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Published in:
CSEE Journal of Power and Energy Systems

DOI (link to publication from Publisher):
10.17775/CSEEJPES.2022.04290

Publication date:
2023

Document Version
Publisher's PDF, also known as Version of record

Microgrid Energy Management with Energy Storage Systems: A Review

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***Abstract*—Microgrids (MGs) are playing a fundamental role in the transition of energy systems towards a low carbon future due to the advantages of a highly efficient network architecture for flexible integration of various DC/AC loads, distributed renewable energy sources, and energy storage systems, as well as a more resilient and economical on/off-grid control, operation, and energy management. However, MGs, as newcomers to the utility grid, are also facing challenges due to economic deregulation of energy systems, restructuring of generation, and market-based operation. This paper comprehensively summarizes the published research works in the areas of MGs and related energy management modelling and solution techniques. First, MGs and energy storage systems are classified into multiple branches and typical combinations as the backbone of MG energy management. Second, energy management models under exogenous and endogenous uncertainties are summarized and extended to transactive energy management. Mathematical programming, adaptive dynamic programming, and deep reinforcement learning-based solution methods are investigated accordingly, together with their implementation schemes. Finally, problems for future energy management systems with dynamics-captured critical component models, stability constraints, resilience awareness, market operation, and emerging computational techniques are discussed.**

***Index Terms*—Architecture, energy management, energy storage systems, microgrids, optimization, uncertainty models.**

I. INTRODUCTION

A microgrid (MG) is a group of interconnected loads and distributed energy resources (DERs) within clearly defined electrical boundaries that acts as a single controllable entity for grid operating in grid-tied and islanded modes [1]. An MG is initially designed for critical loads and remote areas, to improve power system reliability and accelerate the electrification process of other industry sectors. AC, DC, and hybrid AC/DC MGs are being recognized as promising platforms to nourish further power system architectures. Owing to the evolution of power electronics and energy storage system (ESS) technologies, more and more MG variations are emerging recently, e.g., clustering MGs [2], community MGs, interconnected MGs [3], multiple MGs [4], networked MGs (NMGs) [5], marine/aerospace MGs [6]. These variations may further increase efficiency of on-shore distribution systems [7] and reduce emissions of off-shore and aerospace MGs, e.g., all-electric ships (AESs) [8], [9], offshore platforms [10] and hybrid electrical propulsion aircraft [11]. The recent trend in multi-energy integration also leads to multi micro-energy MGs (MMGs) [12]. These architectures might shed light on the ultimate question, i.e., "What will the coming power systems be like more AC or DC, more electromechanical or power electronics?"

Besides structural evolution of MGs, MG infrastructure is strongly influenced by an upgrade in the energy storage domain. To enable islanded operation, MGs are born with ESSs. Various types of ESSs, e.g., mechanical, electrical, chemical, thermal, electrochemical [13], and their hybridizations [14], have been integrated into MGs, dispersedly or centrally. These ESSs can provide versatile power and energy services to MGs [15]. For grid-tied MGs, ESSs can be used for energy arbitrage [16], load shifting [17] and ancillary services provision [15]. These ancillary services can not only increase power system reliability but also benefit MG operators and end users [4]. For islanded MGs, ESSs play central roles on MG stability [18] and reliability [19]. Evolution of MG architectures results in hybrid ESSs [14], community ESSs, mobile ESSs (MESSs) [13], and virtual ESSs [20]. They indicate that ESSs have been the cornerstone of MG infrastructures, introducing many challenges, especially their cost [14], safety [21], and mobility [22], [23].

To accommodate architecture and infrastructure development for MGs, energy management functions are developed to realize optimal operation of MGs under various operating conditions. These functions fall under the umbrella of decision-making problems, generally including monitoring, forecasting, and optimization. These problems are to optimize both active and reactive power generation and consumption, while providing ancillary services and participating in the energy market and/or utility system operation [24]. To address uncertainties from DERs, loads, component failures, etc., tremendous energy management models have been for-

Manuscript received June 29, 2022; revised October 7, 2022; accepted October 24, 2022. Date of online publication December 9, 2022; date of current version December 28, 2022. This work was supported in part by the State Key Laboratory of Alternate Electrical Power System with Renewable Energy Sources under Grant LAPS21002, in part by the National Natural Science Foundation of China under Grant 52061635102, in part by Guangdong Basic and Applied Basic Research Foundation under Grant 2021A1515110583.

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DOI: 10.17775/CSEEJPES.2022.04290

mulated under different energy market economics [25]–[27]. These models have been further reformulated into tractable counterparts under data-driven or model-driven assumptions. These reformulations might be decomposed into smaller size problems and distributed computation with attracting features, e.g., information preservation [10] and computational cost reduction [28]. These techniques have enabled MGs to become powerful and ancillary sharing or trading platforms for users and distribution systems [4]. Despite improvement of energy management problem formulations and solution algorithms, there are research gaps in problem formulations for low carbon applications and resilience management, and solution methods for efficient computation considering information security [29], [30].

By implementing the energy management functions in diverse schemes, MG controllers have been treated as the brain of MG automation [24], [31]. An MG controller is an advanced control system, potentially consisting of multiple components and subsystems, capable of sensing grid conditions, monitoring and controlling operation of an MG to maintain electricity delivery to critical loads during all MG operating modes (grid-tied, islanded, and transitions between the two) [31]. To realize inter-operation among different DERs, MGs, and external systems, real-time control, and energy management functions of MG, controllers are specified in IEEE Std 2030.7™-2017 [24]. To further test performance of MG controllers, standard testing procedures, including verification and performance quantification, are given in IEEE Std 2030.8™-2018 [32]. Notwithstanding the increasing maturity of MG controllers, limitations still exist in communication [33] and control structures [34].

This paper summarizes the recent development on the MG energy management with ESSs, from architectures and energy storage utilization to their inter-operation within energy management models. The focus is on the following areas:

- Architectures for MGs with stationary and mobile applications in accordance with grid-tied and isolated operation modes.
- Energy storage system models for different energy management applications.
- Short-term energy management problems under exogenous and endogenous uncertainties, and system deregulation.
- Mathematical programming, adaptive dynamic programming (ADP), and deep reinforcement learning (DRL) algorithms that can realize energy management in hierarchical, distributed, and decentralized manners.

II. Microgrid Architectures

Various MGs have been playing important roles in current and future power systems because of their high efficiency doing power transfer and conversion, flexibility of renewable connection, and high reliability and resilience of on/off grid operation. Current MGs can be divided into AC, DC, hybrid AC/DC, and MMGs. Within these architectures, different types of conversion, distribution, energy storage, and consumption techniques are combined, resulting in specific component level models and system level models in energy management problem formulations.

A. AC Microgrids

Thanks to the matured AC power system analysis theory, AC MGs are still the main used architecture in the field, as shown in Fig. 1. Many design and analysis theories of AC MGs can be inherited from the conventional power system, which will face less challenges for new project implementation.

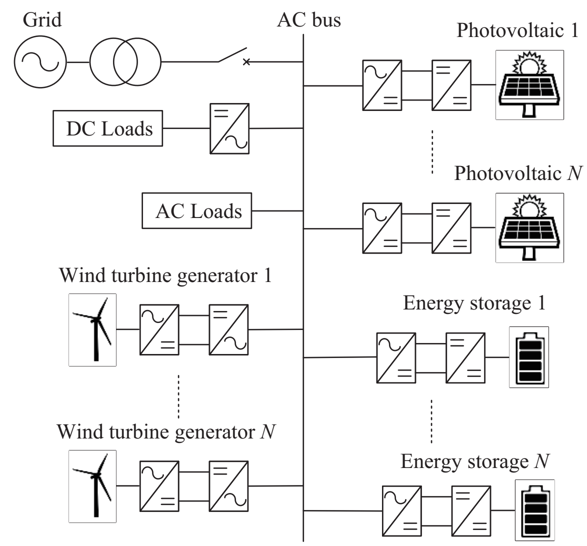

Fig. 1. General AC MG architectures.

However, as the high penetration of renewable energy generation using power electronics technologies, power sources in AC MGs will be inverter dominated rather than based on synchronous generators (SGs). This will pose new challenges such as reduced system inertia and limited fault current capability. The inertia support is critical for system frequency stability while inverters and SGs coexist in AC MGs. ESSs are playing critical roles in AC grid forming functions to support system voltage and frequency including black start. More details for controlling the inverter as a virtual synchronous generator (VSG) for easy synchronization and system frequency support in AC MG will be elaborated in later sections. When a fault happens, the AC MG system level protection shall also coordinate properly with inverters' own protection methods for power semiconductors [35]. The dynamics of low inertia AC MGs should be taken care of by MG energy management via proper modelling.

Another application area of AC MGs is for transportation electrification, e.g., hybrid electrical propulsion system for marine and aerospace systems, as shown in Fig. 2. Architectures for marine and aerospace MGs are the same, which include diesel/turbo-electric, all-electric, series/parallel hybrid electric (hybrid shaft generator), etc. The key difference is that the onboard components, i.e., machines, inverters, batteries for aerospace systems, have much higher power/energy density than their marine counterparts. For example, the target energy density for aerospace propulsion batteries is to achieve 500 Wh/kg by 2030. To achieve high power density, the

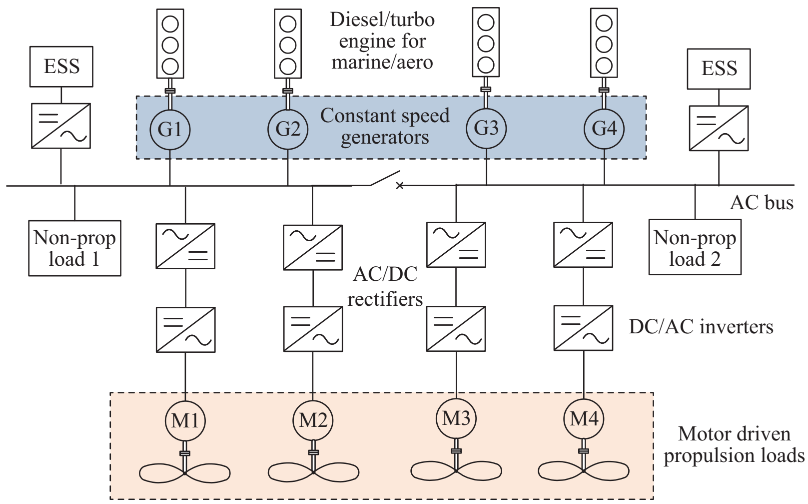

Fig. 2. Typical AC MG architectures for marine and aerospace systems.

machine/inverter operation fundamental frequency is around 1000∼2000 Hz in an aerospace system while the marine system rated frequency is the same as a land-based power system 50/60 Hz. From system integration and operation perspective, marine and aerospace propulsion systems have a lot of commonalities for energy storage usage and battery/power/energy management strategies, which are also similar to a land-based power system.

Operation of a marine hybrid electrical propulsion system must meet the requirements of classification rules set by societies like DNV GL, ABS, CCS, Lloyd's Register, etc. Operation of aerospace hybrid electrical propulsion systems will be governed by rules from organizations like FAA, CAAC, EASA, etc. For example, a marine DP2 operation requires all generators should stay online and the bus-tie breaker should be kept open regardless of the load conditions if there is no ESS installed. With ESS installed, it can serve as an alternative to a diesel generator for reserve and backup power. ESS has four main roles in marine MG, namely strategic loading, spinning reserve, generator capacity extension and full electric for silent and zero emission operation. These roles are realized by energy storage models in MG energy management models, as shown in Section III.B

B. DC Microgrids

The main advantage of DC MG is its friendly power electronics integration feature, as shown in Fig. 3. To connect AC or DC type of sources and loads to AC grid, two-stage energy conversions are required in most cases, for example: AC-DC-AC or DC-DC-AC for source and AC-DC-AC or AC-DC-DC for loads. There exists an intermediate DC-link for the source and load converter interfaces. It is evident that using a common DC-link can help to reduce equipment cost and conversion loss and the main advantages and driving forces for land-based DC MG. In DC MG, a common DC-link voltage can be treated as a communication carrier to ensure power sharing among DGs and ESSs to achieve decentralized control. In this control scheme, the tolerance band of common DC-bus voltage is divided into several regions so the priorities of all converter

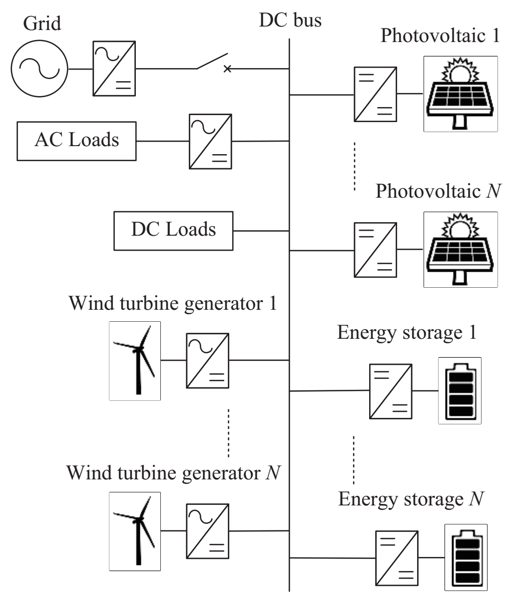

Fig. 3. General DC MG architectures.

units can be differentiated. Operation modes of all converters are controlled by the threshold value of each voltage region. For example, if the DC-link voltage is higher than its rated value during high solar radiation periods, the PV converter will switch to DC bus regulation mode and the battery converter operates at maximum current charging mode. If the DC-link voltage is lower than its rated value, the PV converter will switch to maximum power point tracking (MPPT) mode and the battery converter operates in discharging mode to regulate DC bus voltage.

For applications with limited space like data centers and marine/aerospace electrical propulsion systems, the DC MGs have been commercialized successfully and are continuously growing to replace AC architecture. Recent popularized DC MG for ship power systems is mainly to vary engine speed and improve engine specific fuel consumption efficiency whose purpose is quite different from land-based DC MG systems [36].

A typical DC MG for series hybrid aerospace electrical propulsion system is shown in Fig. 4, and the E-Fan X project was trying to replace one gas turbine engine by an electrial propulsor using series hybrid architecture [37]. Installation of ESS can help reduce the size of a gas turbine engine, whose main function is to provide short-term boost power during flight takeoff and participate in system power dispatch during cruising mode. An ESS together with an engine interfacing generator can also be used to start the engine by controlling a generator working in motoring mode. However, DC MGs for land-based applications are still at laboratories or pilot project stages. Bottlenecks for field application of DC MGs are key equipment performance such as DC circuit breaker, DC fault current limiter (FCL), solid-state transformer (SST), etc. These types of equipment are still in development stage, where for example the cost, efficiency, and reliability performances of SST are still catching up with traditional transformers in AC systems.

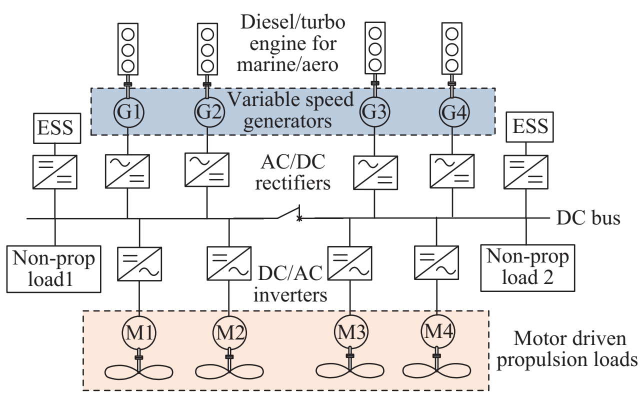

Fig. 4. Typical DC MG architectures for marine and aerospace systems.

C. Hybrid AC/DC Microgrids

As a mixture of AC MGs and DC MGs, hybrid AC/DC MGs can further reduce the number of conversions within MGs, optimizing investment cost and efficiency [38], [39], as illustrated in Fig. 5. Hybrid AC/DC MGs have been the fundamental architecture for land-based distribution systems, e.g., zero and net-zero buildings [40], transportation, and energy integration [12], [41], ranging from utility, municipality, to military applications.

In hybrid AC/DC MGs, ESSs are critical to achieve both AC and DC sub-grids forming capability to support AC bus voltage/frequency and DC bus voltage. Modularized design can be implemented for easy expansion of multiple hybrid AC/DC MGs connection. As shown in Fig. 5, a hybrid AC/DC module for a micro power park (MPP) that can adapt to different renewable energy sources and variable speed diesel generators has been developed in Nanyang Technological University (NTU), which serves primarily as emergency power sources for critical functions in disaster zones and battlefields, as well as doubling as a smart micro-grid for peace time deployment in remote areas and islands. Technically, a hybrid grid system is more efficient compared with conventional AC grids. This is particularly important in remote and emergency deployments where energy should be used as efficiently as possible. A comparison summary and recent projects for AC, DC and hybrid AC/DC MGs are listed in Tables I and II, respectively.

D. Multi Micro-energy Grids

With clearly defined boundaries, MGs can also interact with other MGs using integrated energy networks [42], including electrical networks[1], fluid networks [43], thermal networks [44], transportation networks with electrified vehicles (EVs) [45], etc. Electrical networks can be single-phase or three-phase AC networks [46], DC networks [47], and hybrid AC/DC networks as discussed previously. Using micro-turbine and heat ventilation air conditioning (HVAC) techniques, MGs can share gas and thermal with others interconnected to the same gas and thermal networks. EVs can further realize energy sharing between MGs via spatial movement on the transportation networks. These interconnected energy networks result in formulation of MMGs.

An MMG is defined as a cluster of MGs, interconnected by electrical, thermal, gas or transportation networks. MMGs have been recognized as powerful platforms to increase efficiency and reliability of land-based distribution systems, especially through transactive energy management [4], [46]. Along with electrification of ships [9], ports [6], islands, offshore platforms, MMGs are reducing emissions of offshore and shipping industry significantly, under restrictions on greenhouse gas imposed by International Maritime Organization. MMGs are a promising architecture to depict interaction between AESs and electrified ports during their cold ironing processes [15].

When electrical boundaries of each MG can be adjusted using boundary switches, the NMGs, as a kind of MMGs, can further enhance resilience of MMGs, through optimal reconfiguration of interconnected networks [7]. Reconfiguration can re-balance the supply and demand of given MGs, under multiple faults induced by extreme events [5]. One step further, mobile energy resources, e.g., mobile distributed generators (DGs) [48], MESSs [22], can be integrated into spatially distributed MGs, which can enhance stability [49], security, reliability, and resilience of the overall power system.

E. Possible Further Microgrid Architectures

A future MG is a power electronics dominated power system, which offers flexible integration of AC and DC networks, sources, loads and further versatile interaction with multi-energy systems. However, a power electronics dominated system may suffer from wide frequency oscillations if not carefully designed. MG system operation efficiency may be decreased by Braess Paradox, calling for proper management of conversion, consumption, transmission and storage processes within MGs. MG system flexibility can be explored by perceptive management of redundancy induced by power electronics control and multi-energy within MGs. This flexibility may further enhance local energy reliability [50] in the long run and local energy market economics in the short run.

[1]If the utility grid is part of this electrical network, MMGs are in grid-tied mode, otherwise MMGs are isolated.

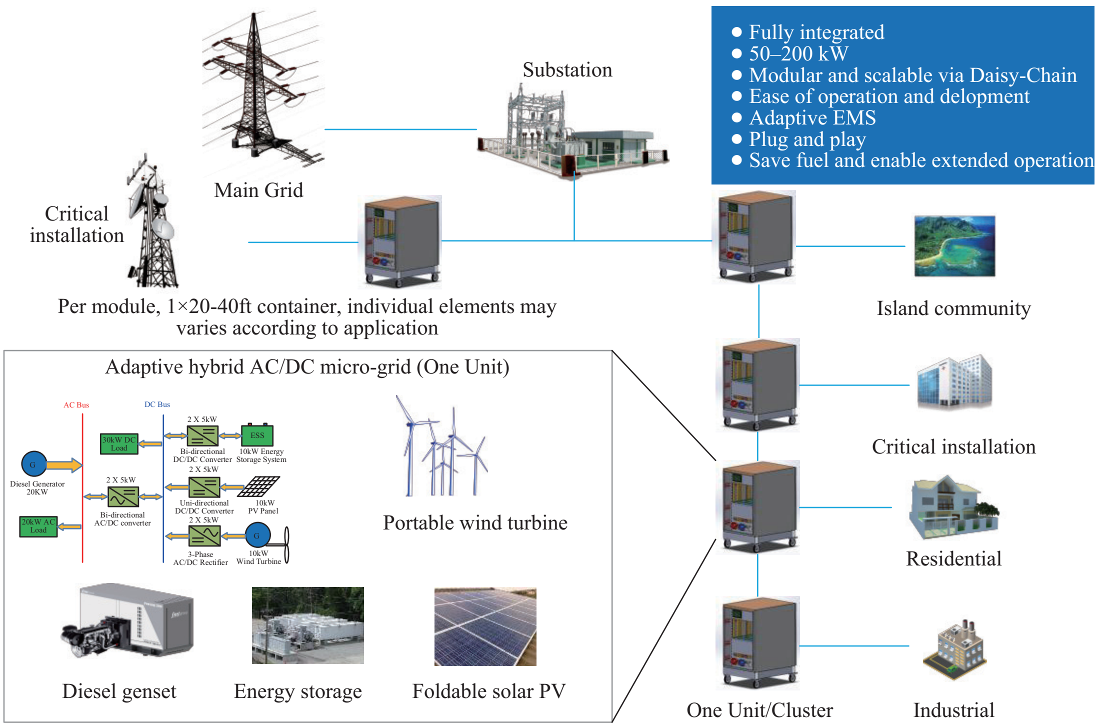

Fig. 5. Adaptive hybrid AC/DC MG power parks.

TABLE I
COMPARISONS FOR AC, DC AND HYBRID AC/DC MGS

Architecture	Advantages	Limitations	Application cases
AC MGs	1. Easy implementation based on the existing infrastructure 2. Protection schemes and devices are available 3. Easy to connect with different voltage levels using transformer	1. Synchronization issue, both frequency and voltage stability issue with cross-coupling effects 2. Less efficient due to large number of conversion stages	1. When diesel generator is one of the main sources, e.g., islands 2. Propulsion system for ships
DC MGs	1. Renewable energy resources friendly due to reduced number of conversion stages 2. The true DC loads are increasing though they are still with AC terminals 3. Only DC voltage stability issue which is relatively easy	1. Solid state transformer is required for larger DC distribution area, which is costly, less efficient 2. Protection schemes and devices are immature 3. The ecosystem for DC loads is not well established yet 4. Need to build new infrastructure	1. Data centers 2. Zero-emission buildings 3. Charging stations 4. Propulsion systems forships and aircraft
Hybrid AC/DC MGs	1. Advantages inherited from both AC and DC MGs which are more efficient to connect various sources and loads 2. Flexible operation and control schemes to handle power exchange through the interlinking AC/DC converter	1. Stability issue is relatively complex due to the coupling effect between AC and DC buses 2. Protection schemes are complex	1. Zero-emission buildings 2. Electrification for rural areas 3. Emergency power supply modules

AC high-frequency link type of MG architecture as shown in Fig. 6 could be a promising solution to integrate various types of resources and loads in a future MG. There are applications for integrating different DC voltage levels, e.g., 10 kV for medium voltage distribution level, and 400 V for low voltage utilization level. To integrate different voltage levels together, a transformer with a properly designed turns ratio is required. Moreover, it can also provide galvanic isolation. To increase power density, a multi-winding-transformer-coupled multiport converter [51], [52] can be designed in Fig. 6. Different terminals can be connected to energy resources, ESSs, and loads, which can either be voltage source or current source. The functions required from a solid-state transformer are inherently incorporated by using this architecture. A high-frequency AC link has the same frequency, e.g., 10 kHz, but with different phase angles, whereas power flows from the module with a leading voltage phase angle to the one with a lagging voltage phase angle.

III. ENERGY STORAGE SYSTEMS AND MODELS

Energy storages play a central role in the reliable and stable operation of MGs. There are many types of ESSs suitable for MG applications under different disturbances from DERs, loads, component failures, etc. These ESSs are typically serial combinations of power conversion systems (PCSs) and energy storages. The distinct physical characteristics of energy storage materials admit specific electrical patterns, which should be properly modelled to enable safe and optimum utilization of ESSs. In this section, ESSs models are summarized from their roles in MG energy management.

TABLE II
RECENT PROJECTS FOR AC, DC AND HYBRID AC/DC MGS

Architecture	Recent Projects
AC microgrid	1. China-Singapore Tianjin Eco-city microgrid with PV, WTG, and ESS AC voltage level 380 V with VSG grid-forming technology demonstration 2. Kongsberg Maritime's Electrical Power SAVe Line AC system for ships 3. The Canadian Renewable Energy Laboratory (CANREL) for design validation of microgrids with high penetration of renewable energy, low-voltage (600 V) AC microgrid connected to a local utility grid (Guelph Hydro) through a power transformer [53]
DC microgrid	1. MW level Jinwutong DC microgrid consisting of PV, battery, ultra-capacitor and charging station using segmented DC bus architecture in Jinzhai, Anhui Province, China 2. 25 MW Shenzhen Baolong Industrial Park DC distribution grid with 10 kV and 400 V DC voltage levels 3. Salisbury Square DC microgrid for an affordable housing community in Randolph, Vermont, United States DC voltage levels 380 V/48 V/24 V with 157 kW solar capacity, and 980 kWh battery capacity [54] 4. Kongsberg Maritime's Electrical Power SAVe Cube DC system for ships; ABB's on board DC Grid system for ships 5. E Fan-X series hybrid aerospace system based on 3 kV DC bus between Rolls-Royce and Airbus which was launched in 2017, and terminated in April, 2020 [55]
Hybrid AC/DC microgrid	1. Renewable Energy Integration Demonstrator–Singapore (REIDS) MW level hybrid AC/DC microgrid in Semakau island; AC voltage level 400 V, DC voltage level 800 V 2. Zhuhai Tangjiawan's world's first multi-voltage, multi-terminal flexible AC/DC hybrid distribution network, Zhuhai, China; AC voltage level 110/10 kV, DC voltage levels ±10 kV, ±375 V 3. 50 kVA hybrid AC/DC multi-port energy router from Shanghai Gcevolution Informational Tech, AC voltage level 380 V, DC voltage level 380 V 4. RHYTHM: Resilient Hybrid Technology for High-value Microgrids project in Imperial College London, UK

TABLE III
SUMMARY OF ESSS APPLICATIONS IN MGS

ESS type	Examples	Stability			Efficiency	Reliability	Resilience
		Inertia	Primary	Secondary	Operating cost/Benefit/Losses		
Mechanical	Flywheel	✓	✓			✓	
	Pumped Hydropower				✓	✓	
	Compressor Air				✓	✓	
	Gravity Energy Storage				✓		
Thermal	Heat and Cold Storage				✓	✓	✓
Electrochemical	Battery	✓	✓	✓	✓	✓	✓
Chemical	Hydrogen						✓
Electrical	Super-capacitor	✓	✓				
	Superconducting Magnetic	✓	✓				

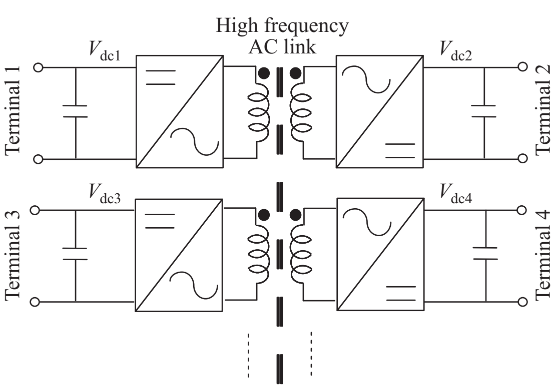

Fig. 6. Further MG architectures with high frequency AC link.

A. Energy Storage Systems for Microgrids

ESSs can be classified into mechanical, thermal, electrochemical, chemical, and electrical systems, based on their formations and composition materials. They can be adopted for different types of MGs, based on their technical characteristics and MG application requirements, as shown in Table III. Requirements are typically event driven, including expected events and unexpected events. Within expected events, they can be classified into short-term and middle-term disturbances, e.g., random failure of components, renewable output intermittency, and load variation, calling for multi-time scale responses, including inertia, primary, secondary, etc. For unexpected events, e.g., extreme weather events, reconfiguration of ESSs is required to support electrical boundary adjustment of MGs.

1) Mechanical ESSs

Energy storage function is realized by bi-directional conversion between electrical and mechanical energy in mechanical ESSs, including kinetic and potential ESSs. Kinetic energy is relocated to an electrical machine rotor by flywheel ESSs. With numerous life cycles, fast response, and low environmental impacts, flywheel ESSs have first been used as an uninterruptible power supply (UPS) for critical users, and later incorporated into MGs under short-term and middle-term disturbances. Pumped hydro and compressed air are also representative potential ESSs, suitable for long-term and large-scale energy storage. As the most matured energy storage techniques, pumped hydro ESSs have been adopted for power systems operation since 1882 and a sewage treatment plant as an MG in Wuhan, China, 2022. When it comes to MGs, pumped hydro ESSs have the potential to be deployed in mountainous areas with rich run-of-river resources [56], e.g., Guizhou and Yunan provinces of China. Compressed air ESSs (CAESs) can realize energy storage in a safe, efficient, and cost-effective manner. They can be deployed for MGs close to caves with fewer construction constraints in comparison with pumped hydro ESSs, e.g., pelagic islands [57]. Gravity energy storage is a novel technology for large-scale and fast energy storage, which is gaining more and more attention.

2) Thermal ESSs

Latent heat, sensible heat, and thermo-chemical sorption are typical variations of thermal ESSs. The latent heat ESSs have high energy density and efficiency at a constant temperature, which is suitable for building MGs [17]. Using solid and liquid mediums, sensible heat ESSs are widely used in daily life. With higher energy density, thermo-chemical sorption ESSs are promising energy storage techniques for MMGs.

3) Electrochemical ESSs

Energy is stored by the bi-directional conversion between electricity and chemical energy in an electrochemical storage system, and the chemical reactions are highly likely to reduce system life. Secondary batteries and flow batteries are two main branches of electrochemical storage systems. Exhibiting high energy density, power density, negligible memory effect, and wide operating temperatures, secondary batteries are dominating the portable energy storage market. They have been widely deployed for mobile MGs, e.g., electric vehicles and AESs. The redox flow battery (RFB) is an example of a flow battery, admitting high life cycle stability, high efficiency, and high power. RFBs are suitable for grid-scale applications [58].

4) Chemical ESSs

Energy, stored in the form of chemical fuels, can be readily converted to electrical energy in chemical ESSs. Hydrogen-based ESSs are popular and available in the market. With a combination of hydrogen and oxygen to produce electricity, hydrogen-based fuel cells (FCs) are carbon-free with high efficiency. They can generate electricity and heat simultaneously, apt for mobile MGs, e.g., vehicles, building MGs, and MMGs.

5) Electrical ESSs

Different from other ESSs, the energy is stored in an electric field by separating charges or magnetic fields by flux in electrical ESSs. Super-capacitors (SCs) and superconducting magnetic ESSs are typical electrical ESSs. With high power capacity, efficiency, and long life cycles, SCs can provide rapid response to external systems with limited energy capacity, and are attractive solutions for power quality improvement and hybridization with other ESSs. Superconducting magnetic ESSs exhibit higher efficiency, longer life cycle, and millisecond scale response, which are fit for military MG applications and fast power demand applications.

B. Energy Storage Models

Energy storage models are to capture and utilize technical and economic characteristics of ESSs for MG energy management, as summarized in Table IV. These technical characteristics are depicted by an electrical circuit, electro-thermal, and spatial models. Economic features are always preserved in degradation models.

1) Electrical Circuit Models of Energy Storage Systems

Electrical circuit models define the relationship between the electrical parameters of ESSs and services provided to ESSs. These electrical parameters cover voltage, current, power, and energy. Power and energy services have been widely discussed in the grid codes [67] and technical standards, e.g., IEEE Std 1547.9™-2021 and IEC TS 62933-3-1. When treating ESSs as black boxes, they can provide power, energy, and combination services to MGs, as summarized in Table IV.

2) Electro-thermal Models of Energy Storage Systems

Thermal management is critical to the safety of ESSs. Several standard testing procedures have been proposed for SESSs, e.g., cell, module, and system-level test in UL-9540 series standards [21]. Inappropriate voltage and current can lead to thermal runaway of ESSs and can be depicted by electro-thermal models of ESSs [44], [68]. Thermal models can be depicted as partial differential equations (PDEs), including heat generation and transfer, e.g., convection, conduction, thermal radiation, and evaporative cooling. Heat is typically generated by power losses or abuse of ESSs. Thermal dynamics of a battery module are captured by a deep neural network to depict a thermal runaway process in [69].

3) Degradation Models of Energy Storage Systems

Degradation is one main factor for the long-term reliability of ESSs, including power capacity degradation and energy

TABLE IV
SUMMARY OF ESS MODELLING IN MG ENERGY MANAGEMENT

Ref.	Type of ESS	Functionalities	Type of MG	Applications	Models	Cost functions
[59]	BESS	Intermittent resource integration	AC MG	Pelagic islands	Linear	–
[57]	CAES	Intermittent resource integration	AC MG	Pelagic islands	Linear	–
[56]	Pumped hydro	Intermittent resource integration	AC MG	Rural areas	Nonlinear	–
[44]	Thermal ESS	Load shifting	AC MG	Buildings	Linear (ODE)	–
[60]	BESS/FC	Load shifting	AC MG	AESs	Linear	Nonlinear (degradation)
[20]	Virtual ESS	Load shifting	AC MG	Water-electricity networks	Linear (ODE)	–
[61]	BESS	Load shifting	AC MG	–	Nonlinear	Nonlinear (degradation)
[62]	BESS	Power quality enhancement	AC MG	Commercial buildings	Linear	–
[63]	BESS	Energy/Inertia	AC MG	–	Linear	–
[64]	BESS/SC	Voltage regulation	DC MG	–	Nonlinear	–
[41]	BESS/Thermal ESS	Energy arbitrage	Hybrid AC/DC MG	Energy hubs	Linear	Linear
[65]	BESS	Capacity firming	Hybrid AC/DC MG	Commercial buildings	Linear	–
[25]	BESS	Load shifting	MMG	–	Linear	Quadratic
[46]	BESS	Energy/Reserve	MMG	–	Linear	Linear
[13]	MESS	Spatial energy sharing	MMG		Linear	Linear
[47]	BESS	Load shifting	MMG	–	Linear	Linear
[66]	BESS	Energy arbitrage	MMG	–	Linear	–

capacity degradation. It is one core factor to link control, operation, and planning processes within MGs. Capacity degradation is generally depicted by linear and nonlinear functions depending on several critical variables, e.g., discharging rate, depth of discharge (DOD), and depth of charge (DOC) [14], [45], [61], [70]. These functions have been widely depicted as nonlinear cost functions in existing energy management problems, as shown in Table IV.

4) Mobility-aware Models of Energy Storage Systems

Emerging MMGs and NMGs introduce spatial dimension flexibility to coordinate operation between ESSs and MGs. Mobility-aware ESSs generally cover a pure transportation purpose MESSs and EVs, where EVs can be classified into plug-in EVs [71] and battery-swapping EVs [72], [73]. The MESSs are train [74] or truck [13], [75] mounted ESSs. To fully harness the flexibility of MESSs, transportation networks, including road, railway, etc., should be properly modelled to capture the temporal and spatial movements of MESSs. Similar to traffic flow analysis, the mobility features of MESSs can be depicted as microscopic [74], [76], mesoscopic [13], [22], and macroscopic models.

C. Discussion on Energy Storage Models for Microgrid Energy Management

Energy storage models are the bridge between the roles of ESSs within MGs and MG energy management. They can be classified into algebra, ordinary differential equations (ODEs), and PDEs, according to their mathematical properties. As shown in Table IV, linear constraints have been widely adopted to capture the relationship between charging rates, discharging rates, state of charge, DOD, DOC, vehicle routine in the electrical circuit, and mobility-aware models. Linear ODEs are used to depict the thermal and fluid dynamics of thermal ESSs and virtual ESSs. Nonlinear algebra functions have been proposed to quantify the impacts of discharging, DOD, and DOC on degradation. Pros of existing linear and nonlinear models are they can be easily embedded in existing MG energy management models as constraints or objective functions, and formulated problems can be solved with low computational cost via piece-wise approximation, finite difference, etc. Cons are they can not capture the electro-thermal dynamic of ESSs, resulting in safety issues that can not be tackled with existing MG energy management. If safety issues of ESSs are to be addressed in MG energy management, accuracy and computational cost balanced electro-thermal models, e.g., reduced order PDEs or some deep networks, should be proposed.

IV. Microgrid Energy Management Problem Formulations and Solution Methods

Along with evolution of MG architectures and inter-operation between ESSs, energy management problems are formulated to realize efficient, reliable, environmentally friendly, and resilient operation of MGs under both grid-tied and isolated modes, by optimally scheduling DERs, ESSs, etc., under uncertain operating conditions. Conditions range from uncertain output of renewable energy sources, loads, etc., to random failure of critical components within MGs. They can be predicted using multiple forecasting techniques and depicted by distinct mathematical models as the input of energy management problems. Towards reliability, resilience, and efficiency, energy management problems are formulated as uncertain optimization problems. Energy management models are further summarized under different energy market economics. Energy management problems are solved by off-the-shelf algorithms via reformulation, including mathematical programming techniques, ADP, and DRL.

A. Uncertainty Models for Microgrid Energy Management

Uncertainty models are to determine how likely certain outcomes are if some aspects of the system are not exactly known [77], and they are always the first step to realize optimal energy management of MGs [78]. Uncertainties can be classified into exogenous and endogenous models [79]. Depicting natural variation, exogenous uncertainties typically refer to loads, renewable energy source outputs, prices, and contingencies that have been extensively addressed by artificial intelligence-based methods, e.g., deep networks [79], [80]. Due to limited knowledge, endogenous uncertainties are also known as model uncertainties, including parameters and structure uncertainties in energy management models, e.g., parameter of demand response models [81], [82], reserve called [83] and trained deep networks [84].

1) Exogenous uncertainty models

Uncertainties within energy management problems have been long formulated as exogenous uncertainties, i.e., uncertainties are independent of decisions. They can be formulated as probability distribution functions (PDFs), robust uncertainty sets, and distributionally robust ambiguity sets.

Uncertainty factors, e.g., loads, PV output, and contingencies, within energy management problems, can be treated as a random vector $\xi : \Xi \longrightarrow \Omega \in \mathbb{R}^{\mathrm{n}}$, where n is the length of vector ξ and $n \geq 1$. Further assume $\xi \sim P$, where P is the probability measure on $(\Xi, \mathcal{F})$. When $n > 1$, P is a multivariate PDF, and correlation between uncertain factors can be depicted by covariance matrix Σ. Ξ can be a set of discrete events or continuous events. Oriented from traditional point forecast techniques, P can be derived using probabilistic prediction, along with the increasing penetration of renewable energy sources. P can be depicted as a parametric and non-parametric [85] PDF using predictive distribution following a pre-defined shape and kernel density estimation method, respectively. For ease of stochastic optimization, trajectories, i.e., scenarios of support set $\Omega := P \circ \xi^{-1}$, can be generated using the Markov chain [86], Gaussian copula, sample average approximation (SAA) [87], and other techniques while preserving interdependence between uncertainty factors, e.g., Taguchi's orthogonal array testing (TAOT) [26].

A robust uncertainty set $\mathcal{U}$ is to quantify uncertainties by polyhedra, i.e., $\mathcal{U} := \{\boldsymbol{C}\xi \leq \boldsymbol{f}\}$. Using interval prediction in probabilistic forecasting techniques, multivariate uncertainties can be depicted as $[\bar{\xi}_i - \Delta\xi_i, \bar{\xi}_i + \Delta\xi_i], i = 1, \cdots, n$, under statistical guarantee [47]. Accounting for interdependence among uncertainties, a budget constraint is introduced [26]. To further support decision-making in a worst case, i.e., extreme points of $\boldsymbol{C}\xi \leq \boldsymbol{f}$, the coherent risk measures can be used to construct this polyhedron [88]. Various uncertainty sets have been used to capture the aleatoric nature of loads, renewable energy output, and contingencies. These uncertainty sets are used for robust, two-stage robust [26], [47], multi-stage robust, and interval [61] MG energy management.

Addressing uncertainty on support Ω and moment information of P, i.e., an epistemic, the ambiguity set $\mathbb{P}$ is proposed, bridging PDFs and uncertainty sets. Shapes and sizes are two main factors to construct an ambiguity set as small as possible and contain the unknown true distribution with certainty [89]. Some representative shapes have been adopted endogenously by an MG operator, e.g., Markov, Chebyshev, Gauss, median-absolute deviation, mixture [90]. The size of $\mathbb{P}$ is typically calculated in a data-driven fashion. Ambiguity sets can be classified into discrepancy-based, moment-based, shape-preserving, and kernel-based variations [91].

2) Endogenous uncertainty models

For decision-dependent uncertainties in MGs, e.g., demand response [81], [82], reserve called [83], endogenous uncertain models are introduced to capture the interaction between uncertainties and decisions, extending PDFs, uncertain sets, and ambiguity sets. For PDFs, the event space Ξ and P can be affected by the decision variables $\boldsymbol{x}$, i.e., $\Xi(\boldsymbol{x})$ and $P(\boldsymbol{x})$. It results in stochastic endogenous uncertainties, first defined in [92]. Real-time reserve called [83], cold load pickups [82], and demand response [81] have been treated as representative applications. For robust uncertain sets, a typical extension has been given as $\mathcal{U}(\boldsymbol{x}) := \{\boldsymbol{C}\xi + \boldsymbol{D}\boldsymbol{x} \leq \boldsymbol{f}\}$, indicating decisions can affect the worst-case realization in two-stage and multi-stage decision making processes [93]. Ambiguity set $\mathbb{P}$ can depend on $\boldsymbol{x}$, ranging from $\Omega(\boldsymbol{x})$, $P(\boldsymbol{x})$, to statistical distances [94]. It should be noted that endogenous uncertainty sets and endogenous ambiguity sets have not been adopted in MG energy management problems, with data shortage and high computational cost.

3) Relation among uncertainty models

Relations among uncertainty models is the premise for realizing conversion among different uncertainty models, under data-driven and non-data-driven approaches [91]. For data-driven uncertainty models, the main concern is asymptotic convergence of the function value, affected by uncertainties, to the known and true unknown distribution. When the PDF is known, the SAA is used to approximate this value. Under ambiguity sets, a robust-SAA algorithm can be used [95]. For non-data-driven uncertainty models, especially when the further ξ does not follow P, coherent risk measures [88], price of optimism and pessimism [96], etc., can be used to calibrate the parameters in uncertainty sets and ambiguity sets, and further quantify correlation among different uncertainty sets.

B. Energy Management Problem Formulations Under Uncertainties

To optimally manage resources within MGs under given operating and control requirements, deterministic optimization problems are formulated as unit commitment (UC), optimal power flow (OPF) [104], economic dispatch (ED), and optimal control problems, with distinctive decision variables, objective functions, and constraint sets, given as the following optimization problem:

$$\begin{aligned} &\min_{x} f(\boldsymbol{x}, \xi) \\ &\text{s.t.} \boldsymbol{x} \in \mathcal{X}(\xi) \end{aligned} \tag{1}$$

where $\boldsymbol{x}$ is the decision variable vector, $f(\boldsymbol{x}, \xi)$ is the objective function, $\mathcal{X}(\xi) := \{g_i(\boldsymbol{x}, \xi) \leq 0, \forall i \in \mathcal{C}\} \bigcap \{h_i(\boldsymbol{x}, \xi) \leq 0, \forall i \in \mathcal{S}\} \bigcap \{k_i(\boldsymbol{x}, \xi) \leq 0, \forall i \in \mathcal{D}\}$ is the constraint set under different control and operation requirements, $g_i(x, \xi)$ refers to component level constraints, $h_i(x, \xi)$ refers to the MG level constraints, and $k_i(x, \xi)$ represents for multi energy level and local energy sharing constraints. Energy management problem formulations are summarized in Table V.

As shown in (1), uncertainties ξ in MGs can affect both objective functions and constraint sets. These impacts can be assessed and addressed using uncertainty energy management problem formulations, including stochastic optimization, robust optimization, distributionally robust optimization, and Markov decision process (MDP) models.

TABLE V
SUMMARY OF ENERGY MANAGEMENT PROBLEM FORMULATIONS FOR MICROGRIDS

Ref.	Objective function $f(x, \xi)$				Decision variables x				Constraints $X(\xi)$		Uncertainties ξ		
	Cost/benefit	Emission	Reliability	Resilience	DGs	Lines	ESSs	DSRs	Security	Stability	Stochastic	Uncertainty	Ambiguity
[14]	✓				✓		✓		✓				
[16]	✓				✓		✓		✓		✓	✓	
[22]				✓	✓	✓	✓	✓	✓		✓		
[23]				✓	✓	✓	✓	✓	✓				
[27]	✓				✓		✓	✓	✓				✓
[46]	✓				✓		✓		✓			✓	
[47]	✓				✓		✓		✓		✓	✓	
[48]				✓	✓	✓	✓	✓	✓				
[89]	✓				✓				✓				✓
[60]	✓	✓			✓	✓	✓		✓				
[97]	✓				✓		✓	✓	✓	✓			
[98]	✓				✓	✓	✓	✓	✓				
[99]	✓				✓	✓			✓				
[100]	✓		✓		✓		✓	✓	✓		✓		
[101]	✓				✓		✓		✓	✓	✓		
[102]	✓				✓		✓	✓	✓				
[103]	✓				✓				✓	✓			

1) Stochastic energy management problem formulations

Assuming $\xi \sim P$, a general stochastic energy management optimization problem is shown as follows:

$$\begin{aligned} &\min_{x} \mathbb{E}_{\mathrm{P}}[f(\boldsymbol{x}, \xi)] \\ &\text{s.t.} \Pr\{\boldsymbol{x} \in \mathcal{X}(\xi)\} \geq 1-\alpha \end{aligned} \tag{2}$$

where α is the given confidence level. If $\alpha = 0$, problem (2) is always feasible. As the frequency response rate is affected by ξ, a chance constraint is formulated in [105]. When multiple constraints are affected by ξ, a joint chance constraint can be adopted to guarantee quality of service within MGs [85]. Problem (2) has been widely adopted for single-stage real-time MG energy management [105].

For a two-stage stochastic energy management, problem (2) is extended as follows:

$$\min_{y} g(\boldsymbol{y}) + \mathbb{E}_{\mathrm{P}}[\mathcal{Q}(\boldsymbol{y}, \xi)] \tag{3}$$

where $\mathcal{Q}(\boldsymbol{y}, \xi) := \{\min_x f(\boldsymbol{x}, \xi) | \boldsymbol{x} \in \mathcal{X}(\xi) \bigcap \mathcal{Z}(\boldsymbol{y}, \xi)\}$, $\boldsymbol{y}$ is the first-stage decision variable, $\boldsymbol{x}$ is the second-stage decision variable, $\mathcal{Z}(\boldsymbol{y}, \xi)$ refers to the coupling constraints between the first-stage and second stage variables. If a chance constraint $\Pr\{\boldsymbol{x} \in \mathcal{X}(\xi) \bigcap \mathcal{Z}(\boldsymbol{y}, \xi)\} \geq 1-\alpha$ is used as a replacement of constraint $\boldsymbol{x} \in \mathcal{X}(\xi) \bigcap \mathcal{Z}(\boldsymbol{y}, \xi)$ in problem (3), a two-stage joint chance constraint programming problem is formulated [41]. Under the uncertainties of renewable energy and loads, a condition value at risk (CVaR) is adopted to approximate the value of $\mathbb{E}_{\mathrm{P}}[\mathcal{Q}(\boldsymbol{y}, \xi)]$. Problem (3) admits the here-and-now and wait-and-see structure, which is suitable to represent the sequential decision making between the day-ahead and real-time energy management of MGs [25], [43], [106]. This problem can be extended for multi-stage stochastic energy management of MGs [107].

When it comes to stochastic endogenous uncertainties, $\mathbb{E}_{\mathrm{P}}[f(\boldsymbol{x}, \xi)]$ and $\mathbb{E}_{\mathrm{P}}[\mathcal{Q}(\boldsymbol{y}, \xi)]$ in equations (2)–(3) should be extended to consider the impacts of decisions on $P(\boldsymbol{x})$. Responding to the joint impacts of control signals, e.g., prices, and exogenous factors on the power consumption processes, the demand response has been managed by stochastic optimization under both exogenous and endogenous uncertainties, to improve operational efficiency [81] and reliability [82]. Grid-tied MGs can provide regulation reserves to power systems. Its real-time power output is affected by the reserve called signal and reserve capacity provided, and a two-stage stochastic programming problem under both exogenous and endogenous uncertainties is formulated to manage risks within the day-ahead market [83].

2) Robust energy management problem formulations

When uncertainty is depicted by an uncertainty set $\mathcal{U}$, a general two-stage robust optimization problem is given as follows:

$$\min_{\boldsymbol{y} \in \mathcal{Y}} g(\boldsymbol{y}) + \max_{\xi \in \mathcal{U}} \mathcal{Q}(\boldsymbol{y}, \xi) \tag{4}$$

Under the convex assumption on the second-stage constraint set w.r.t. $\boldsymbol{x}$, the worst-case ξ^* is always the extreme point of $\mathcal{U}$ [108]. This propriety can guarantee worst-case performance while resulting in over-conservation of energy management solutions. Problem (4) has been adopted for day-ahead management of single MGs [109], cooperative energy sharing among MMGs [26], and dynamic energy management of NMGs [47].

3) Distributionally robust energy management problem formulations

For ambiguity sets, a widely used two-stage distributionally robust optimization (DRO) problem with chance constraints is given as follows:

$$\min_{\boldsymbol{y} \in \mathcal{Y}} g(\boldsymbol{y}) + \max_{P \in \mathbb{P}} \mathbb{E}_{\mathrm{P}}[\mathcal{Q}'(\boldsymbol{y}, \xi)] \tag{5}$$

where

$$\begin{aligned} \mathcal{Q}'(\boldsymbol{y}, \xi) = &\min_{x} f(\boldsymbol{x}, \xi) \\ &\text{s.t.} \min_{P \in \mathbb{P}} \Pr\{\boldsymbol{x} \in \mathcal{X}(\xi) \bigcap \mathcal{Z}(\boldsymbol{y}, \xi)\} \geq 1-\alpha \end{aligned} \tag{6}$$

Ambiguity sets $\mathbb{P}$ can be formulated using data-driven approaches with fewer samples, in comparison with exact PDFs. Problem (5) has been extensively adopted for MG energy management problem formulations under data-driven conditions. Responding to the ambiguity of wind power output, a dynamic ED problem with distributionally robust chance constraint is formulated for isolated MGs [110]. To minimize energy procurement and battery degradation cost, a two-stage DRO problem is proposed for MMGs, where an optimal transportation-based ambiguity set is formulated for the aggregated uncertainty of loads and renewable energy output [27]. To improve reliability of MGs under uncertain line failures, a two-stage DRO problem is proposed to optimally formulate MGs within distribution systems in [111].

4) Markov decision process based problem formulations

MG energy management is typically a sequential decision-making process within a discrete time environment. When uncertainties are stochastic, including both exogenous and endogenous, MG energy management has extensively formulated a MDP recently. To efficiently manage resources within diverse MG architectures as shown in Section II, various MDP problems have been formulated.

A MDP is a particular sequential decision model under uncertainties, including a set of decision time $\mathcal{T}$, states $\mathcal{S}$, actions $\mathcal{A}$, rewards $\mathcal{R}$, and transition probabilities $\mathcal{P}$ depend only on the current state and action, i.e., $\{\mathcal{T}, \mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}\}$ [112]. When $\mathcal{T}$ is finite, the MDP is a finite-horizon problem. When states $\mathcal{S}$ can not be fully observed, a partial observable MDP (POMDP) can be adopted, suitable for limited information or communication applications, e.g., privacy preservation, communication failures [113]. A recent review on MDP-based models within building MGs has been conducted in [114].

For AC MGs, DC MGs, and hybrid AC/DC MGs, MDP-based problems have been formulated to realize optimal energy management under isolated [115] and grid-tied [116], [117] modes. When MGs are isolated, a finite-horizon POMDP is formulated for isolated industry MGs, where transition probabilities are estimated using historical data [115]. A POMDP platform has been further employed to manage communication failures within MGs, where a multi-agent Bayesian MDP is introduced [113]. Different from the traditional reward function only depending on current state and action, an interesting multi-stage reward function is proposed to improve energy balance, economic cost, and reliability, simultaneously, where metrics within the forecasting horizon are included in the reward function [117].

When multiple MGs are interconnected as MMGs, game theoretical approaches have been widely adopted to realize energy sharing within and among MGs, including internal and external markets with distribution systems and transmission systems. Rational behavior of MGs [118], [119] or market clearing process [120] can be treated as a MDP. A two-step energy trading platform is proposed for NMGs, where internal trading prices are optimized based on a Stackelberg game-based MDP [118]. To realize energy trading privately, an MDP-based energy management problem is proposed for the distribution system operator (DSO), realizing energy trading among multiple MGs [120]. A three-stage optimization is proposed for NMGs, where demand response within each MG is realized using the MDP, while the interaction among MGs and the external system is depicted as a potential game [119].

C. Transactive Energy Management Models

Energy management models under different energy market economics are summarized in Table VI. Deployment of local energy resources has accelerated deregulation of power markets on the demand side. Consumers, suppliers, and prosumers can trade energy within single MGs, MMGs, and NMGs, and transactive energy comes out. Transactive energy is commonly referred to as a system of economic and control mechanisms that allows a dynamic balance of supply and demand, using value as a key operational parameter [132]. As an internal market for MGs, transactive energy can be shared with or without prices, as shown in Table VI.

For pricing-based transactive energy management, community-based [127], [128] and peer-to-peer [16], [27], [129], [131] are two-widely adopted mechanisms, where game theory and optimization techniques can be used. Non-cooperative game approaches have been adopted to realize energy and reserve trading of players within MGs [133]. Capturing the hierarchical property between players, the Stackelberg game has been adopted to depict interaction between prosumers within MGs [131], MGs and distribution networks [89], [106], [128], MGs and transmission networks [46], [66], [106], and day-ahead and real-time operation [16]. Optimization methods provide an alternative to quantifying prices. In [27], a day-ahead peer-to-peer trading scheme is proposed for NMGs interconnected by SNOPs. The trading problem is formulated as a DRO problem, where a shadow pricing mechanism is adopted. In [127], real-time energy trading for prosumers within NMGs is formulated as a risk minimization pairing problem. In [25], a real-time energy trading problem among grid-tied NMGs is formulated as a MDP problem. When MGs can interact with

TABLE VI
SUMMARY OF ENERGY MANAGEMENT MODELS UNDER DIFFERENT ENERGY MARKET ECONOMICS AND SOLUTION METHODS

Ref.	Type of MG	Services	Markets	Uncertainty models	Trading mode	Problem formulations	Solution methods
[16]	AC MG	Electricity	Transactive	Stochastic	Peer-to-peer	Bi-level risk-constrained stochastic programming	MILP solver
[106]	AC MG	Electricity	Day-ahead	Stochastic	Community	Two-stage stochastic (Stackelberg game)	MILP solver
[117]	AC MG	Electricity	Transactive	Stochastic	Community	MDP	Deep Q network
[115]	AC MG	Electricity	Transactive	Stochastic	Community	POMDP	FH-DDPG
[121]	AC MG	Electricity	Real-time	Stochastic	–	Mixed-integer SOCP	MuZero
[122]	AC MG	Electricity	Day-ahead and real-time	Stochastic	–	MDP	ADP (value iteration)
[123]	AC MG	Electricity	Real-time	Stochastic	–	MDP	ADP (value iteration)
[124]	AC MG	Electricity	Real-time	Stochastic	–	MDP	ADP (value iteration)
[125]	AC MG	Electricity	Real-time	Stochastic	–	MDP	ADP (policy iteration)
[126]	AC MG	Electricity	Real-time	Stochastic	–	MDP	ADP (mixed iteration)
[59]	AC MG	Electricity	Day-ahead	Robust	Community	Robust optimization (Stackelberg game)	Decentralized bi-level iterative algorithm
[127]	MMG	Electricity	Real-time	–	Community	Matching	Long short-term memory
[128]	MMG	Electricity	Day-ahead	Stochastic	Community	Stochastic dynamic programming (Stackelberg game)	Distributed robust DDPG
[27]	MMG	Electricity	Day-ahead	Ambiguity	Peer-to-peer	DRO	ADMM
[129]	MMG	Electricity/ Heat	Transactive	Stochastic	Peer-to-peer	Multi-agent POMDP	DDPG
[46]	MMG	Electricity/ Reserve	Day-ahead	Robust	Community	Two-stage robust (convex game)	ADMM
[130]	MMG	Electricity	Real-time	–	Community	Stackelberg game	MIQCQP
[119]	MMG	Electricity	Transactive	Stochastic	Community	MDP/Potential game/Multi-objective	DDPG/Distributed/Gradient
[83]	MMG	Electricity	Day-ahead	Stochastic (Endogenous)	–	Stochastic adaptive robust optimization	Benders decomposition
[89]	NMG	Electricity	Transactive	Ambiguity	Community	DRO	Iterative algorithm
[118]	NMG	Electricity	Transactive	Stochastic	Community	MDP/Cooperative game	Reinforcement learning
[131]	Virtual MG	Electricity	Real-time	Stochastic	Peer-to-peer	Stackelberg game	Distributed iterative algorithm

gas networks, a risk-averse transactive energy management strategy is proposed for MG operators to participate in day-ahead wholesale and gas market in [134].

If there is no price signal, e.g., within regulated markets [135], cooperative game-theoretic and optimization approaches can be used, including convex game [46], coalitional game [130], Nash bargaining [136], Vickrey–Clarke–Groves auction [137], two-stage robust optimization [138], etc. In [46], day-ahead optimal operation of NMGs is formulated as a convex game, where uncertainties are managed by the affine robust optimization scheme. A grand coalition is formulated for cost allocation among MMGs [130]. A two-settle transactive energy management problem is formulated for MG operators and aggregators of DERs within MGs [138].

D. Solution Methods of Energy Management Problem Formulations

1) Tractable reformulation of energy management problems under uncertainties

Uncertainty energy management problems are typically intractable, due to existence of uncertain variables in objective functions or constraints, as shown in Problem (1). To fully utilize existing or coming, e.g., mathematical programming, ADP, and DRL toolboxes as summarized in Table VI, the energy management problems under uncertainties are to be reformulated into their tractable counterparts.

Deterministic reformulation is to approximate uncertainty energy management problems, e.g., (2)–(5), by their tractable counterparts. For stochastic optimization problems, continuous PDFs can be approximated by independent identically distributed scenario sets using SAA, with strong asymptotic performance guarantees [87]. Uniform convergence property requires that cardinality of the scenario set can be infinite, resulting in high computational cost of the reformulated problem. To reduce cardinality of scenario sets, an optimal scenario reduction method can be used to minimize the discrepancy distance [139]. The confidence level of obtained solution can be quantified by a replications procedure.

For robust optimization problems, the relationship between the ξ and $\boldsymbol{x}$ can be treated as a zero-sum game. If $\mathcal{Q}(\boldsymbol{y},\xi)$ is convex, the Lagrange dual based method has been widely used to reformulate $\max_{\xi\in\mathcal{U}}\mathcal{Q}(\boldsymbol{y},\xi)$ as a non-convex quadratic programming problem [108]. It can be reformulated into a mixed-integer linear programming (MILP) problem when the worst scenario is an extreme point of $\mathcal{U}$.

A dual method is a general approach to reformulate DRO energy management problems, including Lagrange duality [89], Fenchel duality, conic duality, etc. These problems may admit strong duality properties, under some conditions, e.g., existence of P in $\mathbb{P}$ [91]. For discrepancy-based ambiguity sets, a Lagrange duality is adopted to reformulate the energy trading problem within MMGs in [89]. For moment-based ambiguity sets, a duality theory of infinite-dimensional convex problems can be used to derive semi-infinite programming problems [110], [111]. Apart from duality, a uniform convergent robust SAA is proposed for DRO problems in [95].

2) Decomposition algorithms

By exploring the coupling variable and constraint nature of the deterministic counterpart for energy management problems, decomposition algorithms can solve them in a decentralized or distributed manner, realizing decentralized and distributed energy management. (Augmented) Lagrangian decomposition [140], (generalized) Benders decomposition [141], progressive hedging [142], alternating direction multiplier method (ADMM) [47], [143], [144], convex-concave procedure (CCP) [145], analytical target cascading (ATC) [146], column & constraint generation (C&CG) [108] are popular algorithms to solve MG energy management problems.

Decomposition algorithms admit distinct convergence properties with specific assumptions. Convergence of decomposition algorithms may always be guaranteed under convex assumptions. What is more, a classical ADMM can only converge in a two block structure [47]. Benders decomposition can converge in finite iterations when the recourse problem $\mathcal{Q}(\boldsymbol{y},\xi)$ is convex. C&CG can converge in finite iterations when finite extreme points exist in $\mathcal{U}$ and can be recorded in the master problem.

3) Adaptive dynamic programming algorithms

In recent years, ADP algorithms are gaining increasing attention to solve MDP-based energy management problems, which are also known as approximated dynamic programming algorithms. These problems can be treated as dynamic programming models, suffering from the widely known "curse of dimension". Using Bellman's equation and function approximation, an original MDP problem can be solved efficiently using iterative approaches.

Value iteration [122], [123], policy iteration [125], [147], and mixed iteration [126] are three main branches of ADP algorithms to solve MG energy management problems. Two novel look-up tables are constructed to approximate the value functions around a post-decision state with linear [122] and nonlinear system constraints [123]. When state space is of high dimension, a deep recurrent neural network is adopted to approximate the value function in [124]. Four typical policies, which are suitable for MG energy management, are given in [147]. A customer policy is proposed to accelerate value function approximation progress in [125]. A mixed iterative algorithm is presented to manage batteries within residential MGs [126].

4) Deep reinforcement learning algorithms

Sharing the same theoretical root as ADP, reinforcement learning further employs deep neural networks to enhance its approximation capabilities among state, action, and reward, as DRL [116], [118]. Model-free and model-based DRLs are two main variations to solve MDP-based problems.

For model-free MDP-based problems, deep Q networks [113], [117], [120], deep deterministic policy gradient (DDPG) [119], [129], proximal policy optimization (PPO), and advantage actor-critic [115] can be used to solve discrete, continuous, and hybrid discrete-continuous action space MDP problems. In [119], a rule based DDPG algorithm is proposed to realize a demand response of consumers within MMGs.

When reversible access to the MDP dynamics is used as a model, typically known or learned $\mathcal{R}$ and $\mathcal{P}$ [148], multiple model-based DRL algorithms have been proposed, e.g., MuZero [121], LSTM-DDPG [149], MPC-PPO. In [121], an interesting application of MuZero to solve an online MG energy management problem as a mixed-integer second-order conic programming (MI-SOCP) problem is proposed, where planning is performed over a learned model. In [149], the LSTM is adopted to learn the transition and reward functions.

E. Discussion on Solution Methods of Microgrid Energy Management Problems

Solution methods are the purposeful application of mathematical tools to solve MG energy management problems. Classical mathematical programming algorithms, e.g., stochastic, robust, and distributionally robust optimization, and decomposition techniques, are serving as benchmarks for emerging ADP and DRL algorithms. Even though model-free DRL algorithms have shown considerable success in solving discrete and some continuous action MDP problems, model-based DRL algorithms [121] might be a promising platform to fully utilize domain knowledge of existing mathematical programming algorithms and data-driven techniques. However, higher computational cost during training and planning, memory and potential instability of model-based DRL algorithms should be addressed properly [148].

V. Microgrid Energy Management Schemes

Using different schemes, energy management functions can be implemented in centralized, distributed, decentralized, and hierarchical approaches, as shown in Table VII. Consumers, producers, and prosumers are the players in local energy markets within MGs. MGs, DSOs, and independent system operators (ISOs) are the players in energy markets within MMGs and NMGs. MGs are always acting as the price taker in local energy markets, and local energy markets are playing the role of price marker in wholesale markets. In this section, hierarchical, distributed, and decentralized energy management schemes are summarized.

A. Hierarchical Energy Management Schemes

Hierarchical energy management architecture for MG, including primary, secondary, and tertiary control, is widely accepted by the industry [34], and it is shown in Fig. 7. Bottom level primary control of DG is to sense local voltage and current information without any communication with other DGs to achieve autonomous power management system (PMS) function. Secondary level control is to restore AC grid frequency and DC grid voltage and update information on resources, storage, and loads. Tertiary control is the AC and DC power flow control among different MGs. Secondary and tertiary controls are implemented by local EMS and universal EMS (UEMS) respectively, which need communication links inside the MG, and among MGs and external systems, e.g., distribution systems and power markets [66], [128].

A Stackelberg game-based scheme is proposed for mixed strategic and normal users in AC MGs [131]. To quantify the relationships among energy, reserve, and frequency derivation within isolated MGs, a hierarchical scheme is proposed, where the tertiary control acts as the leader and the primary control acts as the followers [101]. A three-level energy management scheme is proposed for MMGs connecting distribution systems in [151], where energy coordination between MMGs and DSOs is depicted as the upper level, energy balance is guaranteed in the middle level, and real-time power balancing is implemented as the bottom level. In [66], a hierarchical energy management scheme, i.e., a single leader multi follower game, is proposed to depict the strategic interaction between MMGs and DSOs in the real-time balancing market. To explore the coordination potential between isolated MMGs and virtual power plants, a three-stage hierarchical management scheme is proposed, where the service area, MG energy, and virtual power plant management are implemented in consecutive stages [107].

Secondary and tertiary level energy management functions can always be implemented in a distributed [28], [152], [153] or decentralized [59], [105] manner. It indicates that power and

TABLE VII
Summary of Microgrid Energy Management Schemes for Local Energy Markets

Ref.	Local energy market players	Architecture	Pricing mechanism model	Role of MGs in local energy markets	Role of local energy market in transmission systems	Schemes
[16]	MGs	AC MG	Stackelberg Game	Price taker	–	Centralized
[106]	DSO/ISO/MGs	MMG	Stackelberg Game	Price taker	Price maker	Centralized
[66]	DSO/ISO/MGs	MMG	Stackelberg Game	Price taker	Price maker	Centralized
[134]	MGs	AC MG	Distributionally robust chance constrained programming	–	Price taker	Centralized
[118]	MGs/Retailers	NMG	Stackelberg Game	Price taker	–	Hierarchical
[131]	Producers/ consumers	Virtual MG	Stackelberg Game	–	–	Hierarchical
[66]	MGs/DSO	MMG	Stackelberg Game	Price taker	–	Hierarchical
[119]	MGs	MMG	Potential game	–	–	Distributed
[46]	MGs	MMG	Convex game	–	Price taker	Distributed
[130]	MGs	MMG	Coalitions game	Price taker	–	Distributed
[137]	Prosumers	AC MG	Vickrey–Clarke–Groves auction	–	–	Distributed
[138]	MGs/Aggregators	AC MG	Two-stage robust optimization	Price taker	–	Distributed
[129]	MGs	MMG	Multi-agent DRL	–	–	Decentralized
[150]	Producers/ consumers	AC MG	Quadratic programming	–	–	Decentralized

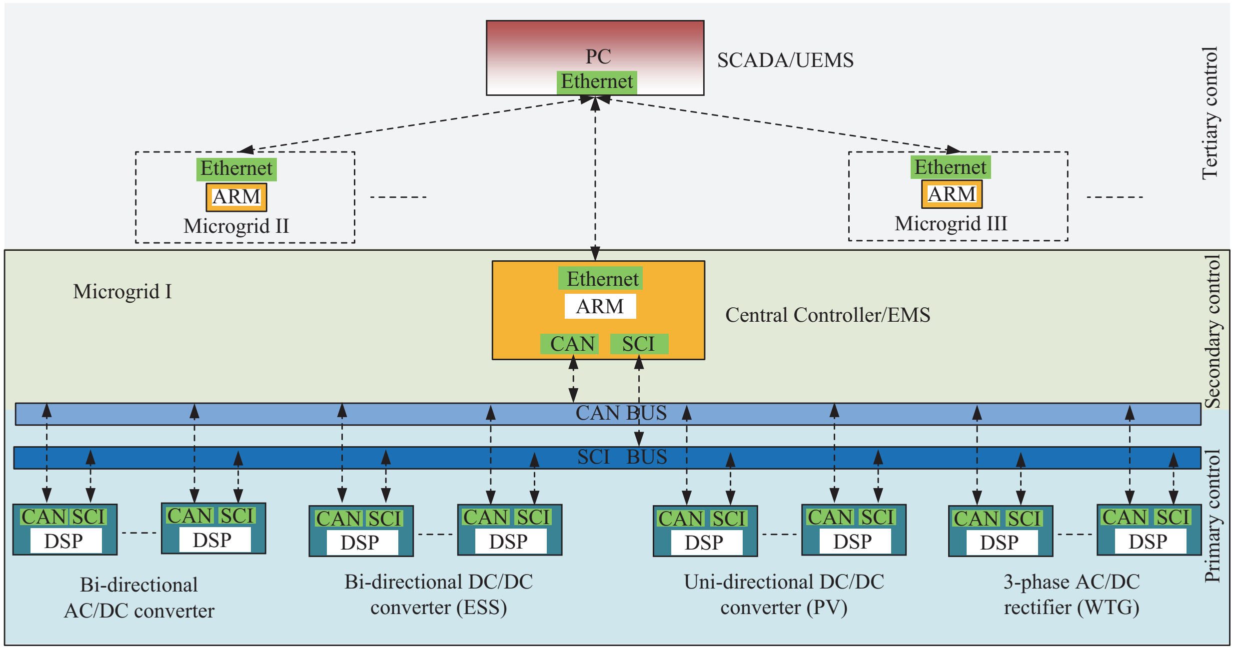

Fig. 7. Example of hierarchical energy management scheme for MGs.

energy characteristics within MGs can be captured properly by the multi-level nature of hierarchical management.

B. Distributed Energy Management Schemes

With high penetration of DERs, which can be owned by different entities, distributed schemes are emerging as a promising solution to realize coordination among them. There exist multiple controllers in SCADA, where each can communicate with its neighbors. With the help of distributed communication [10] and distributed computation algorithms [28], distributed schemes can further avoid single-point communication failures and reduce communication cost. This feature can be enhanced by asynchronous [152] and resilient distributed optimization and control algorithms [153]. Apart from fault-tolerance, distributed schemes bring other merits, e.g., transparency, security, and scalability, in comparison with centralized schemes.

A real-time distributed energy management scheme is proposed for DC MGs in [28], with plug-and-play capability and it has been verified by hardware-in-loop simulation results. To avoid single-point failure and reduce communication requirements of centralized EMS, a two-stage energy management strategy is proposed for remote area MGs in [154]. In [105], a distributed risk-limit energy management scheme is proposed to accelerate restoration of NMGs. Distributed multi-stage energy management is proposed for large-scale MGs, realizing power balance at each node along the scheduling horizon [155]. To mitigate risks from cyber anomalies, blockchain has been used for distributed transactive energy management discussed in [156], [157].

C. Decentralized Energy Management Schemes

There are multiple controllers in communication networks, i.e., SCADA, where each controller acts as an agent to control predefined devices, e.g., DGs, converters under deregulated market environment. Only part of the controllers can communicate with other controllers, which provides a suitable platform to realize coordination of MMGs and NMGs while preserving information privacy within local MGs. Decentralized control can reduce the risk of single-point failures, and increase scalability of centralized ones.

A dynamic Stackelberg game based decentralized energy management scheme is proposed for pelagic islanded MGs [59]. To guarantee secure trading within MGs, a decentralized voltage management scheme is proposed in [150]. In [143], a decentralized energy management scheme is proposed for MMGs under a mixed-stage framework, including day-ahead UC and real-time online adjustment.

D. Discussion on Energy Management Schemes

Information privacy and network security are two main issues addressed by recent energy management schemes, particularly on transactive energy sharing within local energy markets. Distributed and decentralized energy management schemes are the aboriginal of the transitive energy management regime, which are mathematical programming or DRL based approaches, as shown in Table VII. Mathematical programming-based approaches can be implemented efficiently with network security constraints, while can not always realize information security. DRL based approaches have been widely adopted to address information privacy issues among multi entities owned MGs [113] and MMGs [120], [129], including distributed implementation. Along with the maturity of information privacy solutions, network security issues, i.e., physical laws on the multi-energy networks interconnecting MGs, are gaining increasing attention in DRL-based schemes, e.g., voltage security [150], [158] and frequency security [159].

VI. Further Research Works

Towards a low carbon society, MG energy management systems should be more interoperable, foresightful, and resilient, using novel grid converter control strategies, ESSs, power market tools, and decision-making techniques.

A. Dynamics-captured Models of Critical Components

Models are always the first step to realizing energy management functionalities of MGs. Traditional models are for static analysis, which are insufficient for coming low carbon MGs. Further MGs are using more inverter-dominated systems with more complex dynamic characteristics. In addition to droop control function emulation, mechanical inertia shall also be emulated by the inverter control to reduce RoCoF during system transient events. Virtual inertia control can be achieved by adding a low pass filter to the power control loop without modifying the droop control structure as shown in Fig. 8 [160]. The highlighted low pass filter part in Fig. 8 represents the mechanical swing equation of a synchronous generator, where the inertia constant H and damping coefficient D, i.e., reciprocal of frequency droop slope, can be optimized in energy management. The virtual inertia concept was also adopted in a DC MG using the analogy principle as explained in [161].

To realize bi-directional inter-operation between controllable inverters and external systems by optimizing H, D, etc., precise and computational-friendly virtual inertia models should be proposed for MG energy management.

B. Stability Constrained Microgrid Energy Management

In the coming low carbon MGs, distributed renewable generators are integrated via a grid-tied inverter, and lacking of inertia as compared with a conventional synchronous generator having rotating masses. This may jeopardize system stability due to the increased RoCoF. One relevant accident is reported as the 2016 Australia blackout caused by the extensive deployment of power-electronic converters without inertia [162]. Therefore, it is of great importance to properly control a grid-tied inverter in energy management problems [163].

To achieve this target, a virtual synchronous generator (VSG) or grid-forming converter is proposed to operate the inverter similar to a conventional synchronous generator. Unlike a grid-following converter, which is controlled in current mode using a phase-lock-loop (PLL) to extract grid voltage vector angle, a grid-forming converter is controlled in voltage mode without using PLL. Fig. 9 shows a typical wind turbine generator working in grid forming mode, whereas filter capacitor voltage rather than grid side current is controlled. For power electronics-dominated systems installed with multiple DGs, how to configure the inertia constant H from each DG and optimize the size of distributed ESS to accommodate system frequency support requirements, i.e. RoCoF, nadir should be considered in future MG EMS.

C. Resilience-aware Energy Management under Uncertainties

Local renewable energy sources are injecting more and more wind and solar energy into MGs, enhancing interdependence between MGs and climate conditions. Extreme climate conditions, e.g., unexpected or even disastrous climate and weather events, can highly impact renewable energy generation, transmission assets, electrical demand, power market progress, and other grid elements. It calls for preparedness, survivability, and recoverability of renewable energy-dominated MGs against extreme events by using energy management techniques. As extreme weather events and their impacts are both uncertain, energy management should address both exogenous and endogenous uncertainties, when extreme events impose significant impacts on users within MGs and joint impacts of proactive actions.

COVID-19 has tortured the world for years, together with extreme weather events, e.g., typhoons and floods in ur-

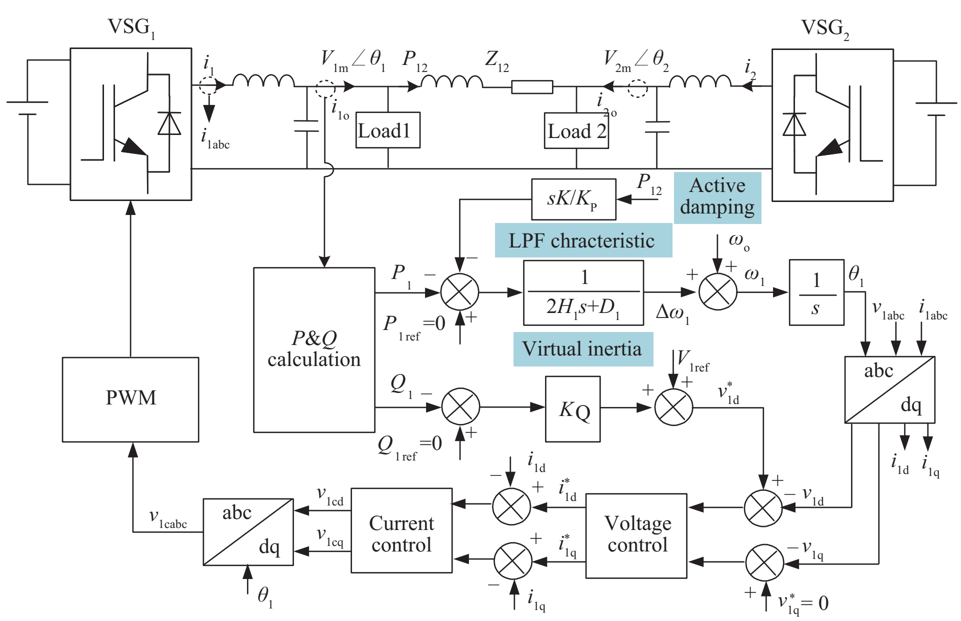

Fig. 8. Control of parallel virtual synchronous generators (VSGs) with power oscillation suppression function.

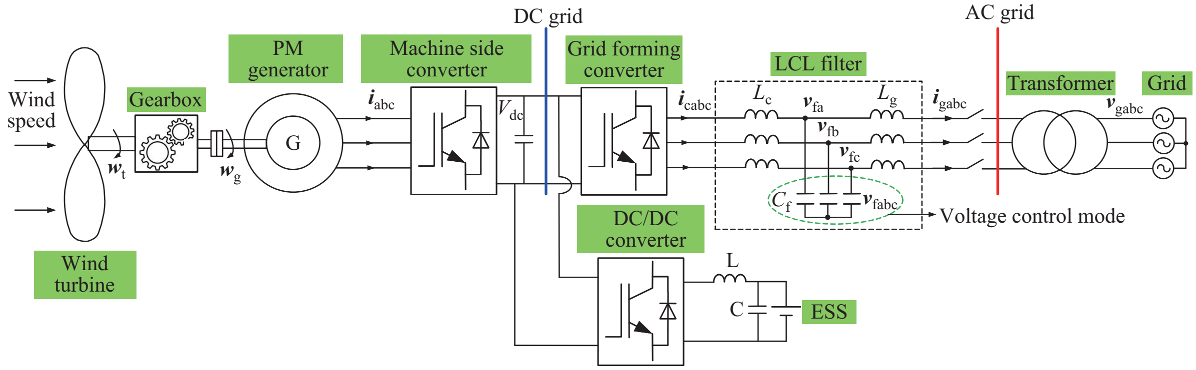

Fig. 9. A wind turbine generator working in grid forming mode using an ESS.

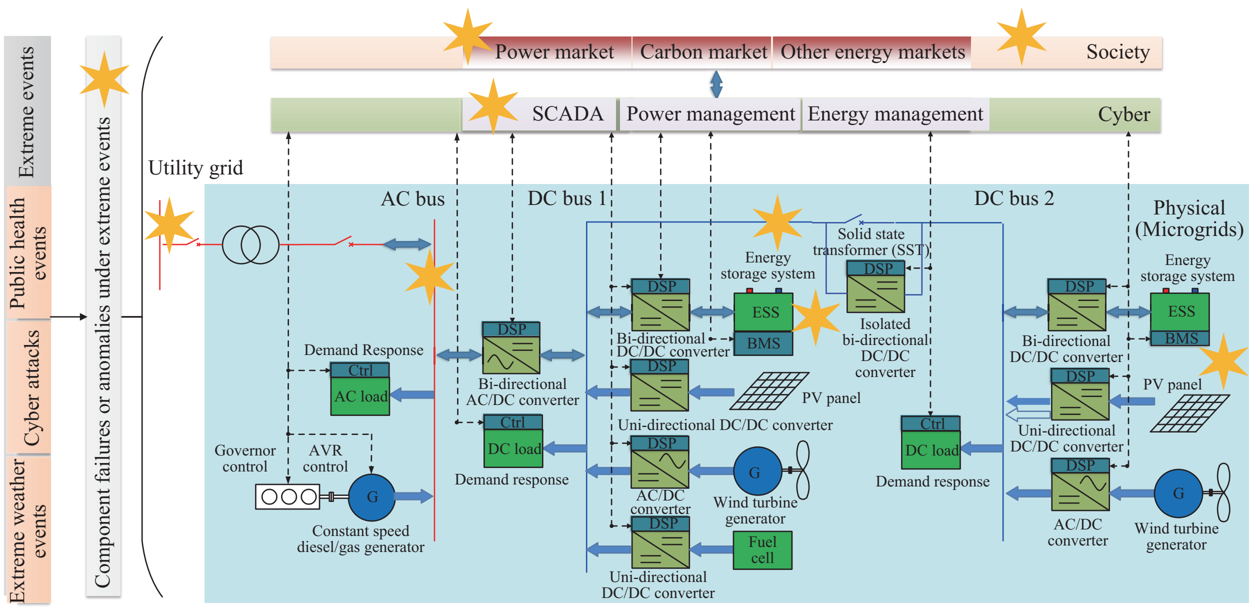

Fig. 10. Failures and anomalies within MGs under extreme events.

ban cities. Their combinational advent imposes impacts on physical, cyber, and social domains of MGs, as shown in Fig. 10. It expands resilience from engineering to social-ecological, introducing transferability requirements to MGs between multiple extreme events. One fundamental feature of these extreme events is data shortage, which makes it challenging to predict the impacts of these events on infrastructure and their further operating status. Construction of disaster scenarios for resilience-aware energy management of MGs will be a fundamental research problem in the further.

D. Market Operation of Microgrids with Distribution and Transmission Systems

To further increase local energy market efficiency and resilience, it is inevitable to clarify the roles of MGs, distribution systems, and transmission systems, under expected events and unanticipated events. In normal conditions, security of power systems and information privacy of MGs are to be balanced by transactive energy management and emerging techniques, e.g., multi-agent DRL.

Under unanticipated extreme conditions, secure transmission and distribution systems are of higher priority. Apart from existing energy and ancillary services, some emergence services, e.g., emergence resource and repair crews, might be introduced to enhance resilience of distribution and transmission systems with active participation of MGs and other critical infrastructure, e.g., transportation systems. Repair crews and emergence resources can be shared among electricity, transportation, gas, building, and other sectors within smart cities using proper market mechanisms.

E. Efficient Solution Algorithms for Energy Management Problems

Integrated energy networks have augmented inter-operation between coming low-carbon MGs and extended energy systems. On one side, MGs can improve their operating efficiency, reliability, and resilience. On the other side, energy dynamics should be incorporated into energy management problems. Dynamics are widely approximated by mixed-integer programming problems as recourses, making it challenging to derive the zero-gap duality functions, and decreasing efficiency of energy management solutions. Co-positive programming is treated as a possible approach to realize zero duality reformulation of MILP problems [164]. Surrogate model-based analysis and optimization are promising directions to harmonize analytical models and computational requirements, especially interpretable deep networks to depict electro-thermal dynamics of ESSs.

Existing decomposition and DRL algorithms can solve some convex or small-scale problems efficiently. Using virtual inertia from converters, stability constraints under extreme operating conditions, climate, and social-ecological resilience requirements, MG energy management problems will be non-convex and even with differential algebra equations. It may make a decomposition algorithm difficult to converge and will bring in significant computation and communication costs.

VII. Conclusion

Local renewable energy resources and energy storage systems are driving the microgrid transition towards a low carbon future. Zero inertia and uncertain nature of renewable energy resources ask for novel architectures, energy storage utilization, energy management models, and solution methods for management. Hybrid AC/DC, multi micro-energy grids are enhancing interoperability between electricity and other energy systems within local areas, including both grid-tied and isolated applications. The multi-physics characteristics of energy storage systems have been embedded into energy management models under uncertainties. Considering the mathematical properties of uncertainties, these models can be further solved by mathematical programming, adaptive dynamic programming, and deep reinforcement learning algorithms, with proper reformulation. Hierarchical energy management schemes are nourishing multiple types of decentralized and distributed energy management schemes, under different energy market economics. The challenges from dynamic-captured models, stability constraints, resilience, market operation, and efficient computation methods are discussed and need to be further analyzed in the future.

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