Energies **2014**, *7*, 2027-2050; doi:10.3390/en7042027

OPEN ACCESS

energies

ISSN 1996-1073

www.mdpi.com/journal/energies

Article

Stochastic Modeling and Optimization in a Microgrid: A Survey

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Received: 7 February 2014; in revised form: 25 March 2014 / Accepted: 25 March 2014 / Published: 31 March 2014

Abstract: The future smart grid is expected to be an interconnected network of small-scale and self-contained microgrids, in addition to a large-scale electric power backbone. By utilizing microsources, such as renewable energy sources and combined heat and power plants, microgrids can supply electrical and heat loads in local areas in an economic and environment friendly way. To better adopt the intermittent and weather-dependent renewable power generation, energy storage devices, such as batteries, heat buffers and plug-in electric vehicles (PEVs) with vehicle-to-grid systems can be integrated in microgrids. However, significant technical challenges arise in the planning, operation and control of microgrids, due to the randomness in renewable power generation, the buffering effect of energy storage devices and the high mobility of PEVs. The two-way communication functionalities of the future smart grid provide an opportunity to address these challenges, by offering the communication links for microgrid status information collection. However, how to utilize stochastic modeling and optimization tools for efficient, reliable and economic planning, operation and control of microgrids remains an open issue. In this paper, we investigate the key features of microgrids and provide a comprehensive literature survey on the stochastic modeling and optimization tools for a microgrid. Future research directions are also identified.

Keywords: microgrid; smart grid; stochastic modeling; stochastic optimization

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1. Introduction

Energy is and will continue to be the backbone of the global economy in the foreseeable future. However, due to fast rising energy prices, climate change and technology advances, reshaping the energy industry has become an international priority. A critical step is to utilize renewable energy sources for economic and environmentally friendly energy production. According to the International Energy Agency forecast, electric power generation from renewable energy sources will nearly triple from 2010 to 2035, reaching 31% of the world's total power generation, with hydro, wind and solar renewable power providing 50%, 25% and 7.5%, respectively, of the total renewable power generation by 2035 [1]. On the other hand, the overall energy efficiency and cost-effectiveness of fossil-fueled power generation can be improved based on the availability of new technologies in terms of the combined heat and power (CHP) plants. The CHP plants can be used to supply both electrical and heat loads by utilizing the wasted heat produced during electric power generation, which, in turn, reduces the thermal pollution in water systems. The utilization of heat output of CHP plants can be further improved by using the heat as a source of energy to drive a cooling system, such as an absorption refrigerator. For instance, the overall energy efficiency of fossil-fueled power plants in the United States is 33% and has remained unchanged for decades, which means that about two thirds of the energy in the fuel is lost as waste heat by most power plants. By using the CHP plants to capture and utilize a significant portion of the waste heat, the overall energy efficiency of CHP plants can reach 80% [2]. Therefore, it is not surprising that the United States Department of Energy has set a target to have CHP constitute 20% of the generation capacity of the country by the year 2030 [3]. Since the intermittent and weather-dependent output of renewable energy sources may jeopardize power system reliability and cause load curtailment, due to an imbalanced power supply and demand, energy storage systems, such as batteries, flywheels and heat buffers (e.g., hot water tanks) can be used to smooth out the intermittent power supply. Furthermore, with an increasing market penetration rate of plug-in electric vehicles (PEVs), vehicle-to-grid (V2G) systems are expected to be a critical auxiliary energy storage infrastructure in the future.

Some of the microsources (in terms of small-scale renewable energy sources and CHP plants), energy storage devices and V2G systems can be efficiently integrated in local areas, such as a small community, a university or school, and a commercial area, which leads to the formation of local, small-scale and self-contained grids, typically referred to as microgrids. A microgrid can operate in either a grid-connected mode to enable energy transactions with the main electrical grid or an islanded (or standalone) mode given there is a fault in the main grid. In addition to the economic and environmental benefits of utilizing renewable energy sources and CHP plants, other advantages of microgrids include:

- Energy loss reduction: Taking advantage of the proximity between microsources and loads, microgrids can significantly reduce the energy losses in electricity and heat transmission/ distribution and improve the utilization of renewable energy;
- Reliability improvement: Since a microgrid can operate in an islanded mode if there is a fault in the main grid, the negative impact of the outages in transmission and distribution systems can be reduced, and thus, system reliability can be improved;

- Enhancement of energy management: With the microsources and loads in a microgrid being managed in a coordinated way, the electric and/or heat power can be better shared among the local customers;
- Benefits to the main grid: Via efficient energy management of microgrids, the energy import from the main grid can be reduced, which relieves power transmission/distribution line congestions. Moreover, microgrids can be used to provide ancillary services (such as frequency regulation) to the main grid, which potentially improves the reliability of the main grid.

In order to realize all the potential benefits of microgrids, effective and efficient management of the microgrids should be in place. Recent advances in information and communication technologies (ICT) have provided opportunities to enable advanced microgrid operation and control, under the umbrella of the smart grid. According to the IEEE 2030 standard [4], the future smart grid is an interconnected network of three subsystems:

- An electric power system based on the traditional view of the electrical grid, which consists of four main domains for electric power generation, transmission, distribution and consumption;
- A communication system, which establishes the connectivity among different systems and devices for information exchange; and
- An information system, which stores and processes data information for decision-making on electric power system operation and control.

The same architecture is applicable to microgrids, which are small-scale and self-contained grids in nature. Based on the two-way communications throughout a microgrid, the information system can collect microgrid status information, process the information and make decisions on microgrid operation and control.

The IEEE 2030 standard defines the interoperability of ICT with the electric power system, end-user applications and loads. However, how to acquire the necessary information and act on the acquired information for optimal microgrid operation and control are application-specific and need extensive research. The issue is even more complicated for microgrid planning, as it requires investigations of not only the operation and control functions of microgrids, but also all potential options and/or combinations of microsources and energy storage devices, such that the overall microgrid planning cost throughout the planning horizon is minimized. In order to address various research challenges, stochastic modeling and optimization tools can be used to facilitate microgrid planning, operation and control. Specifically, stochastic models can be established to characterize the randomness in renewable power generation, the buffering effect of energy storage devices and PEV mobility. Then, stochastic optimization tools can be used for the planning, operation and control of microgrids. In the literature, there are a few surveys and tutorials on smart grid architecture [5,6], smart grid communications [7–11], smart grid information management [12] and middleware architectures for the smart grid [13]. In our previous work [14], we have summarized the stochastic information management schemes for the smart grid, with a focus on the bulk generation and transmission systems (*i.e.*, the main grid). Yet, how to use stochastic modeling and optimization tools to address the research challenges in microgrid planning, operation and control need further investigation.

In this paper, we investigate the architecture of microgrids and identify unique features and challenges in microgrid planning, operation and control, in comparison with traditional power transmission and/or distribution systems. The existing stochastic modeling and optimization tools are presented, and their applications in microgrids are identified. The related literature is surveyed according to different time frames of microgrid planning, operation and control and for microgrids with various types of microsources. Open research issues are also discussed.

The remainder of this paper is organized as follows. Section 2 presents the fundamentals of microgrids and related research challenges. The modeling and analysis tools of microgrids are discussed in Section 3. The state-of-the-art of microgrid planning, operation and control is presented in Sections 4–6, respectively. Section 7 summarizes this study and identifies future research directions.

2. Fundamentals of Microgrid and Research Challenges

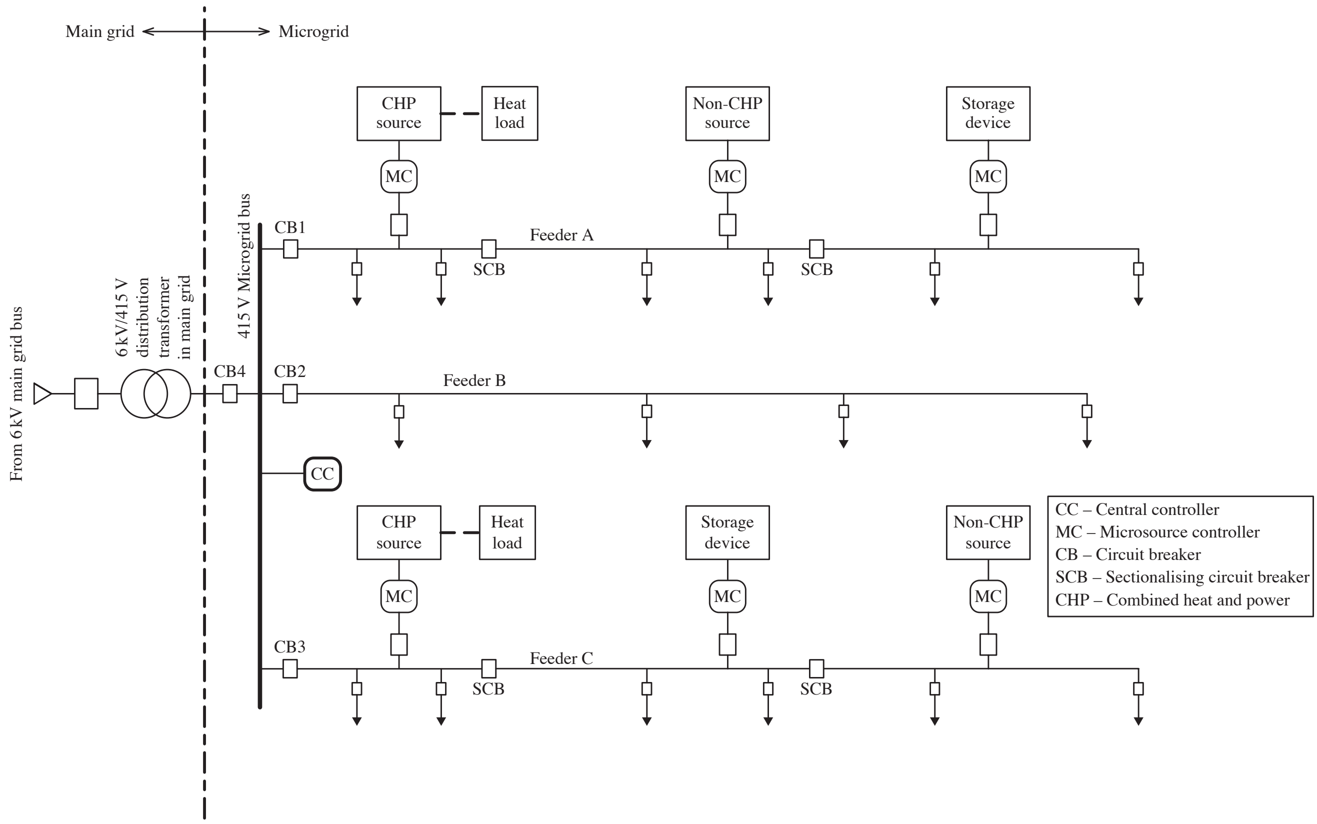
In this section, we introduce the architecture of a microgrid and the planning, operation and control functions in a microgrid. The related research challenges are discussed.

2.1. Microgrid Architecture

The typical configuration of a microgrid is shown in Figure 1 [15], where electrical loads and microsources are connected via a low-voltage distribution network, while the heat loads and CHP sources are placed close to each other to minimize losses during heat transmission. Two CHP microsources, two non-CHP microsources and two energy storage devices are connected to the three feeders in the microgrid. The microgrid is connected to the main utility grid (at a medium voltage level) through a point of common coupling (PCC) circuit breaker, CB4, which can be operated to connect or disconnect the entire microgrid from the main grid. Accordingly, the microgrid has two operation modes, *i.e.*, grid-connected mode and islanded mode. In a normal condition, the microgrid is connected to the main grid to enable energy transactions with the main grid in terms of energy import and export. However, whenever there is a fault in the main grid, CB4 is opened, so that the microgrid operates in an islanded mode. In this case, the microsources are used to feed all loads in the microgrid. Note that a prioritized islanded mode can also be supported in the microgrid. Suppose the electrical loads on Feeders A and C have a higher priority than the loads on Feeder B. The microgrid can be operated in another kind of islanded mode by opening CB1 and CB3. In this case, the loads on Feeders A and C can still be supplied by the microsources, while Feeder B is left to ride through the disturbance. Moreover, the sectionalizing circuit breakers can be used to partition the microgrid for further reliability improvement, to be discussed in Subsection 3.3.

The operation and control of microsources can be established in either a centralized manner or a decentralized manner. Centralized operation and control rely on a central controller (CC) and several microsource controllers (MCs) in the microgrid. Each MC is in charge of the management and protection of individual microsources. The MCs are coordinated by the CC, which provides the overall management of the microgrid in terms of generation scheduling and protection coordination. The information exchanges between the CC and MCs are established via a communication network, typical referred to as the field area network (FAN) or neighborhood area network (NAN) in the future smart grid [4]. The CC is in charge of determining the operation modes of the microgrid.

Figure 1. A typical microgrid configuration [15].



The centralized operation and control have the advantage of high efficiency in terms of global optimality. However, the heavy dependence on the CC may result in the problem of a single point of failure. Moreover, the communication network for information exchanges between the CC and MCs may not exist, especially in remote areas. Therefore, there is a trend in the research community to decentralize the operation and control of microgrids [5], which are established by each MC based on the local measurements of voltage and current. For instance, the decentralized droop control can achieve active and reactive power sharing in a microgrid without relying on a central controller and communication network [16,17]. Some recent studies show that the decentralized microgrid operation and control can be facilitated by decentralized communications via low-cost wireless networks (e.g., WiFi and ZigBee networks), by leveraging the technique of multiagent coordination [18–20].

Since microgrids are designed to supply electrical and heat loads in a local area, the maximum capacity of each microgrid is limited (e.g., 10 MVA as per IEEE recommendations [15]). Therefore, the loads in a relatively large area can be divided into several smaller groups, each of which is supplied by a microgrid. Then, the microgrids can be interconnected via a common distribution network. In this case, each CC should have an additional coordination function with its neighbouring CCs, which potentially improves the reliability of the interconnected microgrids.

2.2. Microgrid Planning, Operation and Control

In comparison with the traditional and well-established electrical grid, the concept of a microgrid is new and just beginning to move into the mainstream. Therefore, microgrid planning will be a critical issue in the next few decades. Microgrid planning is typically performed years ahead to find the optimal combination, design and sizing of microsources to meet the future electrical and heat demand at a minimum lifecycle cost, while satisfying the reliability requirements of the system [21].

Microgrid operation mainly involves unit commitment and economic dispatch. Both functions have their counterparts in the traditional electrical grid [14] since microgrids can be considered as small-scale and self-contained grids.

- Unit commitment, typically performed from one day to one week ahead of time, determines which microsource should be on-line at what time, such that the microgrid operation cost can be minimized [22]. Since there exists a standby cost for some of the microsources, such as fossil-fueled power generators, it is more economic to reduce the number of on-line microsources. On the other hand, due to the non-negligible startup cost, it is not desired to switch a microsource on and off frequently;
- Economic dispatch, typically performed from a few minutes to one hour ahead of time, makes short-term decisions on the output of on-line microsources to minimize the cost of energy production, while meeting the load demand and microgrid operation constraints in terms of system loading, line flow and voltage constraints [23].

Microgrid control is performed in a relatively small time scale (in terms of minutes/seconds or even shorter) to achieve short-term balance between power generation and demand [24]. The control functions are typically referred to as automatic generation control in the traditional electrical grid [25], which adjusts the output of power generators by measuring power supply-demand balance, reflected by the system frequency. For instance, if system frequency increases, which means that more power is generated than used, so that all generators in the microgrid are accelerating, the power output of some or all of the generators need to be reduced. In order to avoid a single point of failure and reduce information/communication system deployment cost, decentralized droop control is typically used in microgrids [24]. The active and reactive power generation by each microsource is adjusted based on its local measurements of system frequency and voltage, without relying on a CC.

2.3. Research Challenges

Due to the integration of renewable energy sources and energy storage devices (including V2G systems), new technical challenges arise in microgrid planning, operation and control. The randomness in renewable power generation should be taken into account in addition to the randomness in load demands. As the renewable power generation may deviate from forecasted values, predefined microgrid operation schedules may be violated. Moreover, the seasonal and yearly variation of weather conditions may affect the operation cost of a microgrid in the long run, which should be investigated during microgrid planning. The buffering effect of energy storage devices requires the modeling of inter-period buffer state transitions over the entire time frame of microgrid planning, operation and control, which results in high computational complexity. In addition, the highly dynamic PEV mobility leads to randomness in the number of PEVs at a specific location and, thus, the randomness in the capacity of the V2G system. In order to address these challenges, stochastic modeling and optimization tools can be used for microgrid planning, operation and control. Yet, the unique issues (or features) of microgrids need to be investigated, as follows:

1. The two operation modes (*i.e.*, islanded mode and grid-connected mode) of a microgrid have two different microgrid operation objectives. In islanded operation, each microgrid is to minimize its own generation cost. However, in a grid-connected operation mode, which allows energy transactions between the microgrid and main grid, such an objective may conflict with the objective of the main grid operation in terms of minimizing distribution cost or energy loss. To accommodate both operation modes, different stochastic models should be developed for different operation modes of a microgrid, and a tradeoff between operation objectives of the main grid and microgrids needs to be investigated;
2. A microgrid is designed to supply the electrical and heat loads in a small geographical area, within which the weather conditions, such as wind speeds and solar radiation, are likely to be similar. As a result, the renewable power generation and/or electrical and heat loads may exhibit substantial spatial correlations. The spatial correlation should be investigated to improve the accuracy of microgrid modeling. Exploiting the spatial correlation may facilitate microgrid operation and control in terms of computational complexity reduction, as less variables are needed for microgrid representation and decision-making;
3. Different from traditional electric power systems, which only supply electrical loads, both electrical and heat loads may exist in a microgrid due to the implementation of CHP plants. A two-dimensional model of electricity and heat flows should be developed for microgrids with CHP plants. Moreover, the differences in the storage and charging/discharging characteristics of electricity and heat buffers should be investigated in microgrid modeling and optimization.

There is a large body of research on stochastic information management in the smart grid [14]. Some of the tools can be applied to address the technical challenges in microgrid planning, operation and control, as discussed in the following sections.

3. Stochastic Models of Microgrids

In the literature, there exist some research works on stochastic modeling of microgrids. These models are developed for microgrid performance evaluation and have the potential to be applied in specific planning, operation or control functions. A summary of the stochastic models is shown in Table 1.

3.1. State Evolution Model

The framework of a stochastic hybrid system (SHS) can be used to establish a stochastic model for a microgrid [26]. The SHS model can capture the interaction between probabilistic events (such as a failure of a device) and discrete/continuous mode dynamics in a microgrid. The discrete modes can be used to describe the operation status of devices, such as CHP plant (on/off/shutdown), wind turbine (connected/

disconnected), energy storage (supply/store/load) and electrical loads (connected/disconnected), as well as the status of the connection between the main grid and microgrid (connected/disconnected). Further, each discrete mode is associated with specific continuous dynamics. For instance, a wind turbine in a connected mode provides a certain amount of electric power to the microgrid based on its physical configuration and wind speed. On the other hand, no electric power is provided by a wind turbine in a disconnected mode. Based on the SHS model, the trajectory of state evolution in microgrid operation (e.g., the amount of power generated by each generator over time) can be obtained. Such a model can be potentially applied for generation scheduling and demand response in microgrids by leveraging stochastic control.

Table 1. Stochastic models of a microgrid. MCS, Monte Carlo simulation.

Function	**Tool**	**Main feature**
State evolution model	Stochastic hybrid system [26]	Trajectory of state evolution
State estimation	Triangular factorization [27,28]	Utilization of pseudo measurements
	Belief propagation [29]	Spatial-temporal model for renewable power generation
Reliability analysis	MCS with sequential sampling [30]	System operation cycles with temporal correlation
	Markov chain analysis [31]	Spatial-temporal model for renewable power generation
	MCS with simple random sampling [32]	Load priority

3.2. State Estimation

State estimation is a technique used to estimate power system states (such as bus voltage magnitudes and phase angles of the entire system) based on available measurements [27]. Three types of measurements are typically used:

- Analog measurements, which include bus voltage magnitudes, active/reactive power injections and active/reactive power flows;
- Logic measurements, which include the status of switches and circuit breakers; and
- Pseudo measurements, which include forecasted power generation and loads.

The observability of an electric power system depends on the number of measurements and their geographical distribution. Given a sufficient number of measurements with good geographical distribution, the state estimator can provide estimates of system states. If all states can be determined, the system is observable, and *vice versa*. The weighted least squares algorithm, which is based on maximum likelihood estimation, is widely used for the state estimation in a traditional electrical grid [33].

However, the real-time measurements in a microgrid may be insufficient for system observability, in comparison with that in a traditional electrical grid. The main reason is that each microgrid is a small-scale grid used to supply local loads, so that it is relatively cost-sensitive and not suitable for the extensive deployment of measurement units. In order to address this issue, the theory of the network observability test can be applied [27,28]. If a microgrid is not observable, pseudo measurements can be generated from historical data and then used for state estimation to ensure system observability. Since the state estimation algorithm is based on triangular factorization, the computational complexity is relatively low. The spatial-temporal correlation in the output of renewable energy sources can be captured via a belief propagation-based state estimation technique [29]. The belief propagation algorithm is similar to a message passing algorithm, which is used to compute marginal distributions. The algorithm is organized in a tree structure. The messages are real valued functions, which represent the influence that each variable has on its parent/descendent variable, and are passed among variable nodes. In microgrid applications, the posterior distribution of state variables can be calculated based on the traditional measurements from the supervisory control and data acquisition (SCADA) system and the automated meter reading (AMR) system, as well as the high-resolution smart metering data from the advanced metering infrastructure (AMI) and phasor measurement units (PMUs) with a relatively high sampling rate.

3.3. Reliability Analysis

Microgrid reliability is usually measured through various reliability indices, such as the system average interruption frequency index (SAIFI), the system average interruption duration index (SAIDI), the customer average interruption frequency index (CAIFI), the expected energy not supplied (EENS) and the loss of load expectation (LOLE). Stochastic models are widely used to analyze microgrid reliability, since the outages in a microgrid (possibly due to device failure and/or insufficient output from a renewable energy sources) occur in a probabilistic manner. The stochastic models presented in this subsection can be potentially used to assist microgrid planning, since one of the major requirements of microgrid planning is to ensure system reliability.

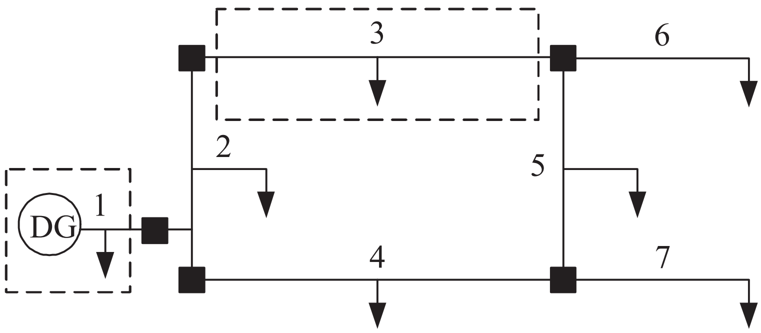
Monte Carlo simulation (MCS) can be used to evaluate the reliability of a microgrid [30]. Scenarios are randomly generated based on the probability density functions (pdfs) of the output of microsources in terms of photovoltaic (PV) panels and wind turbines. A sequential sampling technique is used to model the up and down cycles of all components. Since the transition probabilities among different states are considered in sequential sampling, realistic system operation cycles with temporal correlations can be established. The microgrid reliability is analyzed based on the status of microgrid under each scenario, which is further determined by the status of microsources and energy storage devices. Under the condition of a storage failure or storage non-failure, but with exhausted energy storage, some loads should be shed, since the output of renewable energy sources is unstable. If there is no other stable microsource (e.g., diesel generator) in the microgrid, microgrid service is interrupted, and an outage occurs. Taking into account all of the randomly generated scenarios, microgrid reliability indices can be calculated based on the probability that each scenario occurs. However, since the MCS in [30] is performed under the assumption of independent component failures, one of the main characteristics of the microgrid, *i.e.*, the spatial correlation among the output of multiple microsources and/or loads, cannot be captured. To address this issue, the overall generation-to-load ratio of an entire microgrid can be represented as a Markov chain [31] and incorporated in a reliability evaluation. The reliability indices are calculated based on the stationary distribution and state transition probabilities of the Markov chain, without resorting to MCS, which significantly reduces the computational complexity.

Load priority is considered in [32] for microgrid reliability analysis. An islanded microgrid is represented as a network of loads, sections and microsources, as shown in Figure 2, where the dark squares represent sectionalizing circuit breakers. Each section is a portion of the microgrid that can be isolated if there is a fault anywhere within the section. The loads are aggregated at each section. A loss of load of a specific section may happen due to two reasons:

1. Fault: A section may fail, and the microgrid needs to be reconfigured by disconnecting some of the sections;
2. Insufficient generation: The power generated by renewable energy sources is random, which may not be sufficient to supply all loads.

In either case, the available power in a microgrid is allocated to the sections according to their priorities, such that more frequent or more sustained outages are expected for sections with lower priorities. MCS is used to generate scenarios for component failure and repair processes [32]. Further, a sinusoidal curve is used to model the load on each section over time, such that the correlation among the output of microsources and/or loads can be characterized. By shifting the phase of the sinusoidal curve, the influence of the correlation on microgrid reliability can be evaluated.

Figure 2. An islanded microgrid one-distributed generation (DG) microsource [32].



4. Microgrid Planning

The impact of renewable energy sources on microgrid planning is two-fold. On the one hand, the lifecycle power generation cost in a microgrid can be reduced by utilizing renewable energy sources. On the other hand, the intermittent nature of renewable power generation can lead to insufficient generation and, hence, reliability issues, especially during the islanded operation. If necessary, energy storage devices and traditional dispatchable microsources, such as diesel generators, should be integrated in a microgrid to improve system reliability. Furthermore, microgrid planning is subject to other external uncertainties, such as long-term fluctuations in electricity, fuel and the construction/installation cost of microsources and energy storage devices. Therefore, stochastic optimization tools should be used to take into account the statistics of the uncertainties and make optimal decisions on microgrid planning. A summary of the stochastic optimization tools for microgrid planning is given in Table 2.

Table 2. Stochastic optimization tools for microgrid planning. CHP, combined heat and power.

Tool	**Main feature**
MCS with genetic algorithm [21]	Fluctuating electricity price
Stochastic differential equation [34]	Uncertainty in natural gas price
MCS with particle swarm optimization [35]	Yearly variation of construction and installation cost of microsources and the fluctuation of international price of crude oil
MCS with simulated annealing algorithm [36]	Model of the micro-CHP plant

In order to select cost-minimum generation components, the fluctuating electricity price should be investigated [21]. MCS can be used to obtain the pdfs of microgrid performance metrics, such as annual energy cost, value at risk (VaR) and losses, based on the pdfs of the random variables in the microgrid. In selecting generation components, repetitions of the MCS are performed for each combination of generators. The "brute force" method has a high computational complexity, and a genetic algorithm can be used to reduce the computational complexity. The impact of the uncertainties in natural gas price on microgrid planning with gas generation integration is presented in [34]. Stochastic differential equations are used to model and analyze investment decisions, by assuming that the long-term natural gas prices evolve according to a geometric Brownian motion. It is observed that the investment strategies with the installation of renewable power generation are more attractive when the gas price volatility (or uncertainty) increases. The yearly variation of construction and the installation cost of microsources and the fluctuation of the international price of crude oil can be considered in microgrid planning [35]. The concept of levelled cost of electricity (LCOE) is used to model the trend of variations in power supply from different energy sources, for high oil price, low oil price and balanced scenarios, respectively. MCS combined with a particle swarm optimization algorithm is used to solve the microgrid planning problem.

The problem of optimal sizing of a renewable energy and microturbine combined heat and power (micro-CHP) hybrid energy microgrid is studied in [36]. The objective is to achieve an hourly energy balance with a minimum system annual cost. Different from the renewable energy sources, such as wind turbines and PVpanels, a micro-CHP can have a stable power output. However, a key challenge is that the heat-to-power ratio and fuel consumption of a micro-CHP varies with respect to its loading, which should be considered in the optimal sizing problem. To address this issue, the operation data of micro-CHP plants can be used. For instance, the operation data of a C60 micro-CHP plant from Capstone is shown in Table 3 [36]. With only partial data available, a curve fitting method can be used to obtain the continuous functions of the heat-to-power ratio and fuel consumption with respect to loading, respectively. MCS combined with a simulated annealing algorithm can be used to solve the microgrid planning problem.

Table 3. Operation data of a C60 micro-CHP plant from Capstone [36].

Loading	Heat to power ratio	Fuel consumption (m^3/h)
100%	1.99	22.2
75%	2.33	17.4
50%	2.84	13.2
25%	4.44	7.8

5. Microgrid Operation

The integration of renewable energy sources, energy storage devices and a V2G system in microgrids governs microgrid operation. Its impact (and the corresponding solution) varies with the specific operation functions, which are performed at certain time scales. The stochastic optimization tools for microgrid operation are summarized in Table 4.

Table 4. Stochastic optimization tools for microgrid operation. V2G, vehicle-to-grid.

<table>
<tr><th>Function</th><th>Tool</th><th>Main feature</th></tr>
<tr><td rowspan="2">Unit commitment</td><td>MCS with scenario reduction [22]</td><td>For islanded microgrid with energy storage devices</td></tr>
<tr><td>MCS with Latin Hypercube Sampling and scenario reduction [37]</td><td>For grid-connected microgrid with energy storage devices</td></tr>
<tr><td rowspan="7">Economic dispatch</td><td>Stochastic dynamic programming [23]</td><td>Uncertainties in electricity price fluctuation</td></tr>
<tr><td>Chance constrained programming [38]</td><td>Model of CHP plants</td></tr>
<tr><td>Lyapunov optimization [39]
MCS with particle swarm optimization [40]
MCS [41]</td><td>For microgrids with stationary energy storage devices</td></tr>
<tr><td>MCS with Latin Hypercube Sampling
$M/M/N$ queue [42]
MCS [43]</td><td>For microgrids with V2G systems</td></tr>
<tr><td>H_∞ control [44]
MCS [45]
Adaptive scheduling [46,47]</td><td>Power market perspective</td></tr>
<tr><td>Bio-inspired optimization [48]</td><td>Joint design of microgrid operation and network reconfiguration</td></tr>
<tr><td>Robust optimization [49,50]</td><td>Distributed economic dispatch</td></tr>
</table>

5.1. Unit Commitment

In a microgrid with renewable energy sources, unit commitment is a challenging issue. Due to the uncertainties in forecasting, the realization of renewable power generation may significantly deviate from the forecasted value. Therefore, a significant number of traditional dispatchable (e.g., fossil-fueled) power generators should stay on-line. However, more on-line generators lead to higher microgrid operation cost, due to the non-negligible standby cost of the generators. A solution is to integrate energy storage devices in a microgrid. A long-term unit commitment problem can be formulated to minimize the operation cost of an islanded microgrid and the cost of unreliability [22]. Here, the cost of unreliability is evaluated based on the expected energy not supplied in the microgrid (which equals the expected amount of loads that are shed, due to insufficient power supply) and is calculated in a probabilistic approach. This problem can be solved based on MCS. In order to reduce the computational complexity, a scenario reduction technique can be used that eliminates the scenarios with low probabilities and bundling the scenarios that are close in terms of statistical metrics [37]. The concept of a high reliability distribution system is applied to the Illinois Institute of Technology microgrid, which operates in a grid-connected mode [37]. The objective is to minimize the operation cost of distributed generation, including startup and shutdown costs, the cost of energy supplied by the main grid and the penalty cost related to the events of load curtailments in the microgrid. The microgrid storage stores energy when the market price of electricity is low and supplies energy to the microgrid when the market price is high. A stochastic security-constrained unit commitment problem is formulated, in which the random outages in both the main grid and microgrid are considered. The problem can be solved based on MCS combined with a Latin Hypercube Sampling technique and scenario reduction. The main advantage of the technique is that a large number of scenarios can be generated with equal probability, while keeping the independency among the scenarios.

5.2. Economic Dispatch

Economic dispatch in a microgrid is more complicated in comparison with that in the traditional electrical grid. With a relatively small power capacity, the relative load variability in a microgrid is higher than that of the total load in the main grid [23]. The reduction in load predictability introduces higher uncertainties in the power generation scheduling. Similarly, the predictability of renewable energy sources is lower due to their smaller capacity in comparison with utility-scale wind/solar farms.

Subject to electricity market fluctuations, a stochastic optimization method can be used for the optimal scheduling of microsources and the energy exchange between the main grid and microgrid [23]. First, a deterministic problem is formulated, which belongs to a class of sequential decision-making problems. Then, the deterministic problem is extended by considering two kinds of stochastic inputs, in terms of:

1. Market-related inputs, such as electricity prices;
2. Power-related inputs, such as load forecasting and renewable power generation forecasting.

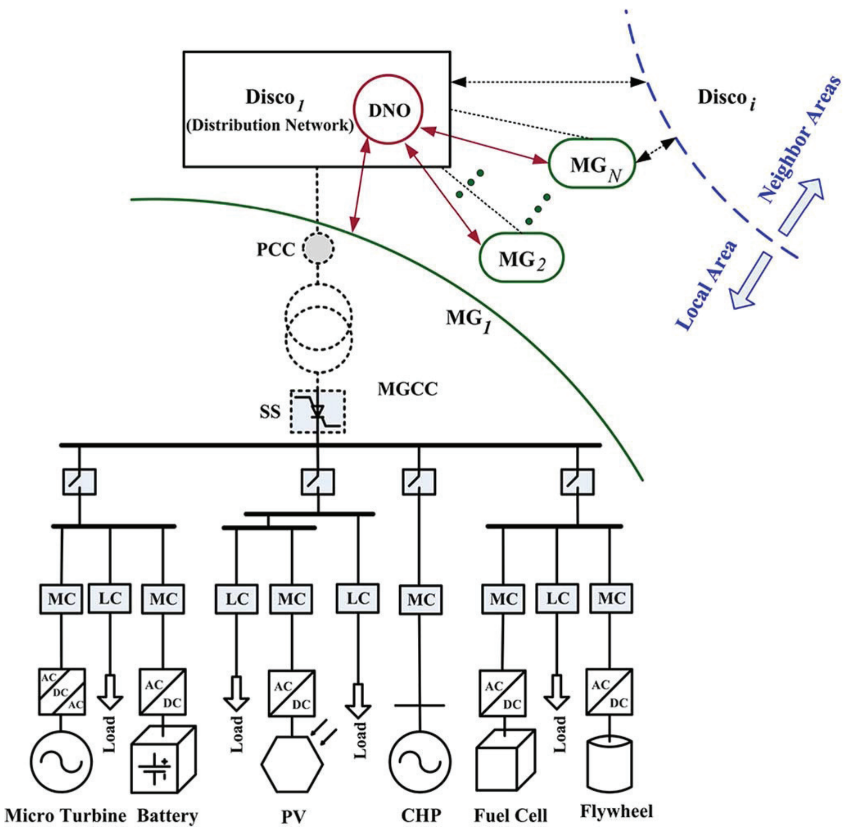
Stochastic dynamic programming can be used to solve complex stochastic optimization problems by breaking the original problems down into simpler subproblems and solving each subproblem only once. For the daily microgrid operation problem [23], the decomposition can be performed over time with respect to each hour of the day. An optimal operation problem of a CHP microgrid is investigated in [38]. The operation cost of the microgrid consists of the cost of purchasing power from the main grid, the cost of using natural gas by the fuel cell and gas boiler and the maintenance cost. The operation cost can be reduced when electricity is sold to the main grid. The optimal operation problem is formulated as a chance constrained programming (CCP) problem, which takes into account the randomness in wind and solar power generation and thermal/electrical loads. Based on the CCP, the inequality constraints with random variables are defined in a probabilistic manner and satisfied at a certain confidence level.

To better manage the energy storage devices in a microgrid, the concept of quality-of-service in electricity (QoSE) is introduced in [39]. The residential energy demand is classified into basic usage and quality usage, respectively. The basic usage is always guaranteed by the microgrid, while the quality usage is controlled based on the state of the microgrid. The central controller of a microgrid schedules the renewable energy sources and energy storage devices, such that the microgrid operation cost is minimized, while the QoSE (in terms of the outage probability of quality usage) is maintained. A Lyapunov optimization technique is used to derive an adaptive electricity scheduling algorithm. The algorithm is online in the sense that it does not require any statistics and future knowledge of electricity supply, demand and price processes. Based on an autoregressive model, the autocorrelation of the solar radiation, wind speed and load demand can be investigated in the optimal operation problem of an islanded microgrid [40]. MCS is used for scenario generation, and the expected operation cost of the microgrid (which depends on the fuel cost of diesel generator) is minimized over the generated scenarios. A particle swarm optimization technique is used to solve this problem. The energy system of a smart building may have various energy storage devices, such as batteries, ice/heat storage units and water tanks, which can be utilized to reduce the energy cost of a smart building [41]. The energy storage devices can be installed, scheduled and coordinated with the controllable loads in a smart building. In order to minimize the average energy cost of a smart building by taking into account the randomness in solar radiation and load demand, a stochastic optimization problem is formulated in [41]. The problem can be solved based on a scenario tree method, where the scenarios generated by MCS are organized in a tree structure to reduce computational complexity. When the solar radiation and load demand vary only slightly, the stochastic problem can be approximately simplified to a deterministic problem with only one scenario of solar radiation and load demand. The deterministic problem has a significantly reduced computational complexity, but the energy cost achieved by solving the deterministic problem is slightly higher than that by solving the stochastic problem.

The batteries of PEVs in a V2G system can be considered as energy storage devices in microgrids. Different from traditional stationary energy storage devices, PEVs are mobile in nature, which poses new technical challenges on dispatch optimization. In the context of V2G, the coordinated wind-PEV dispatch problem is studied in [51]. The objective is to promote user demand response through optimizing the utilization of wind power generation, as well as meeting the dynamic load demands. The problem can be studied in a stochastic framework capturing the uncertainties of wind power generation and statistical PEV driving patterns. The energy demand of each PEV is derived based on the National Household Travel Survey, where the log-normal distribution is used to model the daily driving distance of each PEV. The wind power generation is assumed to follow a normal distribution. Latin Hypercube Sampling is employed for scenario generation, and a scenario reduction technique is used to reduce the computational complexity. On the other hand, for V2G ancillary services that do not necessarily involve energy transactions, the capacity provided by a V2G parking lot (depending on the number of PEVs in the parking lot) needs to be estimated. Due to the random arrivals and departures of PEVs, queuing theory can be used to determine the distribution of the number of PEVs in a V2G parking lot, based on an analogy between the number of PEVs in the parking lot and the number of customers in a queue. Specifically, the parking lot can be modeled as an $M/M/N$ queue [42], where both the arrivals and departures of PEVs are modeled as a Poisson process, and N represents the number of power connection points in the parking lot. Based on the stationary distribution of the $M/M/N$ queue, the economic value of V2G in a microgrid can be analyzed. PEVs are considered as controllable loads in [43], similar to the concept of an unidirectional V2G system [52], where energy only flows from the grid to the PEVs, but at an adjustable rate. A stochastic problem formulation is developed to minimize the expected operation cost of the microgrid and energy losses. The expectation is calculated based on MCS over a certain number of scenarios with respect to the power generation of wind turbines and PV panels.

The energy management problem in a microgrid can be investigated from a power market perspective [44]. An H_∞ performance index can be used to set the parameters in a pricing control scheme, so that the robustness of market dynamics can be ensured, given the randomness in power generation. Through the participation of a microgrid in a pool-type market, the microgrid is able to purchase energy from the main grid [45]. The microgrid is treated as a hybrid mini-utility, which comprises of a collection of interconnected microsources and consumers. When the microgrid operates in a grid-connected mode, the microsources and consumers are exposed to the real market environment. Because of the market exposure, the microgrid is subject to various operational risks, including price, demand volume, non-dispatchable microsource output and system reliability. The issues of daily earnings and risks arising from uncertainties in the spot market can be investigated based on the risk measures in terms of cash flow at risk (CFaR) and expected shortfall (ES). The CFaR is defined based on the concept of value at risk (VaR), which is a standard in the banking industry. The VaR measures the maximum amount of money that can be lost at a given confidence level in a specific period of time. For example, given a specific confidence level, α, the VaR of a portfolio is the lowest amount, ξ, such that the loss does not exceed ξ with probability α. In the energy business, the VaR is used to evaluate monthly or yearly contracts, while the CFaR is used with respect to the spot (day-ahead) market. The ES is a modified form of the VaR. For example, given a confidence level, α, the ES is defined as the expected return of the portfolio in the worst $(1 - \alpha) \times 100\%$ of the cases. MCS can be performed to evaluate the CFaR and ES. For multiple interconnected microgrids, the economic dispatch problem can also be addressed from a power market point of view. A load management problem is studied in [46] for interconnected microgrids. The objective is to minimize the network operation cost, while satisfying the random demands within the microgrid. A cooperative power dispatch algorithm can be used to address this problem, based on the definition of dynamic purchase price per each unit of power at each microgrid. Each microgrid progressively updates its price and adaptively regulates its transactions with the rest of the grid (in terms of power flows), based on its realized demand and the prices announced by other microgrids. A communication infrastructure is needed to achieve the information exchange. The energy transactions among groups of microgrids are studied in [47]. A distribution network with connected microgrids (MGs) is considered for the energy consumption scheduling problem, managed by a single distribution network operator (DNO), as shown in Figure 3. A microgrid central controller (MGCC) provides the interface between a microgrid and the distribution network (main grid), while the controllable loads in microgrids are managed by load controllers (LCs). The distribution network is partitioned into a local area with a known demand and neighbouring areas with an uncertain demand. The optimal energy consumption scheduling problem is formulated with an objective to minimize total operation cost. For both works in [46,47], adaptive scheduling approaches with online stochastic iterations are used to capture the randomness in demand, using stochastic estimates of the random variables in the original problem formulation in each iteration.

Figure 3. Local and neighbor areas in a distribution network [47].



In a distribution system, network reconfiguration can be performed to reduce energy losses, maintain power balance and isolate faults, by changing the states of sectionalizing circuit breakers. On the other hand, to better utilize renewable energy, microsources can be grouped in microgrids, which are further connected to a distribution system. Most existing research works investigate economic dispatch in microgrid without taking into account network reconfiguration. However, it is shown in [48] that power flow analysis can be used to minimize the total operation cost of a distribution network with multiple microgrids. The operation cost includes the cost of power loss on all transmission lines, the cost of power generation by microgrids and the cost of power purchased from utility. The optimization is based on the expected (or forecasted) values of the power generation by wind turbines and PV panels and of the load demands. Four bio-inspired optimization schemes (including a genetic algorithm, particle swarm optimization, an artificial immune system and a vaccine-enhanced artificial immune system) are used to solve the problem.

Most of the existing research addresses microgrid operation problems in a centralized manner. In order to reduce communication overhead and improve robustness to a single point of failure, there is another stream of research that addresses the economic dispatch problem from a distributed control perspective [49,50]. The objective is to minimize microgrid net cost, which includes non-renewable microsource power generation cost, the utility of elastic loads, the penalized cost of energy storage devices and a worst-case transaction cost. A robust optimization formulation is used to calculate the worst-case transaction cost, based on the lower and upper bounds of the energy harvested via the renewable energy sources. Based on dual decomposition, the economic dispatch problem in a microgrid is solved in a distributed way by the local controllers of microsources, energy storage devices and dispatchable loads.

6. Microgrid Control

The objective of microgrid control is to achieve a balance between power generation and demand in real time. With the integration of renewable energy sources in a microgrid, a large increment or decrement in renewable power generation may occur due to changes in local weather conditions. The randomness in renewable power generation can jeopardize microgrid stability. One solution is to incorporate stochastic modeling and optimization tools in microgrid control to improve system stability. A summary of the stochastic modeling and optimization tools for microgrid control is given in Table 5.

Table 5. Stochastic modeling and optimization tools for microgrid control.

Tool	Main feature
Two-point estimate method [53]	Small signal stability analysis
MCS with Latin Hypercube Sampling supplemented with a restricted pairing technique [24]	Capacity factor analysis with spatial correlation of wind speeds
Stochastic dynamic programming [54]	For a microgrid with a stationary storage device
Stochastic control [55]	For a microgrid with V2G systems
Stochastic dynamic programming [56,57]	Regulation service reserves by microgrids

Small signal stability analysis can be used to evaluate microgrid stability subject to small disturbances [58]. The microgrid is stable if the oscillations of microgrid states caused by small disturbances can be suppressed over time, and *vice versa*. Under small disturbances, the state evolution equations of a microgrid can be linearized around an equilibrium point, and the stability of the microgrid is determined by the eigenvalues of the resulting system matrix. If the real parts of all eigenvalues are negative, the microgrid is stable. On the other hand, the microgrid is unstable if the real part of any of the eigenvalues is positive. In order to analyze the small signal stability of microgrids with uncertainties, the pdfs of the real parts of all eigenvalues are needed, which leads to high computational complexity. An alternative is to use a two-point estimate method to calculate the first two moments of the real part of each eigenvalue of the small signal model [53]. Then, the stability of the microgrid can be determined by considering the real part of each eigenvalue as a normally distributed random variable with the corresponding mean and variance calculated based on the two-point estimate method. A method for computing the capacity factor (CF) of power delivery by an off-grid droop-regulated microgrid is presented in [24]. The CF of a generator is defined as its actual average power generation as a function of its rating (*i.e.*, maximum power generation). In terms of wind generation, the CF indicates the percentage of power that a specific wind turbine can supply from the available wind at a given site. However, the CF of a microgrid cannot be calculated by simply modeling the microgrid as a "large generator" and summing up the average generation and rating of the individual wind turbines, due to the correlation of wind speeds at different wind power generation sites. MCS combined with Latin Hypercube Sampling can be used to solve this problem, where the MCS is supplemented with a restricted pairing technique to capture the correlation among wind speeds at different generation sites.

Microgrid stability can be improved by utilizing stochastic control to address the uncertainties in renewable power generation. Stochastic model predictive control can be used to improve the utilization of renewable energy sources, while keeping a storage device (*i.e.*, a battery) to its maximum charging state and minimizing the power generated by micro-CHP plants [54]. A central controller is considered to control the operation of the microgrid, and the objective of microgrid operation is to meet the predicted demand based on the forecasted renewable power generation. Empirical mean and dynamic programming are used to handle the constraints and computes expected values in the model predictive control problem. A microgrid model that emphasizes V2G connections and a rotational generator machine are presented in [55]. Two categories of V2G systems are considered: one for distributed PEVs with random plug-in connections to the grid; and the other for PEVs in a charging station of a large-scale public parking lot. Accordingly, two frequency stabilizing control problems are formulated based on stochastic control theory. In the first problem, the objective is to design a distributed feedback control law for the mechanical power injection to ensure microgrid stability in a stochastic sense, given the disturbances cased by the charging and discharging of PEVs. In the second problem, the objective is to select the charging/discharging power of the charging station such that the microgrid is stable, given the random connections of distributed PEVs. The microgrid stability can be investigated based on an extension of the conventional Lyapunov theorems for ordinary differential equations.

The future smart grid is expected to be an interconnected network of microgrids. Each microgrid plays an important role in facilitating the control of the main grid. Regulation services can be provided by microgrids to balance power generation and demand in the main grid in a small time scale (in a few minutes or an even shorter period). In the conventional electrical grid, the regulation services are mainly provided by centralized generators. To reduce cost and greenhouse gas emissions, enabling microgrids to offer regulation service is promising. Currently, the participation of loads in regulation service reserves has been allowed by PJM, which is a regional transmission organization and independent system operator (ISO) serving all or parts of Delaware, Illinois, Indiana, Kentucky, Maryland, Michigan, New Jersey, North Carolina, Ohio, Pennsylvania, Tennessee, Virginia, West Virginia and the District of Columbia. The other ISOs are contemplating similar regulation service reserves [56]. The next generation intelligent buildings or communities are equipped with smart meters and actuators to form a smart microgrid. The smart meters and actuators can be accessed by not only the occupants, but also the smart microgrid operator (SMO). Smart grid communications can be utilized to enable close-to-real-time power market transactions. In [56,57], a market-based mechanism is developed to enable the SMO to provide regulation services. The SMO controls the behaviours of internal loads through price signals and provides feedback to the ISO. The selection of an optimal short time scale dynamic pricing policy can be modeled as a stochastic dynamic program, with the objective of maximizing average SMO and ISO utility. To reduce the computational complexity, a nonlinear programming static problem can be formulated to provide an upper bound on the optimal utility, based on which, a static pricing policy can be obtained.

7. Summary and Future Research Directions

In this paper, we have presented the state-of-the-art on stochastic modeling and optimization tools for microgrid planning, operation, and control. The tools can be used to address the randomness in renewable power generation, the buffering effect of energy storage devices and the mobility of PEVs in V2G systems. Furthermore, the unique features of microgrids, such as the dual (islanded and grid-connected) operation modes, the spatial correlation of renewable power generation and the integration of CHP plants with both electricity and heat outputs, are taken into account. Despite there existing stochastic modeling and optimization tools for microgrid planning, operation and control in the literature, many microgrid research issues remain open. As we can observe from this literature survey, a majority of the existing works is based on MCS. Despite the simplicity in microgrid modeling via MCS, its high computational load requires highly efficient computational devices, such as powerful servers and workstations, with a non-negligible cost. Therefore, theoretical models still need to be developed for microgrid planning, operation and control. A few potential stochastic modeling and optimization tools are given below:

- Stochastic game: The stochastic game represents a class of dynamic games with one or more players via probabilistic state transitions [59]. In a distribution system with interconnected microgrids, the randomness in power generation/demand of each microgrid can be modeled by probabilistic state transitions. Moreover, due to the competitive nature of the players in the game, the interactions among multiple microgrids in a dynamically changing system can be characterized, such as in a real-time electricity market;
- Stochastic inventory theory: The theory concerns the optimal design of an inventory (or storage) system to minimize its operation cost [60]. Different from the queueing models, the ordering (or arrival) process of an inventory system can be regulated. In a grid-connected microgrid, energy supply from the main grid is available. The stochastic inventory theory can be applied to optimize the amount of energy drawn from the main grid to recharge the energy storage devices, based on an analogy between energy storage and inventory level;
- Partially observable Markov decision process (POMDP): Low-cost wireless (such as ZigBee and WiFi) networks can be used to facilitate decentralized microgrid control, but with a non-negligible communication delay [19]. In such a case, microgrid states may not be observed in real time. To achieve optimal microgrid control under a communication delay, POMDP can be used by modeling the system state (e.g., the output of a renewable energy source) evolution as a Markov process [61].

In the practical applications of stochastic modeling and optimization tools, there are two major research challenges:

- Computational complexity: In comparison with deterministic modeling and optimization, the computational complexity of the stochastic counterparts is significantly higher. Reducing the computational complexity is a critical step to bridge the gap between research and implementation;

- Availability of statistics: The statistics of power generation from renewable energy sources and PEV mobility are needed for stochastic modeling and optimization. However, such information may not be available in microgrid operation. For instance, vehicle traffic monitoring systems, such as piezoelectric sensors and magnetic loops [62], need to be deployed in roadways to calculate the arrival rate of PEVs at a V2G parking lot, such that a queueing model can be established to determine the capacity of the V2G system. In the absence of such monitoring systems, a joint statistical learning and optimal decision-making technique is needed for microgrid operation. The framework of reinforcement learning can be used, where the statistics of system states (e.g., the capacity of the V2G system) and their evolutions can be learned from the system's sample paths [63]. As shown in a recent research work [64], reinforcement learning can help an electricity customer in a microgrid to establish efficient strategies of energy use in constantly changing environments in terms of wind speeds. Yet, how to apply reinforcement learning for microgrid operation and control needs further investigation.

Despite all the technical challenges, stochastic information management is a major avenue for microgrid operation in order to harness renewable energy sources and energy storage devices, such that the economical and environmental benefits of microgrids can be fully realized. The related research is interdisciplinary in nature and calls for a close collaboration between the researchers in the power/energy system discipline and in the information/communication system discipline.

Conflicts of Interest

The authors declare no conflict of interest.

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