STOCHASTIC MODELING AND OPTIMIZATION IN A MICROGRID

[1]Zaheeruddin, [2]Munish Manas

[1]Professor, [2]Ph.D. Student, Department of Electrical Engineering

Faculty of Engineering and Technology, Jamia Millia Islamia, New Delhi -110025, (India)

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

I 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].

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.

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.

II 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. 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].

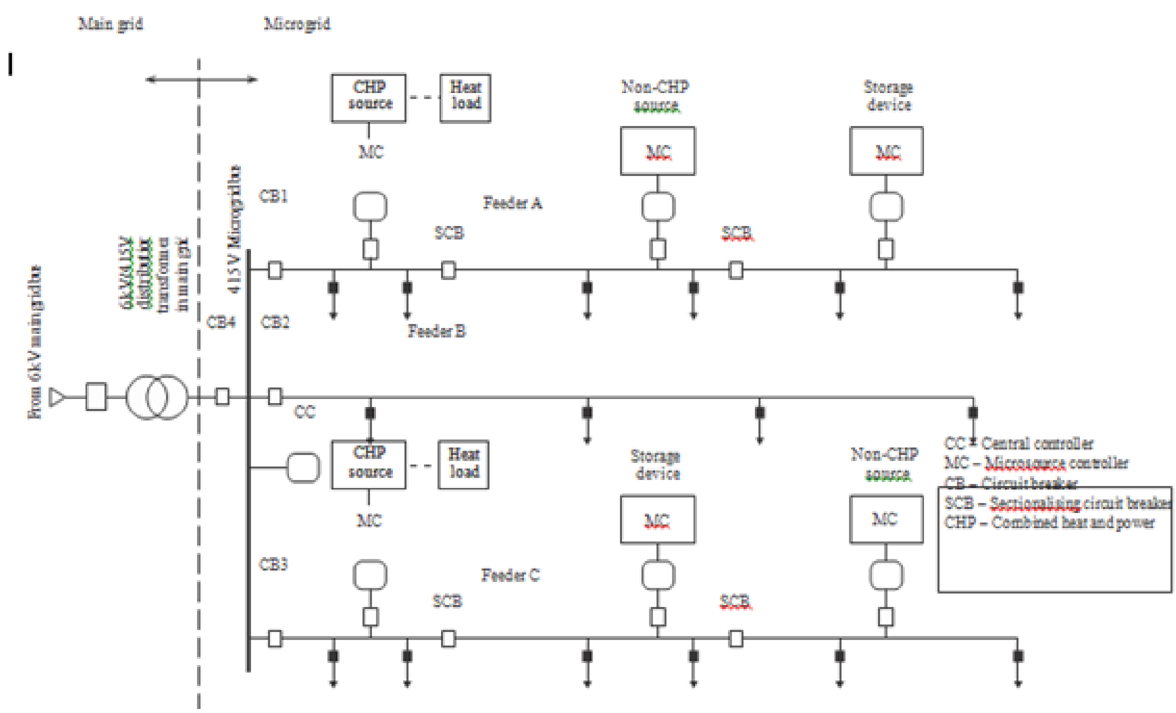


Fig 1: A Typical microgrid

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. 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.

III 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 . 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 ,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 Belief Propagation[29]	Triangular factorization[27,28]	Utilization of pseudo measurements
		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. 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.

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 . 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.

IV MICROGRID PLANNING

The impact of renewable energy sources on microgrid planning is two-fold. The lifecycle power generation cost in a microgrid can be reduced by utilizing renewable energy sources. 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

The "brute force" method has a high computational complexity, and a genetic algorithm can be used to reduce the computational complexity.

For instance, the operation data of a C60 micro-CHP plant from Capstone is shown in Table 3. 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 (m3 /h)
100%	1.99	22.2
75%	2.33	17.4
50%	2.84	13.2
25%	4.44	7.8

V 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.

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

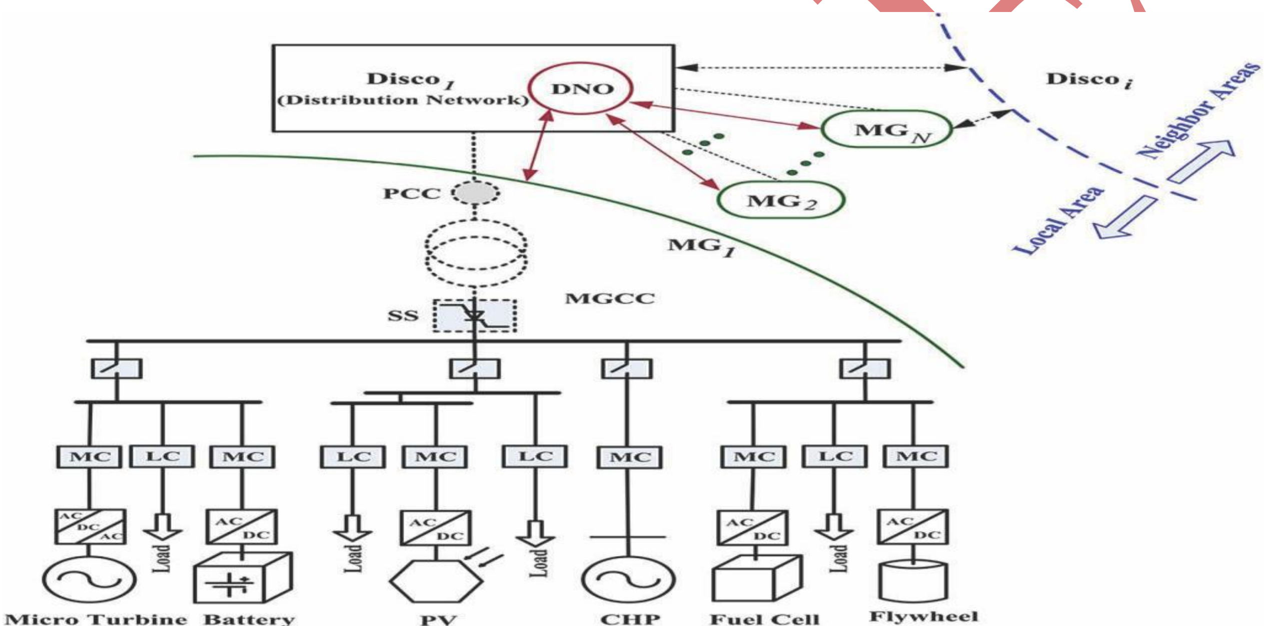
5.1. Unit Commitment

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.

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.

Figure 3. Local And Neighbor Areas In A Distribution Network .



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 sub problems and solving each sub problem only once.

VI 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

VII 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. 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. 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 . 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].
- 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 calls for a close collaboration between the researchers in the power/energy system discipline.

REFERENCES

1. International Energy Agency. World Energy Outlook 2012; International Energy Agency: Paris, France, 2012.
2. United States Environmental Protection Agency—Combined Heat and Power Partnership. Available online: http://www.epa.gov/chp/ (accessed on 27 March 2014).
3. U.S. Department of Energy. Combined Heat and Power: A Decade of Progress, A Vision for the Future; U.S. Department of Energy: Washington, DC, USA, 2009.
4. IEEE 2030—Guide for Smart Grid Interoperability of Energy Technology and Information Technology Operation with the Electric Power System, and End-Use Applications and Loads; IEEE Standard, 2011. Available online: http://standards.ieee.org/findstds/standard/2030-2011.html (accessed on 27 March 2014).
5. Farhangi, H. The path of the smart grid. IEEE Power Energy Mag. 2010, 8, 18–28.
6. Fang, X.; Misra, S.; Xue, G.; Yang, D. Smart grid—The new and improved power grid: A survey. IEEE Commun. Surv. Tutor. 2012, 14, 944–980.
7. Wang, W.; Xu, Y.; Khanna, M. A survey on the communication architectures in smart grid. Comput. Netw. 2011, 55, 3604–3629.
8. Hossain, E.; Han, Z.; Poor, V. Smart Grid Communications and Networking; Cambridge University Press: Cambridge, UK, 2012.
9. Cao, J.; Xiao, Y.; Liu, J.; Liang, W.; Chen, C.L.P. A survey of communication/networking in smart grids. Future Gener. Comput. Syst. 2012, 28, 391–404.
10. Ye, Y.; Yi, Q.; Sharif, H.; Tipper, D. A survey on smart grid communication infrastructures: Motivations, requirements and challenges. IEEE Commun. Surv. Tutor. 2013, 15, 5–20.
11. Zhong, F.; Kulkarni, P.; Gormus, S.; Efthymiou, C.; Kalogridis, G.; Sooriyabandara, M.; Zhu, Z.; Lambotharan, S.; Chin, W.H. Smart grid communications: Overview of research challenges, solutions, and standardization activities. IEEE Commun. Surv. Tutor. 2013, 15, 21–38.
12. Cao, J.; Wan, Y.; Tu, G.; Zhang, S.; Xia, A.; Liu, X.; Chen, Z.; Lu, C. Information system architecture for

smart grids. Chin. J. Comput. 2013, 36, 143–167.

13. Martinez, J.F.; Rodriguez-Molina, J.; Castillejo, P.; de Diego, R. Middleware architectures for the smart grid: survey and challenges in the foreseeable future. Energies 2013, 6, 3593–3621.
14. Liang, H.; Tamang, A.K.; Zhuang, W.; Shen, X. Stochastic information management in smart grid. IEEE Commun. Surv. Tutor. 2014, in press.
15. Chowdhury, S.; Chowdhury, S.P.; Crossley, P. Microgrids and Active Distribution Networks; Institution of Engineering and Technology: London, UK, 2009.
16. Pogaku, N.; Prodanovic, M.; Green, T.C. Modeling, analysis and testing of autonomous operation of an inverter-based microgrid. IEEE Trans. Power Electron. 2007, 22, 613–625.
17. Mohamed, Y.; El-Saadany, E.F. Adaptive decentralized droop controller to preserve power sharing stability of paralleled inverters in distributed generation microgrids. IEEE Trans. Power Electron. 2008, 23, 2806–2816.
18. Liang, H.; Choi, B.J.; Abdrabou, A.; Zhuang, W.; Shen, X. Decentralized economic dispatch in microgrids via heterogeneous wireless networks. IEEE J. Sel. Areas Commun. 2012, 30, 1061–1074.
19. Liang, H.; Choi, B.J.; Zhuang, W.; Shen, X. Stability enhancement of decentralized inverter control through wireless communications in microgrids. IEEE Trans. Smart Grid 2013, 4, 321–331.
20. Liang, H.; Abdrabou, A.; Choi, B.J.; Zhuang, W.; Shen, X. Multiagent coordination in microgrids via wireless networks. IEEE Wirel. Commun. 2012, 19, 14–22.
21. Hawkes, A.D. Optimal Selection of Generators for a Microgrid under Uncertainty. In Proceedings of the IEEE Power and Energy Society General Meeting, Minneapolis, MN, USA, 25–29 July 2010; pp. 1–8.
22. Bahramirad, S.; Reder, W. Islanding Applications of Energy Storage System. In Proceedings of the IEEE Power and Energy Society General Meeting, San Diego, CA, USA, 22–26 July 2012; pp. 1–5.
23. Costa, L.M.; Kariniotakis, G. A Stochastic Dynamic Programming Model for Optimal Use of Local Energy Resources in a Market Environment. In Proceedings of the IEEE Lausanne Power Tech, Lausanne, Switzerland, 1–5 July 2007; pp. 449–454.
24. Diaz, G.; Abd-el-Motaleb, A.M.; Mier, V. On the capacity factor of distributed wind generation in droop-regulated microgrids. IEEE Trans. Power Syst. 2013, 28, 1738–1746.