework for MMG congestion management. Stochastic optimization ensures reliable operation under uncertainty, though effectiveness depends on well-characterized uncertainties.

A hybrid robust data predictive control framework [89] integrates outlier-robust extreme learning machine for price forecasting with a two-layer distributed control approach. This method enhances cost efficiency in MMGs but is susceptible to inaccuracies in price prediction and coordination challenges. Hybrid control strategies also combine robust and decentralized MPC for improved resilience. Scenario-based MPC using extreme scenarios (minimum and maximum) together with an expected scenario to push control trajectories away from operational boundaries was presented in [103]. The expected scenario focuses on economic optimization, while extreme scenarios prioritize safety and robustness. This approach produces enhanced system resilience against low-probability but high-impact events with a tradeoff in economic losses. These studies highlight the potential of distributionally robust and chance-constrained MPC methods for MMG operation. While they enhance stability and efficiency, computational complexity, and optimization challenges must be addressed for large-scale applications.

6) Summary: Table IV summarizes the techniques, highlighting that traditional distributed and decentralized MPC focuses on MMG coordination, congestion management, and uncertainty mitigation. These methods are effective in improving system stability and efficiency but may require significant communication infrastructure. Robust and stochastic MPC for uncertainty management employs optimization techniques to account for uncertainties in microgrids. Some incorporate machine learning to enhance prediction accuracy. AI and data-driven MPC approaches leverage machine learning and online learning techniques for adaptive control, making them promising for real-time applications but requiring large datasets. Stochastic MPC for EV charging dispatch specializes in managing the uncertainties of EV integration in microgrids, emphasizing cost efficiency and real-time adaptation. Hybrid MPC methods provide alternative uncertainty modeling techniques, balancing computational efficiency with robustness.

VI. Cyber-Resilient MPC for Microgrids

Microgrid control systems are increasingly vulnerable to cyber-attacks due to their reliance on digital communication and distributed control. These cyber threats pose significant risks to system stability, security, and economic performance. In particular, the attacks can be targeted at the following five key system parts [17]:

1) DER and power converter hardware;
2) control algorithms in the controller;
3) communication links;
4) connection to the main power grid; and
5) sensors/smart meters.

A. Cyber-Attacks and Mitigation Principles

One of the most critical attacks, false data injection attacks, manipulate sensor readings to mislead control decisions, causing incorrect power dispatch and voltage instability. AI-based anomaly detection and blockchain technology can enhance data integrity and prevent such intrusions. The DoS attacks, which overwhelm network traffic, can delay or disable control actions, making the microgrid vulnerable to instability. Countermeasures include redundant communication paths and intrusion detection systems.

More advanced threats like man-in-the-middle attacks and replay attacks exploit vulnerabilities in communication links. They can lead to unauthorized control or repeated execution of malicious commands, causing grid instability. Secure encryption and authentication protocols effectively mitigate these threats. Also, malware, ransomware, and command/control hijacking can compromise control devices, leading to data breaches or loss of control. Regular software updates, role-based access control, and behavior-based malware detection enhance security. Global positioning system (GPS) spoofing attacks, targeting time-sensitive controllers, disrupt synchronization, which can be prevented through secure GPS receivers and cross-verification mechanisms. Overall, securing microgrid control requires a multilayered approach, integrating cryptographic techniques, anomaly detection, and network resilience strategies.

B. State of the Art Cyber-Resilient MPC Techniques

A few cyber-attack mitigation strategies for resilient MPC in cyber-physical microgrids have been proposed in the literature. The enhanced virtual inertia control [94], [110] approach employs so-called improved resilient MPC and enhanced resilient MPC to mitigate DoS attacks by using an attack detection mechanism, an autoregressive-based estimator, and an MPC-based virtual energy storage system. This method is particularly effective in restoring control signal losses caused by DoS attacks. It improves frequency stability and reduces the rate of change of frequency, ensuring smooth operation under attack. However, the method is computationally intensive and relies on the accuracy of the autoregressive-based signal estimator, which may affect its real-time implementation.

In contrast, the privacy-preserving distributed MPC [111], [112] method introduces parameter-adaptive distributed MPC to maintain privacy while ensuring microgrid stability. This approach utilizes time-varying constraints and quadratic programming to balance the privacy preservation of real-time values against the control performance. Although the strategy secures data exchange and mitigates unauthorized access, the encryption algorithms introduce delays, affecting the system's real-time response.

Another approach is the use of deep RL-based defense [113], which employs a soft actor–critic-based deep RL algorithm to dynamically control DERs and minimize voltage violations during cyber-attacks. This method adapts to unknown attack scenarios without needing explicit threat modeling and can provide real-time corrective actions for voltage stability. However, it is computationally intensive and demands large training datasets and real-time tuning, which limits its applicability in resource-constrained microgrids.

The robust MPC strategies for cyber-physical systems in [109] (shown in Fig. 11) and [114] utilize novel robustness constraints and multistep transmission strategies to enhance resilience against DoS attacks. These approaches ensure closed-loop stability even under prolonged cyber-attacks and reduce communication overhead by using a multistep transmission strategy. However, these methods are less effective against sophisticated adaptive DoS attacks, and their implementation complexity may introduce response time delays, affecting the overall system performance.

VII. Challenges and Future Trends

Several robust MPC have been covered in the preceding microgrids. However, despite reported advantages in handling uncertainties while optimizing control decisions, robust MPC methods face several challenges that hinder their practical deployment. Challenges include computational complexity, tradeoffs between robustness and optimality, and scalability issues. These challenges and the future research trends (see Fig. 12) are discussed in this section.

A. Challenges

1) Computational Complexity and Real-Time Feasibility: One of the key limitations of robust MPC is its high computational burden, which makes real-time implementation difficult. At the converter-level, several studies report similar or slightly increased computational burden than the nominal MPC schemes. Conversely, at the system level, robust MPC requires solving large-scale optimization problems at each control step while considering worst-case uncertainties. Methods such as tube-based MPC, distributionally robust MPC, and stochastic MPC involve complex iterative computations that may not be feasible for fast-response applications. While parallel computing and real-time solvers offer potential solutions, their practical implementation remains costly and technically demanding.

2) Tradeoff Between Robustness and Optimality: Robust MPC is designed to maintain system stability even in worst-case scenarios. However, this often results in overly conservative control actions, which reduce operational efficiency. In renewable-dominated microgrids, such conservatism leads to higher costs and wasted energy resources. While adaptive and data-driven MPC approaches have been proposed to enhance optimality, they introduce new challenges, such as requiring extensive historical data for training. This tradeoff between robustness and performance remains a critical barrier to the widespread adoption of robust MPC in microgrid applications.

3) Scalability Issues in MMG Systems: Many robust MPC methods have been developed for single microgrid operation, but scaling these methods to MMG systems is a significant challenge. Future power systems will consist of networked microgrids, where multiple DERs must be coordinated efficiently. Hierarchical and distributed MPC approaches have been introduced to address this, but they require synchronized communication and real-time data sharing, which introduces new challenges related to latency, stability, and computational feasibility.

4) Cybersecurity Vulnerabilities: Despite the rapid advancement of robust MPC techniques, there has been limited attention to their cybersecurity risks. Microgrids are increasingly reliant on communication networks (wired and wireless) for real-time data exchange between controllers, sensors, and distributed generation units. This dependence makes them highly vulnerable to cyber threats, such as DoS attacks, data tampering, spoofing, and malware infiltration. A cyberattack on an MPC-based microgrid controller could lead to suboptimal control actions, system instability, or even blackouts. To address these threats, cyber-resilient MPC architectures must be developed, integrating advanced cybersecurity strategies within the MPC framework. Some of the most promising approaches include the *a) AI-based anomaly detection:* Machine learning algorithms can detect and classify malicious activities in real time, allowing proactive response to cyber threats.

b) Blockchain authentication: Decentralized ledger technology facilitate the authentication and security of microgrid transactions and data exchanges.

c) End-to-end encryption and multifactor authentication: Safeguard control signals and data from interception or unauthorized access.

d) Redundant communication pathways and intrusion detection systems: These enhance resilience by providing backup channels and early threat detection.

e) Timestamp verification and secure GPS: These help prevent replay attacks and ensure accurate synchronization of control actions in networked microgrids. As microgrids become more interconnected and reliant on cloud-based and IoT-driven control architectures, integrating cyber-resilient strategies into robust MPC frameworks is essential to ensure secure and stable energy management.

B. Future Trends

1) Decentralized and Distributed Control for Enhanced Resilience: Microgrid control has traditionally relied on centralized architectures, making systems vulnerable to single points of failure. A shift toward decentralized and distributed decision-making will improve system resilience by enabling multiple controllers to collaborate and reach consensus without relying on a central authority. Distributed control mechanisms will facilitate more reliable information sharing in microgrids, ensuring that no single point of failure can compromise the entire system. Secure energy trading between microgrids will also benefit from blockchain-based consensus mechanisms, which can prevent fraud and manipulation by providing transparent and tamper-proof transaction records. Meanwhile, the latency introduced by the blockchain layer needs to be compensated proactively [115]. In addition, distributed decision-making frameworks will enhance fault tolerance, ensuring that local controllers can operate independently if communication with the central system is disrupted.

2) Multitimescale and Multispatial Controllability: Traditional MPC methods primarily operate at fixed timescales, focusing on short-term control objectives. However, resilient microgrids require control strategies that function across multiple time and spatial scales. Also, uncoordinated actions from higher level MPC could conflict with lower level stability objectives. So, the possible interactions between hierarchical control levels which can be triggered by disturbances should be accounted for and mitigated. Future research will explore methods to coordinate long-term cybersecurity updates with real-time power system disturbances, ensuring control decisions remain effective across varying timescales. This approach will also improve spatial coordination by integrating device-level, microgrid-level, and grid-level responses to maintain system stability, even when communication networks are compromised. Furthermore, the economic impact of cyberattacks on energy markets must be considered, as attackers could manipulate pricing signals to disrupt energy trading. Future MPC models should incorporate economic resilience strategies to counteract such vulnerabilities, ensuring both operational security and financial stability.

3) Event-Driven and Self-Triggered Control: Current MPC implementations rely on continuous control updates, making microgrids more vulnerable to data interception and cyberattacks. A shift toward event-driven and self-triggered control strategies can enhance both cybersecurity and operational efficiency. Event-triggered MPC updates control signals only when system deviations exceed predefined thresholds, reducing unnecessary communication and limiting exposure to cyber threats. Self-triggered MPC, on the other hand, schedules control actions based on internal state forecasts, reducing dependency on external data exchanges that could be compromised. In addition, anomaly detection mechanisms will play a critical role in cybersecurity by identifying inconsistencies between expected control events and real-time measurements. This approach allows microgrids to detect and neutralize malicious data injections before they impact system stability.

4) Data-Driven MPC for Computational Efficiency and Enhanced Decision-Making: Artificial intelligence is increasingly being integrated into MPC frameworks to enhance data-driven decision-making in microgrids. On the one hand, model-free techniques are increasing, e.g., hybrid methods combining ultra-local principles with state-gradient and observer-based MPC [56]. On the other hand, improved learning-based MPC methods are necessary for computationally efficient advanced MPC emulation, and adaptive tuning of parameters for stability and optimality. AI-powered digital twins will simulate cyberattacks and disturbances, allowing MPC controllers to preemptively adjust their strategies. RL-based MPC can improve adaptability by learning from past disturbances and dynamically adjusting control strategies. Furthermore, ML algorithms can be used for cybersecurity, analyzing real-time system data to detect anomalous control commands indicative of cyber threats. The success of these AI-driven MPC approaches will depend on the quality and volume of historical and real-time data available. As such, research will need to focus on developing reliable data collection and classification methods to ensure accuracy in AI-based decision-making.

5) AI-Enhanced, Cloud-Based MPC Solutions: In the industry, there is a growing trend toward AI-enhanced, cloud-based MPC solutions that enable remote microgrid optimization and cybersecurity monitoring. Cloud-based MPC platforms will provide software-as-a-service models, allowing energy operators to access AI-driven optimization tools without requiring extensive in-house computational resources. These platforms will also integrate built-in cybersecurity features, such as real-time anomaly detection and automated threat mitigation. As cyber threats become more prevalent, regulatory bodies are likely to introduce stricter cybersecurity requirements for energy management systems, compelling industries to adopt secure and compliant MPC solutions. The transition to cloud-based MPC will improve scalability, allowing microgrid operators to monitor and control multiple DERs from a centralized interface while ensuring robust cybersecurity measures are in place.

6) Digital Twin-Based Testing for Cyber-Resilient MPC: Industries are increasingly adopting digital twin technology to test and validate MPC strategies before deployment in real-world microgrids. Digital twins allow energy operators to simulate cyberattack scenarios, grid disturbances, and equipment failures to assess the effectiveness of MPC in responding to such events. This proactive approach enables companies to identify vulnerabilities and refine their control strategies before implementing them in actual microgrids. In addition, fault and attack simulation capabilities within digital twins will support AI-powered optimization, allowing control strategies to evolve based on historical and simulated data. By integrating digital twin-based testing into their workflows, industries can enhance the reliability and cybersecurity of MPC implementations while reducing the risk of operational failures.

7) Secure and Autonomous GFM Converters: Another key industry trend is the development of secure and autonomous GFM inverters that can operate independently during grid failures. Unlike conventional GFL inverters, which rely on external frequency references, GFM inverters can establish voltage and frequency references autonomously, enabling microgrids to sustain operations during blackouts. Future MPC implementations will play a critical role in optimizing the performance and security of these inverters. AI-powered intrusion detection systems will monitor inverter control commands for anomalies, ensuring protection against cyberattacks that attempt to manipulate inverter settings. In addition, blockchain authentication mechanisms will be integrated to prevent unauthorized access and ensure the integrity of inverter control data. By enhancing the security and autonomy of GFM inverters, industries can improve the resilience of microgrids and support seamless transition between grid-connected and islanded modes.

VIII. Conclusion

Robust MPC techniques have emerged as crucial solutions for addressing uncertainties in microgrid control. This article reviewed various robust MPC strategies for both converter-level and system-level applications, highlighting their strengths and limitations. Converter-level robust MPC methods focus on enhancing local control stability in power converters, while system-level robust MPC ensures coordinated energy management across interconnected microgrids. In addition, we explored cyber-resilient MPC approaches aimed at protecting microgrids from evolving cyber threats. Despite their advantages, robust MPC implementations face challenges such as high computational complexity, tradeoffs between robustness and optimality, scalability issues in MMG systems, and cybersecurity concerns. Future research should focus on developing decentralized and distributed MPC frameworks to enhance resilience, integrating multitimescale and multispatial control strategies, and leveraging data-driven and AI-enhanced MPC for real-time adaptability. Industry trends indicate a shift toward AI-powered, cloud-based MPC solutions, digital twin-based cyber-resilient testing, and secure autonomous GFM converters. As microgrid deployments expand, these advancements will play a critical role in ensuring reliable, secure, and efficient operation. Robust MPC, combined with emerging technologies, will be pivotal in shaping the future of intelligent, resilient microgrids.

Appendix

A. GFM Converter Parameters

The GFM converter control schemes shown in Fig. 7 were simulated in Simulink/MATLAB with the following system and control parameters. DC-link voltage $V_{\rm dc} = 500$ V, nominal frequency $f^* = 50$ Hz, nominal voltage $V^* = 250$ V, filter parameters: $R_f = 0.1\ \Omega$, $L_f = 2.4$ mH, $C_f = 25\ \mu$F; line impedance ($R_l = 0.73\ \Omega$, $L_l = 13.33\ \mu$H); droop coefficients ($k_p = 2.1$ mV/Var, $k_q = 5.2$ mrad/W); moment of inertia $= 0.64$ kg $\cdot$ m^2; weighting factor for each of inductor current and capacitor voltage feedback ($\lambda_i = \lambda_v = 5.0$); sampling period $T_s = 25\ \mu$s. Note that the virtual synchronous generator scheme is the simplified version studied in [116].

B. GFL Converter Experimental Setup

Experimental results in Fig. 8 for the control schemes in Fig. 9 were validated on a laboratory test bench. PLECS software was used to write the codes for B-BOX RCP$^{3.0}$ controller. Imperix's two-level power SiC MOSFET converter modules were utilized. The key parameters of the system are: dc-link voltage $V_{\rm dc} = 130$ V, grid frequency $f = 50$ Hz, grid voltage (rms) $e_g = 25$ V, filter parameters $R_f = 0.04\Omega, L_f = 5.0$ mH, load resistance $R_L = 40\ \Omega$, sampling period $T_s = 20\ \mu$s, PI controller gains $k_{\rm pvdc} = 0.3$ A/V, $k_{\rm ivdc} = 40$ A/V, ESO bandwidth $\omega_0 = 3$ krad/s. Methods compared include conventional MPC (described in [34]), and model-free MPC based on: conventional ESO [117], cascade ESO [50], cascade-parallel ESO [73], parallel-casacade ESO [34], and structurally adaptive ESO [34].

Acknowledgment

Author Jose Rodriguez would like to thank the support of ANID through Project AFB240002.

References

[1] T. Dragicevic, "Model predictive control of power converters for robust and fast operation of AC microgrids," *IEEE Trans. Power Electron.*, vol. 33, no. 7, pp. 6304–6317, Jul. 2018.

[2] Z. Zhao et al., "Distributed robust model predictive control-based energy management strategy for islanded multi-microgrids considering uncertainty," *IEEE Trans. Smart Grid*, vol. 13, no. 3, pp. 2107–2120, May 2022.

[3] J. M. Guerrero, M. Chandorkar, T. L. Lee, and P. C. Loh, "Advanced control architectures for intelligent microgridspart i: Decentralized and hierarchical control," *IEEE Trans. Ind. Electron.*, vol. 60, no. 4, pp. 1254–1262, Apr. 2013.

[4] T. Dragičević, S. Vazquez, and P. Wheeler, "Advanced control methods for power converters in DG systems and microgrids," *IEEE Trans. Ind. Electron.*, vol. 68, no. 7, pp. 5847–5862, Jul. 2021.

[5] O. Babayomi, Y. Li, Z. Zhang, and K.-B. Park, "Advanced control of grid-connected microgrids: Challenges, advances, and trends," *IEEE Trans. Power Electron.*, vol. 40, no. 6, pp. 7681–7708, Jun. 2025.

[6] P. Cortes, G. Ortiz, J. I. Yuz, J. Rodriguez, S. Vazquez, and L. G. Franquelo, "Model predictive control of an inverter with output *LC* filter for UPS applications," *IEEE Trans. Ind. Electron.*, vol. 56, no. 6, pp. 1875–1883, Jun. 2009.

[7] Y. Wang, F. Liu, S. Chen, G. Shen, and Q.-G. Wang, "Prediction errors analysis and correction on FCS-MPC for the cascaded H-bridge multilevel inverter," *IEEE Trans. Ind. Electron.*, vol. 69, no. 8, pp. 8264–8273, Aug. 2022.

[8] P. Karamanakos and T. Geyer, "Guidelines for the design of finite control set model predictive controllers," *IEEE Trans. Power Electron.*, vol. 35, no. 7, pp. 7434–7450, Jul. 2020.

[9] T. Dorfling, H. du Toit Mouton, T. Geyer, and P. Karamanakos, "Long-horizon finite-control-set model predictive control with nonrecursive sphere decoding on an FPGA," *IEEE Trans. Power Electron.*, vol. 35, no. 7, pp. 7520–7531, Jul. 2020.

[10] J. B. Rawlings et al., *Model Predictive Control: Theory, Computation, and Design*. Madison, WI, USA: Nob Hill Publishing, 2017, vol. 2.

[11] H. Zamani, K. Abbaszadeh, M. H. Karimi, and J. Gyselinck, "Adaptive model predictive control for LCL-filter grid-tied inverters," *IEEE Trans. Ind. Electron.*, vol. 71, no. 8, pp. 8903–8914, Aug. 2024.

[12] A. Oshnoei, A. A. Derbas, S. Peyghami, and F. Blaabjerg, "Robust control of voltage source converters: A tube-based model predictive approach," *IEEE Trans. Circuits Syst. II: Exp. Briefs*, vol. 70, no. 9, pp. 3464–3468, Sep. 2023.

[13] L. Huang, J. Lygeros, and F. Dörfler, "Robust and kernelized data-enabled predictive control for nonlinear systems," *IEEE Trans. Control Syst. Technol.*, vol. 32, no. 2, pp. 611–624, Mar. 2024.

[14] E. Buraimoh and I. E. Davidson, "Modeling and fault ride-through control of a photovoltaic-based grid supporting microgrid using a secondary control dsc algorithm," in *Proc. Conf. Sustain. Energy Supply Energy Storage Syst.*, 2021, pp. 1–8.

[15] E. Buraimoh and I. E. Davidson, "Fault ride-through analysis of current- and voltage-source models of grid supporting inverter-based microgrid," *IEEE Can. J. Elect. Comput. Eng.*, vol. 44, no. 2, pp. 189–198, Spring 2021.

[16] E. Buraimoh, I. E. Davidson, and F. Martinez-Rodrigo, "Decentralized fast delayed signal cancelation secondary control for low voltage ride-through application in grid supporting grid feeding microgrid," *Front. Energy Res.*, vol. 9, 2021, Art. no. 643920.

[17] S. Sahoo, T. Dragičević, and F. Blaabjerg, "Cyber security in control of grid-tied power electronic converters—Challenges and vulnerabilities," *IEEE Trans. Emerg. Sel. Topics Power Electron.*, vol. 9, no. 5, pp. 5326–5340, Oct. 2021.

[18] N. Bazmohammadi, A. Tahsiri, A. Anvari-Moghaddam, and J. M. Guerrero, "Stochastic predictive control of multi-microgrid systems," *IEEE Trans. Ind. Appl.*, vol. 55, no. 5, pp. 5311–5319, Sep./Oct. 2019.

[19] V. Casagrande, M. Ferianc, M. R. D. Rodrigues, and F. Boem, "Online end-to-end learning-based predictive control for microgrid energy management," *IEEE Trans. Control Syst. Technol.*, vol. 33, no. 2, pp. 463–478, Mar. 2025.

[20] H. Chen, Z. Zhang, P. Karamanakos, and J. Rodriguez, "Digital twin techniques for power electronics-based energy conversion systems: A survey of concepts, application scenarios, future challenges, and trends," *IEEE Ind. Electron. Mag.*, vol. 17, no. 2, pp. 20–36, Jun. 2023.

[21] J. Hu, Y. Shan, J. M. Guerrero, A. Ioinovici, K. W. Chan, and J. Rodriguez, "Model predictive control of microgrids—An overview," *Renewable Sustain. Energy Rev.*, vol. 136, 2021, Art. no. 110422.

[22] Z. Zhang et al., "Advances and opportunities in the model predictive control of microgrids: Part I—Primary layer," *Int. J. Elect. Power Energy Syst.*, vol. 134, 2022, Art. no. 107411.

[23] O. Babayomi et al., "Advances and opportunities in the model predictive control of microgrids: Part II–Secondary and tertiary layers," *Int. J. Elect. Power Energy Syst.*, vol. 134, 2022, Art. no. 107339.

[24] C. Bordons, F. Garcia-Torres, and M. A. Ridao, *Model Predictive Control of Microgrids*, vol. 358. Berlin, Germany: Springer, 2020.

[25] B. Marinescu and H. Bourles, "Robust predictive control for the flexible coordinated secondary voltage control of large-scale power systems," *IEEE Trans. Power Syst.*, vol. 14, no. 4, pp. 1262–1268, Nov. 1999.

[26] A. Bidram and A. Davoudi, "Hierarchical structure of microgrids control system," *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 1963–1976, Dec. 2012.

[27] J. Rodriguez and P. Cortes, *Predictive Control of Power Converters and Electrical Drives*, vol. 40. Hoboken, NJ, USA: Wiley, 2012.

[28] Q. Xing et al., "Bias-free predictive control of power converters with LCL filter in micro-energy systems," *IEEE Trans. Ind. Electron.*, vol. 70, no. 6, pp. 5907–5916, Jun. 2023.

[29] P. Cortes, J. Rodriguez, S. Vazquez, and L. G. Franquelo, "Predictive control of a three-phase ups inverter using two steps prediction horizon," in *Proc. IEEE Int. Conf. Ind. Technol.*, 2010, pp. 1283–1288.

[30] T. Geyer, P. Karamanakos, and R. Kennel, "On the benefit of long-horizon direct model predictive control for drives with LC filters," in *Proc. IEEE Energy Convers. Congr. Expo.*, 2014, pp. 3520–3527.

[31] A. N. F., J. S. Gómez, J. Llanos, E. Rute, D. Sáez, and M. Sumner, "Distributed predictive control strategy for frequency restoration of microgrids considering optimal dispatch," *IEEE Trans. Smart Grid*, vol. 12, no. 4, pp. 2748–2759, Jul. 2021.

[32] W. Yang, H. Fang, D. Xu, B. Jiang, and P. Shi, "A stochastic model predictive control-based energy management approach for microgrids with electric vehicles," *IEEE Trans. Transport. Electrific.*, vol. 11, no. 1, pp. 3137–3145, Feb. 2025.

[33] P. Karamanakos, E. Liegmann, T. Geyer, and R. Kennel, "Model predictive control of power electronic systems: Methods, results, and challenges," *IEEE Open J. Ind. Appl.*, vol. 1, pp. 95–114, 2020.

[34] O. Babayomi, Z. Zhang, Z. Li, M. L. Heldwein, and J. Rodriguez, "Robust predictive control of grid-connected converters: Sensor noise suppression with parallel-cascade extended state observer," *IEEE Trans. Ind. Electron.*, vol. 71, no. 4, pp. 3728–3740, Apr. 2024.

[35] D. Q. Mayne, J. B. Rawlings, C. V. Rao, and P. O. Scokaert, "Constrained model predictive control: Stability and optimality," *Automatica*, vol. 36, no. 6, pp. 789–814, 2000.

[36] R. Heydari et al., "Model-free predictive control of grid-forming inverters with LCL filters," *IEEE Trans. Power Electron.*, vol. 37, no. 8, pp. 9200–9211, Aug. 2022.

[37] H. Zamani, K. Abbaszadeh, J. Gyselinck, and M. Karimi, "Robust continuous control set model predictive control in synchronous reference frame for grid-tied inverters," *IEEE J. Emerg. Sel. Topics Ind. Electron.*, vol. 4, no. 1, pp. 209–218, Jan. 2023.

[38] Y. Sun, Z. Zhang, Y. Wang, Z. Li, and J. Rodriguez, "Robust predictive control of grid-tied modular multilevel converters for HVDC systems with virtual-flux based online inductance estimation," *IEEE Trans. Power Del.*, vol. 37, no. 4, pp. 3189–3199, Aug. 2022.

[39] M. M. Mardani, R. D. Lazar, N. Mijatovic, and T. Dragičević, "Artificial neural network-based constrained predictive real-time parameter adaptation controller for grid-tied VSCs," *IEEE Trans. Emerg. Sel. Topics Power Electron.*, vol. 11, no. 2, pp. 1507–1517, Apr. 2023.

[40] J. S. Costa, A. Lunard, L. F. N. Lourenço, L. Rodrigues, and A. J. S. Filho, "Disturbance robust generalized predictive control applied to an EV charger grid converter," *IEEE Open J. Ind. Appl.*, vol. 6, pp. 69–78, 2025.

[41] D. Q. Mayne, M. M. Seron, and S. V. Raković, "Robust model predictive control of constrained linear systems with bounded disturbances," *Automatica*, vol. 41, no. 2, pp. 219–224, 2005.

[42] B. Cartes et al., "Design method for polynomial orders in ARX-based model-free predictive controllers," *IEEE J. Emerg. Select. Topics Power Electron.*, vol. 13, no. 1, pp. 604–614, Feb. 2025.

[43] O. Babayomi, Z. Zhang, Y. Li, and R. Kennel, "Adaptive predictive control with neuro-fuzzy parameter estimation for microgrid grid-forming converters," *Sustainability*, vol. 13, no. 13, 2021, Art. no. 7038.

[44] A. Tregubov, P. Karamanakos, and L. Ortombina, "Robust direct model predictive control with reduced computational effort for medium-voltage grid-connected converters with LCL filters," in *Proc. 25th Eur. Conf. Power Electron. Appl.*, 2023, pp. 1–8.

[45] S. Kiani, A. Salmanpour, M. Hamzeh, and H. Kebriaei, "Learning robust model predictive control for voltage control of islanded microgrid," *IEEE Trans. Autom. Sci. Eng.*, vol. 22, pp. 3021–3032, 2025.

[46] P. Burgos, H. Young, C. Matus, C. Cifuentes, and D. Obando, "Observer-based ultralocal model-free predictive voltage control of a grid forming inverter," in *Proc. IEEE Int. Conf. Automation/XXVI Congr. Chilean Assoc. Autom. Control*, 2024, pp. 1–6.

[47] T. Zhao, M. Zhang, C. Wang, and Q. Sun, "Model-free predictive current control of three-level grid-connected inverters with LCL filters based on Kalman filter," *IEEE Access*, vol. 11, pp. 21631–21640, 2023.

[48] D. Pérez-Estévez and J. Doval-Gandoy, "A model predictive current controller with improved robustness against measurement noise and plant model variations," *IEEE Open J. Ind. Appl.*, vol. 2, pp. 131–142, Oct. 2021, doi: 10.1109/OJIA.2021.3074502.

[49] L. Liu et al., "A robust high-quality current control with fast convergence for three-level NPC converters in microenergy systems," *IEEE Trans. Ind. Informat.*, vol. 19, no. 11, pp. 10716–10726, Nov. 2023.

[50] O. Babayomi and Z. Zhang, "Model-free predictive control of power converters with multifrequency extended state observers," *IEEE Trans. Ind. Electron.*, vol. 70, no. 11, pp. 11379–11389, Nov. 2023.

[51] K. Łakomy et al., "Active disturbance rejection control design with suppression of sensor noise effects in application to DC–DC buck power

converter," *IEEE Trans. Ind. Electron.*, vol. 69, no. 1, pp. 816–824, Jan. 2022.

[52] X. Yang, H. Hu, H. Hu, Y. Liu, and Z. He, "A quasi-resonant extended state observer-based predictive current control strategy for three-phase PWM rectifier," *IEEE Trans. Ind. Electron.*, vol. 69, no. 12, pp. 13910–13917, Dec. 2022.

[53] V.-T. Le and H.-H. Lee, "Grid-voltage sensorless model-free predictive current control for pwm rectifiers with measurement noise suppression," *IEEE Trans. Power Electron.*, vol. 37, no. 9, pp. 10681–10697, Apr. 2022.

[54] H. Zhang, C. Xue, R. Liu, and Y. Li, "Model-predictive dual-control loop with improved current-limiting capability for grid-forming inverter under grid faults," *IEEE Trans. Power Electron.*, vol. 40, no. 1, pp. 813–827, Jan. 2025.

[55] P. Falkowski and A. Sikorski, "Finite control set model predictive control for grid-connected AC–DC converters with LCL filter," *IEEE Trans. Ind. Electron.*, vol. 65, no. 4, pp. 2844–2852, Apr. 2018.

[56] C. Hu et al., "A novel modulated model-free predictive control for LC-filtered grid-forming inverters with double-difference updating," *IEEE Trans. Ind. Electron.*, vol. 71, no. 9, pp. 10806–10817, Sep. 2024.

[57] B. Long et al., "Passivity-based partial sequential model predictive control of t-type grid-connected converters with dynamic damping injection," *IEEE Trans. Power Electron.*, vol. 38, no. 7, pp. 8262–8281, Jul. 2023.

[58] H. Wang, Q. Huang, and Z. S. Li, "A dynamic Bayesian network control strategy for modeling grid-connected inverter stability," *IEEE Trans. Rel.*, vol. 71, no. 1, pp. 75–86, Mar. 2022.

[59] M. Novak and T. Dragicevic, "Supervised imitation learning of finite-set model predictive control systems for power electronics," *IEEE Trans. Ind. Electron.*, vol. 68, no. 2, pp. 1717–1723, Feb. 2021.

[60] S. Saadatmand, P. Shamsi, and M. Ferdowsi, "Power and frequency regulation of synchronverters using a model free neural network-based predictive controller," *IEEE Trans. Ind. Electron.*, vol. 68, no. 5, pp. 3662–3671, May 2021.

[61] M. Babaie and K. Al-Haddad, "Self-training intelligent predictive control for grid-tied transformerless multilevel converters," *IEEE Trans. Power Electron.*, vol. 38, no. 10, pp. 12482–12496, Oct. 2023.

[62] S. A. Zaid et al., "From mpc-based to end-to-end (E2E) learning-based control policy for grid-tied 3l-NPC transformerless inverter," *IEEE Access*, vol. 10, pp. 57309–57326, 2022.

[63] P. R. Bana, M. Amin, and M. Molinas, "ANN-based surrogate PI and MPC controllers for grid-connected VSC system: Small-signal analysis and comparative evaluation," *IEEE J. Emerg. Select. Topics Power Electron.*, vol. 12, no. 1, pp. 566–578, Feb. 2024.

[64] M. Baker, H. Althuwaini, and M. B. Shadmand, "Resilient model based predictive control scheme inspired by artificial intelligence methods for grid-interactive inverters," in *Proc. 6th IEEE Workshop Electron. Grid*, 2021, pp. 1–6.

[65] Z. Zhang, Z. Li, M. P. Kazmierkowski, J. Rodriguez, and R. Kennel, "Robust predictive control of three-level NPC back-to-back power converter PMSG wind turbine systems with revised predictions," *IEEE Trans. Power Electron.*, vol. 33, no. 11, pp. 9588–9598, Nov. 2018.

[66] C. Zheng, Z. Gong, X. Wu, T. Dragičević, J. Rodriguez, and F. Blaabjerg, "Finite-set quasi-sliding mode predictive control of LC-filtered voltage source inverters," *IEEE Trans. Ind. Electron.*, vol. 69, no. 12, pp. 11968–11978, Dec. 2022.

[67] J. S. Costa, A. Lunardi, L. F. N. Lourenço, and A. J. S. Filho, "Robust predictive repetitive current control for a grid-connected inverter under parametric uncertainty," *IEEE Trans. Emerg. Sel. Topics Power Electron.*, vol. 11, no. 5, pp. 4693–4703, Oct. 2023.

[68] M. N. S. K. Shabbir, X. Liang, W. Li, S. Imtiaz, and J. Quaicoe, "A novel model predictive controller for distributed generation in isolated microgrids—Part II: Model predictive controller implementation," *IEEE Trans. Ind. Appl.*, vol. 58, no. 5, pp. 5860–5870, Sep./Oct., 2022.

[69] O. Babayomi, Z. Li, and Z. Zhang, "Distributed secondary frequency and voltage control of parallel-connected VSCs in microgrids: A predictive VSG-based solution," *CPSS Trans. Power Electron. Appl.*, vol. 5, pp. 342–351, 2020.

[70] Y. Li, Z. Zhang, C. Hu, M. Abdelrahem, R. Kennel, and J. Rodriguez, "A full state-variable direct predictive control for islanded microgrids with parallel converters," *IEEE Trans. Emerg. Sel. Topics Power Electron.*, vol. 9, no. 4, pp. 4615–4628, Aug. 2021.

[71] B. Long, J. Zhang, D. Shen, J. Rodríguez, J. M. Guerrero, and K. T. Chong, "Ultralocal model-free predictive control of T-type grid-connected converters based on extended sliding-mode disturbance observer," *IEEE Trans. Power Electron.*, vol. 38, no. 12, pp. 15494–15508, Dec. 2023.

[72] T. Rui et al., "Double-vector model-free predictive current control method for voltage source inverters with sampling noise suppression," *IEEE Trans. Ind. Electron.*, vol. 71, no. 6, pp. 5797–5806, Jun. 2024.

[73] O. Babayomi and Z. Zhang, "Model-free predictive control of power converters with cascade-parallel extended state observers," *IEEE Trans. Ind. Electron.*, vol. 70, no. 10, pp. 10215–10226, Oct. 2023.

[74] Y. Zhang, Z. Zhao, T. Lu, L. Yuan, W. Xu, and J. Zhu, "A comparative study of Luenberger observer, sliding mode observer and extended kalman filter for sensorless vector control of induction motor drives," in *Proc. IEEE Energy Convers. Congr. Expo.*, 2009, pp. 2466–2473.

[75] Y. Zhang and Z. Min, "Model-free predictive current control of a PWM rectifier based on space vector modulation under unbalanced and distorted grid conditions," *IEEE Trans. Emerg. Sel. Topics Power Electron.*, vol. 10, no. 2, pp. 2319–2329, Apr. 2022.

[76] N. Panten, N. Hoffmann, and F. W. Fuchs, "Finite control set model predictive current control for grid-connected voltage-source converters with LCL filters: A study based on different state feedbacks," *IEEE Trans. Power Electron.*, vol. 31, no. 7, pp. 5189–5200, Jul. 2016.

[77] A. Sepehr, O. Gomis-Bellmunt, and E. Pouresmaeil, "Employing machine learning for enhancing transient stability of power synchronization control during fault conditions in weak grids," *IEEE Trans. Smart Grid*, vol. 13, no. 3, pp. 2121–2131, May 2022.

[78] Z. Pu, R. Yuan, J. Yi, and X. Tan, "A class of adaptive extended state observers for nonlinear disturbed systems," *IEEE Trans. Ind. Electron.*, vol. 62, no. 9, pp. 5858–5869, Sep. 2015.

[79] H. Sun, R. Madonski, S. Li, Y. Zhang, and W. Xue, "Composite control design for systems with uncertainties and noise using combined extended state observer and kalman filter," *IEEE Trans. Ind. Electron.*, vol. 69, no. 4, pp. 4119–4128, Apr. 2022.

[80] K. Łakomy and R. Madonski, "Cascade extended state observer for active disturbance rejection control applications under measurement noise," *ISA Trans.*, vol. 109, pp. 1–10, Mar. 2021.

[81] O. O. Babayomi, Z. Zhang, Z. Li, and K.-B. Park, "Bidirectional DC-DC converters for distributed energy resources: Robust predictive control with structurally-adaptive extended state observers," *Int. J. Elect. Power Energy Syst.*, vol. 158, 2024, Art. no. 109913.

[82] X. Shen et al., "Adaptive second-order sliding mode control for grid-connected NPC converters with enhanced disturbance rejection," *IEEE Trans. Power Electron.*, vol. 37, no. 1, pp. 206–220, Jan. 2022.

[83] B. Guo, S. Bacha, M. Alamir, A. Hably, and C. Boudinet, "Generalized integrator-extended state observer with applications to grid-connected converters in the presence of disturbances," *IEEE Trans. Control Syst. Technol.*, vol. 29, no. 2, pp. 744–755, Mar. 2021.

[84] T. V. Tran, K.-H. Kim, and J.-S. Lai, "Optimized active disturbance rejection control with resonant extended state observer for grid voltage sensorless LCL-filtered inverter," *IEEE Trans. Power Electron.*, vol. 36, no. 11, pp. 13317–13331, Nov. 2021.

[85] N. N. Nam, N. D. Nguyen, C. Yoon, M. Choi, and Y. I. Lee, "Voltage sensorless model predictive control for a grid-connected inverter with LCL filter," *IEEE Trans. Ind. Electron.*, vol. 69, no. 1, pp. 740–751, Jan. 2022.

[86] X. Liu, Y. Zhang, H. Yang, and J. Rodriguez, "Model-free predictive current control for three-phase power converters with LCL filter," in *Proc. 2020 IEEE Energy Convers. Congr. Expo.*, 2020, pp. 5916–5921.

[87] S. Zhu et al., "Robust speed control of electrical drives with reduced ripple using adaptive switching high-order extended state observer," *IEEE Trans. Power Electron.*, vol. 37, no. 2, pp. 2009–2020, Aug. 2022.

[88] E. Petri, R. Postoyan, D. Astolfi, D. Nešić, and V. Andrieu, "Towards improving the estimation performance of a given nonlinear observer: A multi-observer approach," in *Proc. IEEE 61st Conf. Decis. Control*, 2022, pp. 583–590.

[89] I. Brahmia, J. Wang, H. Xu, H. Wang, and L. D. O. Turci, "Robust data predictive control framework for smart multi-microgrid energy dispatch considering electricity market uncertainty," *IEEE Access*, vol. 9, pp. 32390–32404, 2021.

[90] P. Omrani, H. Yektamoghadam, A. Nikoofard, M. R. Salehizadeh, and J. J. Liu, "Dynamic congestion management with chance-constrained MPC in networked microgrids under consumers-related uncertainties," *IEEE Trans. Consum. Electron.*, vol. 70, no. 4, pp. 6738–6746, Nov. 2024.

[91] W. Huang, W. Zheng, and D. J. Hill, "Distributionally robust optimal power flow in multi-microgrids with decomposition and guaranteed convergence," *IEEE Trans. Smart Grid*, vol. 12, no. 1, pp. 43–55, Jan. 2021.

[92] S. Sen and V. Kumar, "Distributed adaptive-MPC type optimal PMS for PV-battery based isolated microgrid," *IEEE Syst. J.*, vol. 17, no. 1, pp. 546–557, Mar. 2023.

[93] Y. Zhang, R. Wang, T. Zhang, Y. Liu, and B. Guo, "Model predictive control-based operation management for a residential microgrid with considering forecast uncertainties and demand response strategies," *IET Gener., Transmiss. Distrib.*, vol. 10, no. 10, pp. 2367–2378, 2016.

[94] S. Muangchuen, J. Pahasa, and I. Ngamroo, "Improved resilient model predictive control for enhanced microgrid virtual inertia emulation by virtual energy storage system under DoS attacks," *IEEE Access*, vol. 11, pp. 96817–96830, 2023.

[95] M. Mottaghizadeh, F. Aminifar, T. Amraee, and M. Sanaye-Pasand, "Distributed robust secondary control of islanded microgrids: Voltage, frequency, and power sharing," *IEEE Trans. Power Del.*, vol. 36, no. 4, pp. 2501–2509, Aug. 2021.

[96] F. Jiao, Y. Zou, X. Zhang, and B. Zhang, "A three-stage multitimescale framework for online dispatch in a microgrid with EVs and renewable energy," *IEEE Trans. Transport. Electrific.*, vol. 8, no. 1, pp. 442–454, Mar. 2022.

[97] D. Romero-Quete and C. A. Cañizares, "An affine arithmetic-based energy management system for isolated microgrids," *IEEE Trans. Smart Grid*, vol. 10, no. 3, pp. 2989–2998, May 2019.

[98] J. Liu, Y. Miura, and T. Ise, "Cost-function-based microgrid decentralized control of unbalance and harmonics for simultaneous bus voltage compensation and current sharing," *IEEE Trans. Power Electron.*, vol. 34, pp. 7397–7410, Aug. 2019.

[99] P. Xie, Y. Jia, H. Chen, J. Wu, and Z. Cai, "Mixed-stage energy management for decentralized microgrid cluster based on enhanced tube model predictive control," *IEEE Trans. Smart Grid*, vol. 12, no. 5, pp. 3780–3792, Sep. 2021.

[100] H. Dong, Z. Tian, K. Liao, J. Yang, and J. W. Spencer, "Three-stage energy management of urban rail transit-based microgrid and EV charging station with V2T technology," *IEEE Trans. Transport. Electrific.*, vol. 11, no. 3, pp. 8604–8616, Jun. 2025.

[101] Y. Shan, J. Hu, K. W. Chan, Q. Fu, and J. M. Guerrero, "Model predictive control of bidirectional DC-DC converters and AC/DC interlinking converters—A new control method for PV-wind-battery microgrids," *IEEE Trans. Sustain. Energy*, vol. 10, no. 4, pp. 1823–1833, Oct. 2019.

[102] V. Casagrande, I. Prodan, S. K. Spurgeon, and F. Boem, "A robust MPC method for microgrid energy management based on distributed optimization," in *Proc. Eur. Control Conf.*, 2021, pp. 1963–1968.

[103] J. Vasilj, D. Jakus, and P. Sarajcev, "Robust nonlinear economic MPC based management of a multi energy microgrid," *IEEE Trans. Energy Convers.*, vol. 36, no. 2, pp. 1528–1536, Jun. 2021.

[104] Z. Zhao, J. Xu, J. Guo, Q. Ni, B. Chen, and L. L. Lai, "Robust energy management for multi-microgrids based on distributed dynamic tube model predictive control," *IEEE Trans. Smart Grid*, vol. 15, no. 1, pp. 203–217, Jan. 2024.

[105] J. Hu et al., "Economic model predictive control for microgrid optimization: A review," *IEEE Trans. Smart Grid*, vol. 15, no. 1, pp. 472–484, Jan. 2024.

[106] A. Tavakoli, M. Negnevitsky, and K. M. Muttaqi, "A decentralized model predictive control for operation of multiple distributed generators in an islanded mode," *IEEE Trans. Ind. Appl.*, vol. 53, no. 2, pp. 1466–1475, Mar./Apr. 2017.

[107] A. Ingalalli and S. Kamalasadan, "Data-driven decentralized online system identification-based integral model-predictive voltage and frequency control in microgrids," *IEEE Trans. Ind. Inform.*, vol. 20, no. 2, pp. 1963–1974, Feb. 2024.

[108] A. Parisio, E. Rikos, and L. Glielmo, "A model predictive control approach to microgrid operation optimization," *IEEE Trans. Control Syst. Technol.*, vol. 22, no. 5, pp. 1813–1827, Sep. 2014.

[109] Y. Dai, M. Li, K. Zhang, and Y. Shi, "Robust and resilient distributed MPC for cyber-physical systems against DOS attacks," *IEEE Trans. Ind. Cyber- Phys. Syst.*, vol. 1, pp. 44–55, 2023.

[110] S. Muangchuen, J. Pahasa, and C. Rakpenthai, "Enhanced resilient model predictive control electrolyzers for frequency regulations under severe denial-of-service attacks," *IEEE Access*, vol. 12, pp. 65352–65361, 2024.

[111] Z. Wang, L. Zhou, L. Xiong, H. Yang, J. Wang, and S. Huang, "Parameter-adaptive distributed model-predictive control for islanded AC microgrids: Privacy-preserving perspective," *IEEE Trans. Smart Grid*, vol. 15, no. 5, pp. 4424–4435, Sep. 2024.

[112] M. Baker, A. Y. Fard, H. Althuwaini, and M. B. Shadmand, "Real-time AI-based anomaly detection and classification in power electronics dominated grids," *IEEE J. Emerg. Sel. Topics Ind. Electron.*, vol. 4, no. 2, pp. 549–559, Apr. 2023.

[113] A. Selim, J. Zhao, F. Ding, F. Miao, and S.-Y. Park, "Adaptive deep reinforcement learning algorithm for distribution system cyber attack defense with high penetration of DERs," *IEEE Trans. Smart Grid*, vol. 15, no. 4, pp. 4077–4089, Jul. 2024.

[114] Q. Sun, K. Zhang, and Y. Shi, "Resilient model predictive control of cyber-physical systems under DoS attacks," *IEEE Trans. Ind. Informat.*, vol. 16, no. 7, pp. 4920–4927, Jul. 2020.

[115] M. D. R. Greidanus, G.-S. Seo, and S. K. Mazumder, "A proactive–reactive methodology for cyber-resilient inverter control system," *IEEE Access*, vol. 12, pp. 69051–69065, 2024.

[116] C. Zheng, T. Dragicevic, and F. Blaabjerg, "Model predictive control based virtual inertia emulator for an islanded AC microgrid," *IEEE Trans. Ind. Electron.*, vol. 68, no. 8, pp. 7167–7177, Aug. 2021.

[117] Y. Zhang, J. Jin, and L. Huang, "Model-free predictive current control of PMSM drives based on extended state observer using ultralocal model," *IEEE Trans. Ind. Electron.*, vol. 68, pp. 993–1003, Feb. 2021.

Oluleke Babayomi (Senior Member, IEEE) received the B.Sc. (Hons.) and M.Sc. degrees in electrical and electronics engineering from the University of Lagos, Akoka, Nigeria, in 2006 and 2016, respectively, and the Ph.D. degree in electrical engineering from Shandong University, Jinan, China, in 2023.

Until 2019, he was a Principal Engineer and Software Development Team Lead with the National Space Research and Development Agency, Lugbe, Nigeria. He was a Postdoctoral Researcher with the Korea Advanced Institute of Science and Technology, Daejeon, South Korea. His research interests include advanced and data-driven control of power electronics and microgrids.

Dr. Babayomi was the recipient of the 2024 IEEE-PELS Ph.D. Thesis Talk Award. He is the Chair of the IEEE Smart Village Marketing Committee.

Rafal Madonski (Senior Member, IEEE) received the B.Eng., M.Sc., and Ph.D. degrees in automation and robotics from the Poznan University of Technology, Poznan, Poland, in 2009, 2010, and 2016, respectively.

From 2017 to 2019, he was a Postdoctoral Researcher with the School of Automation, Southeast University, Nanjing, China. In 2020, he joined the Energy and Electricity Research Center, Jinan University, Zhuhai, China, as an Associate Professor. He was with the Faculty of Automatic Control, Electronics and Computer Science, Silesian University of Technology, Gliwice, Poland. His research interests include design, analysis, and application of active disturbance rejection control (ADRC).

Zhenbin Zhang (Senior Member, IEEE) was born in Shandong, China, in 1984. He received the Ph.D. (*summa cum laude*) degree in electrical and energy engineering from the Technical University of Munich, Munich, Germany, in 2016.

He was a Postdoctoral in Electrical and Energy Engineering with the Technical University of Munich. Since 2017, he has been a Full Professor with Shandong University, Jinan, China, where he is currently the Director for both the Laboratory of More Power Electronics Energy Systems and the Institute of Sustainable Energy and Smart Grids. His research interests include power electronics and electrical drives, sustainable energy system, smart grids, and microgrids.

Dr. Zhang was the recipient for VDE Award-2017 in Suedbayern, Germany, and an Associate Editor for IEEE TRANSACTIONS POWER ELECTRON. He is currently an IET Fellow Member and IET Chartered Engineer.

Jose Rodriguez (Life Fellow, IEEE) received the Engineer degree in electrical engineering from the Universidad Tecnica Federico Santa Maria, Valparaiso, Chile, in 1977, and the Dr.-Ing. degree in electrical engineering from the University of Erlangen, Erlangen, Germany, in 1985.

Since 1977, he has been with the Department of Electronics Engineering, Universidad Tecnica Federico Santa Maria, where he was a Full Professor and President. Since 2015 to 2019, he was the President of Universidad Andres Bello, Santiago, Chile. From 2022 to 2023, he was President of Universidad San Sebastian, Santiago, Chile. He is the Director of the Center for Energy Transition, Universidad San Sebastian. He has coauthored two books, several book chapters and more than 1000 journal and conference papers. His main research interests include multilevel inverters, new converter topologies, control of power converters, and adjustable-speed drives.

Dr. Rodriguez was the recipient of the number of best paper awards from journals of the IEEE. He is a Member of the Chilean Academy of Engineering. In 2014, he was also the recipient of the National Award of Applied Sciences and Technology from the government of Chile, and the Eugene Mittelmann Award from the Industrial Electronics Society of the IEEE in 2015, In years 2014 to 2024, he has been included in the list of Highly Cited Researchers published by Web of Science.

Innocent Davidson (Senior Member, IEEE) received the B.Sc. (Eng.) (Hons.) and M.Sc. (Eng.) degrees in electrical engineering from the University of Ilorin, Ilorin, Nigeria, in 1984 and 1987, respectively, the Ph.D. degree in electrical engineering from the University of Cape Town, Cape Town, South Africa, in 1998, the PG Diploma degree in business management from the University of KwaZulu-Natal, Durban, South Africa, in 2004.

He is currently a Full Professor and Director with the French South African Institute of Technology (F'SATI), Pretoria, South Africa, and the African Space Innovation Center (ASIC), Cape Peninsula University of Technology (CPUT), Bellville, South Africa. He is the author/coauthor of more than 425 technical papers in accredited journals, peer-reviewed conference proceedings, and book chapters. His current research interests include Space and CNS Innovation, machine design, smart grids, and applied artificial intelligence.

Dr. Davidson is a Fellow of Institute of Engineering and Technology, U.K., Fellow, South African Institute of Electrical Engineers; a Chartered Engineer in the U.K., and a Registered Professional Engineer (Pr. Eng.) of the Engineering Council of South Africa.

Dong-Seong Kim (Senior Member, IEEE) received the Ph.D. degree in electrical and computer engineering from Seoul National University, Seoul, South Korea, in 2003.

From 1994 to 2003, he was a Full-Time Researcher with the ERC-ACI, Seoul National University. From March 2003 to February 2005, he was a Postdoctoral Researcher with the Wireless Network Laboratory, School of Electrical and Computer Engineering, Cornell University, New York, NY, USA. Between 2007 and 2009, he was a Visiting Professor with the Department of Computer Science at the University of California, Davis, CA, USA. He was a Dean of IACF from 2019 to 2022. He is currently a Professor with the Department of IT Convergence Engineering, School of Electronic Engineering, Kumoh National Institute of Technology, Gumi, South Korea. He is also the Director of the KIT Convergence Research Institute and the ICT Convergence Research Center (ITRC and NRF advanced research center program), supported by the Korean government at Kumoh National Institute of Technology, and the Director of NSLab Company, Ltd. His primary research interests include real-time IoT and smart platforms, industrial wireless control networks, networked embedded systems, Fieldbus, metaverse, and blockchain.

Dr. Kim is a Senior Member of ACM.