

Chapter 2

Reliability in Smart Grids

This chapter introduces a reliable method of power distribution in a smart power network with high penetration of Distributed Renewable Resources (DRRs). From many reliability concerns regarding the smart grids, this chapter is devoted to the following couple of major issues: *power adequacy improvement* and *electric congestion prevention* in large-scale presence of green energy.

Section 2.1 provides an introduction to the literature of reliability in smart grids powered by conventional generation and green energy. Section 2.2 presents some preliminaries on how the reliability of smart grids can be measured utilizing the probabilistic methods and formal metrics. Afterwards, Sect. 2.3 proposes an example of reliability quantification of power networks with high penetration of distributed renewable (green) resources which have an increasingly important role in the future power networks.

Additionally, Sect. 2.4 addresses power congestion as a crucial reliability challenge in smart distribution power networks. It also introduces the mitigation mechanisms which help to reduce the power congestion in power lines of distribution networks. Finally, Sect. 2.5 summarizes the materials presented in this chapter in order to obtain an accurate understanding of some reliability issues in smart grids.

2.1 Introduction

Smart power grids deploy many technologies in order to turn the classic power network into a more distributed customer-driven one. On this way, electric vehicles [1], smart home appliances [2], Distributed Renewable Resources (DRRs) [3], and many other technologies have emerged and continue to emerge. One of the major challenges facing the aforementioned transition from a centralized generation-driven power network toward the modern smart power grids is balancing the demand and supply values which fluctuate much more than what is expected in a traditional

network [4, 5]. Without balancing the highly fluctuating values of demand and supply in the modern smart grids, the dream of enjoying its benefits will face major reliability issues as the loss of load probability will go through the roof if smart grids don't modernize its power resource management.

Here, we introduce a number of recent attempts to solve the aforementioned reliability issues in smart grids and keep the loss of load probability acceptably low in presence of DRRs and other new technologies which make the power demand values fairly unpredictable. Kekatos et al. presented an effective non-deterministic reactive power management scheme in [6]. Additionally, [7] proposed a distributed control scheme in order to manage the stochastic demand side of a smart grid by following the desired set-points for distributed level controllers. Likewise, another decentralized control approach was designed in [8] in order to have a low-cost DRR-based smart micro-grids. Moreover, [9] had a complete review of resource management schemes in a smart grid with non-deterministic nature of demand and generation.

In [10], Iyengar et al. proposed a new scheme for quantifiably reliable resource management and balancing the demand side and fluctuating generation of DRRs. Furthermore, they introduced a novel two-tier controlling scheme in [11] which handles the problem of uncertain demand and generation in modern architecture of smart power network. Additionally, distributed sensor networks, which are mathematically studied in [12], can help monitor the future power networks management and control.

A report of U.S. Department of Energy in 2008 [11] shows that recent progress in IT and communication technologies has made it possible to develop cost efficient power distribution systems. Smart distribution networks might have some specific functionalities such as self-healing, self-decision making, and resiliency [13, 14]. These requirements compel a new way of designing smart distribution grids for an economically-dispatched power distribution. As economic dispatch (ED) is one of the optimization problems related to the power systems operation, several techniques are used in the literature to solve this problem, e.g., mixed integer linear programming (MILP), constraint relaxation, and network approach [15]. Due to large-scale nature of the optimization problems in power systems, we have to utilize numerically efficient algorithms to overcome the complexity of these problems, specifically the ED problem [16].

Economic Dispatch ED is a major minimization problem in the field of power systems management and aims to compute the best way of satisfying the demand side of the power system by having enough committed generation units. In contrast, the unit commitment (UC) problem is another optimization problem with the goal of balancing the demand and generation of a power system on a day-ahead basis. This is while the ED is defined as the problem of balancing demand and generation for the next hour relying on the optimization solution of UC [17, 18].

Economic dispatch is considered as one of the most challenging issues facing the wide deployment of smarter grids with high penetration of DRRs [19]. A survey on the current methods of solving the ED problem has been accomplished in [9].

In the smart distribution networks, because of wide-usage of the DRRs, there is a need for designing new ED methods which prevents the power congestion in the connections and buses of a smarter network. Moreover, in demand side of the story, the customers have a more fluctuating usage pattern as a result of emergence of new technologies like electric vehicles, smart appliances, etc. [20, 21].

During many years of research and mathematical efforts to reach a solution for economic dispatch problem, many heuristic and strategies have been built to solve ED problem. In [22], an optimization strategy inspired by particle swarm is proposed to economically dispatch electricity in the network. The specialty of this optimization problem is that it is not solvable with conventional convex optimization strategies as the ED problem is not defined as a convex optimization problem. In [23], a multi-agent systems-based load management is introduced in a smart decentralized power network. In [24], the focus of addressing ED was placed on the structural form of the representing graph of the electric network topology.

Moreover, Sanjari et al. in [25] proposed a bilevel optimization scheme for economically dispatching the resources in a smart grid. This approach is a combination of two multi-scale optimization schemes (one daily and one hourly optimizer) with the aim of creating an online dispatcher. According to [26, 27], today's common ED solutions utilized MILP to find the best way of balancing demand and supply in a power network. Botterud et al. introduced a load dispatch when wind generation plays a significant role [28]. However, [29] considers the possibility of storing energy in storage units and turning the identity of ED optimization problem into a non-convex one which is not the same as the conventional convex problems. According to Li et al., there are some relaxation techniques that dissolve the non-convexity of the problem and make it possible for conventional methods to find the best dispatching solution [30] which minimizes the cost of dispatching power from the distributed generation toward the demand side. The objective function in this work constitutes two expressions, a deterministic cost of dispatching through the power connections and a stochastic power generation cost. Khator et al. proposed a mixed binary linear programming formulation to model the ED problem since the cost function can be modeled as a *concave* function of power flows.

In 2003, Yi Liu et al. in [21] introduced a minimization scheme for smart power dispatching in a power network which dispatches power from distributed generation through two-way power connections. In this work, which utilizes a pricing model with two levels, there is a high penetration of DRRs in the grid. In this model, the demand side is divided into two different power demands: deferrable and essential power demands. They modelled a scheme to satisfies both demand types by creating a trading policy and pricing protocol.

Oblivious Network Design One of the powerful mathematical tools that can play a crucial role in solving complex network optimization problems like ED is called oblivious network routing. There have been many efforts in the recent years by the researchers to develop various schemes for solving optimization problems with few known constraints. In some of these optimization problems, the objective function may change in different conditions and the constraints are not specified in advance.

In other words, oblivious network routing aims to give a solution to a set of optimization problems with a *set* of possible objective functions and a set of *possible* constraints. As a result, the solution to such problem does not aim to find the best solution for all the possible conditions. In fact, there may be no common solution to the set of given optimization problems. Instead, the oblivious network routing tries to give a routing solution to a set of network optimization problems so that the objective functions don't differ from their optimum values by an *approximation ratio* in all the cases [31, 32].

2.2 Preliminaries on Reliability Quantification

This section presents some preliminary concepts regarding the power adequacy, system reliability, and the quantification method for measuring the level of system reliability. Let $x_1, x_2, \dots, x_n$ denote n customers spread over a residential smart power grid. Each customer x has a power load profile $p.(t)$ which specifies the time path of the power load that the customer needs over time and expects the smart grid to satisfy it in a timely manner. Also, consider that this load profile consists of two terms: a deterministic predictable term $\hat{p}.(t)$ and a stochastic unpredictable term $\varepsilon.(t)$ which is considered as the *prediction error* of the load profile and assumed to be a Gaussian White Noise (GWN) of standard deviation less than σ_d .

On the generation side, there are two types of power generations that are distributed over the smart power grids and together manage to satisfy the customers' demand values over time: DRRs and conventional power plants. The conventional power plants as a global source of energy are expected to generate a deterministic *base generation* $G(t)$ over time. The DRRs, which are considered as the main source of power, are distributed over the power grid. Assume that $y_1, y_2, \dots, y_n$ denote the n DRRs corresponding to the n customers and designed to satisfy their corresponding customers. Consider $g.(t)$ as the power generation profile of an arbitrary DRR y . Also, let $\hat{g}.(t)$ and $\delta.(t)$, respectively, represent the predictable and stochastic part of the output for every renewable resource y where $\delta.(t)$ is a GWN of standard deviation less than σ_g .

Balancing Supply and Demand

After modeling the demand and generation side, it is time to come up with a scheme that aims to balance the supply and demand in a power network and make customers of the electric system satisfied. Based on the aforementioned model, the total generation load profile in the under-studied system is $G(t) + \sum_i \hat{g}_i(t) + \sum_i \delta_i(t)$, while its total demand load profile is $\sum_i \hat{p}_i(t) + \sum_i \varepsilon_i(t)$. The first step toward balancing the demand and supply is keeping the deterministic (predictable) part of demand profile satisfied by the deterministic part of the generation side; i.e.

$G(t) + \sum_i \hat{g}_i(t) \geq \sum_i \hat{p}_i(t)$. Additionally, considering the constraints of conventional power plants, the amount of power generation can't fall below some low-threshold $G_{\min}$. As a result, we conclude that $G(t)$ should be set on the following value:

$$G(t) = \max \left\{ G_{\min}, \sum_i \max\{0, \hat{p}_i(t) - \hat{g}_i(t)\} \right\}. \quad (2.1)$$

In the time periods that $G(t) = \sum_i \max\{0, \hat{p}_i(t) - \hat{g}_i(t)\}$, every customer receives a base generation of amount $g_i^{\text{base}}(t) = \max\{0, \hat{p}_i(t) - \hat{g}_i(t)\}$. Otherwise, the generation base is used to charge the distributed storage units of the customers. Here, we continue the discussion in the following two cases:

Demand Exceeding the Supply

In this case, customers' demand exceeds the base generation plus the power generated by their corresponding DRRs; i.e. $p_i(t) > g_i(t) + \hat{p}_i(t) - \hat{g}_i(t)$ for a certain period of time. In such cases, the storage unit deployed in the customer side is charged with the rate of $\min\{C_{\max}, \varepsilon_i(t) - \delta_i(t)\}$ over that specific period where $C_{\max}$ represents the maximum charging rate of the storage unit which is a physical characteristic of the unit.

Supply Exceeding the Demand

On the other hand, there are some cases that customers' demand falls below the power generated by their corresponding DRRs; i.e. $p_i(t) < g_i(t)$ for a certain period of time. In such cases, the storage unit deployed in the customer side is discharged with the rate of $\min\{D_{\max}, g_i(t) - d_i(t)\}$ in that specific period where $D_{\max}$ represents the maximum discharging rate of the storage unit which is a physical characteristic of the unit.

2.3 System Adequacy Quantification

An electrical system maintains its adequacy as long as the customer demand is satisfied by the generation side of the system. Since we consider a storage unit connected to each customer, the system is called adequate if and only if the available energy $S_i(t)$ to any customer x doesn't fall below a specific value $s_{\min}$; i.e. $S_i(t) \geq s_{\min}$. Additionally, assume that the initial available energy to every customer is $S_i(t) = s_0 > s_{\min}$. Henceforth, the Loss of Load Probability for a given customer at the given moment t is defined as $1 - \Pr[\forall t' \leq t : S_i(t') \geq s_{\min}]$.

Here, we quantify the LOLP in the case that there exists no realtime change in the base generation, there is a high chance of having a power shortage. Mathematically, since $S.(t) = \int_0^t (g.(t') - p.(t') + g^{(\text{base})}(t'))dt' + s_0$, the value of LOLP for a given customer x . would be not less than $\Pr[\sup_{t' \leq t} \{\int_0^{t'} (\varepsilon.(t') - \delta.(t'))dt'\} > s_0 - s_{\min}]$. Since $\varepsilon(t)$ and $\delta(t)$ are two GWN process, $\int_0^t (\varepsilon.(t') - \delta.(t'))dt'$ is a Brownian Motion Process and $\sup_{t' \leq t} \{\int_0^{t'} (\varepsilon.(t') - \delta.(t'))dt'\}$ is a *running maximum process* which concludes that the LOLP value does not exceed $1 - \text{erf}\left(\frac{s_0 - s_{\min}}{\sqrt{2t(\sigma_d^2 + \sigma_g^2)}}\right)$.

2.4 Congestion Prevention: An Economic Dispatch Algorithm

This section discusses power congestion as one of the most important reliability challenges in smart distribution networks. Congestion prevention is a crucial constraint in dispatching power from generators to the demand side. Hence, the Economic Dispatch (ED) algorithms in smart grids need to prevent line power congestion while dispatching power efficiently. Although, this requirement is important in the classic deployment of centralized power generation in distribution networks, it gets more crucial in presence of distributed renewable resources where there are many paths for power flow to be dispatched to the demand side. As a result, congestion prevention in traditional power distribution networks turns into a challenging reliability issue in modern smart grids where there are a wide variety of power sources in the network and the topology of power lines is not *radial* anymore. This issue should be considered in the core of the ED algorithms where the power flows are routed through different paths in the complex topology of modern distribution networks. This section proposes a novel method of power dispatch which is based on a modern way of routing called *oblivious network routing*.

Oblivious routing is a heuristic way of approaching the Minimum-Cost Flow Problem (MCFP) which approximate the optimal congestion free solution to the flow problem when the current state of the network is unknown (oblivious). In fact, oblivious routing aims to find an acceptable solution of the MCFP when either the current traffic flow and/or flow cost functions are oblivious [31].

Consider a power distribution network which is designed to dispatch the power generated by the distributed generators $g_1, g_2, \dots, g_n$ to a set of residential communities $c_1, c_2, \dots, c_m$ through the network of communities $(\{c_i\}, E)$ where E is the set of power lines connecting two close by communities. The generation cost of the generator g_i for generating p units of power is a quadratic function of p with relatively small positive quadratic coefficient and large positive constant cost [33]. Also, assuming that power loss in the line $e \in E$ is a linear function of the power flow f_e , the traditional ED problem focuses on the problem of minimization the total generation cost subject to the following constraints:

- $f_e < \text{line capacity of } e \text{ for every } e \in E$.
- $m_i < \text{generation of } g_i < M_i$ where m_i and M_i specify the low/high threshold of power generation for generator g_i .
- Kirchhoff's current laws.
- Total generation = total loss + total demand

In order to consider the congestion prevention challenge while solving the ED problem, we need to keep the value of f_e 's low while approximating the economically efficient solution. As [31] mathematically proves, the top-down oblivious network routing algorithm can solve the oblivious MCFP problem in a way that the total cost asymptotically competes with the optimal cost; while the line congestion does not exceed a constant fraction of its minimum possible congestion.

As another example of reliability-driven ED problem, consider a distribution network which meets $N - 1$ reliability criterion; i.e. the ED solution re-dispatches the power in the case of a failure in a power line. As an example, consider the IEEE 38-bus test system [36] in Fig. 2.1. This figure depicts one possible power dispatch configuration; which Fig. 2.2 shows another way of power dispatch if the line connecting busses 18 and 31 crashes. In such circumstances where the topology of the distribution network is changing and unknown, the economic dispatch algorithm can improve the process of power re-dispatching tremendously.

2.5 Summary and Conclusion

This chapter introduced a reliable method of power distribution in a smart power network with high penetration of Distributed Renewable Resources (DRRs). From many reliability concerns regarding the smart grids, this chapter was devoted to the following couple of major issues: *power adequacy improvement* and *electric congestion prevention* in large-scale presence of green energy. Section 2.1 provided an introduction to the literature of reliability in smart grids powered by conventional generation and green energy. Section 2.2 presented some preliminaries on how the reliability of smart grids can be measured utilizing the probabilistic methods and formal metrics. Afterwards, Sect. 2.3 proposed an example of reliability quantification of power networks with high penetration of distributed renewable (green) resources which have an increasingly important role in the future power networks.

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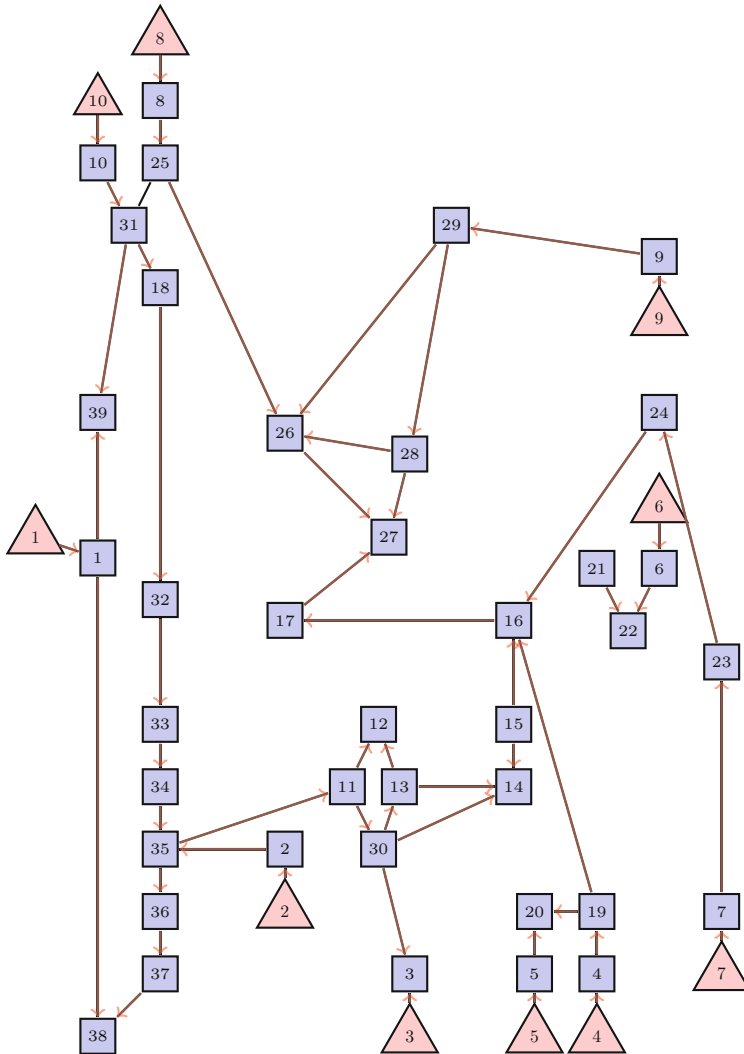


Fig. 2.1 IEEE 38-Bus standard test network

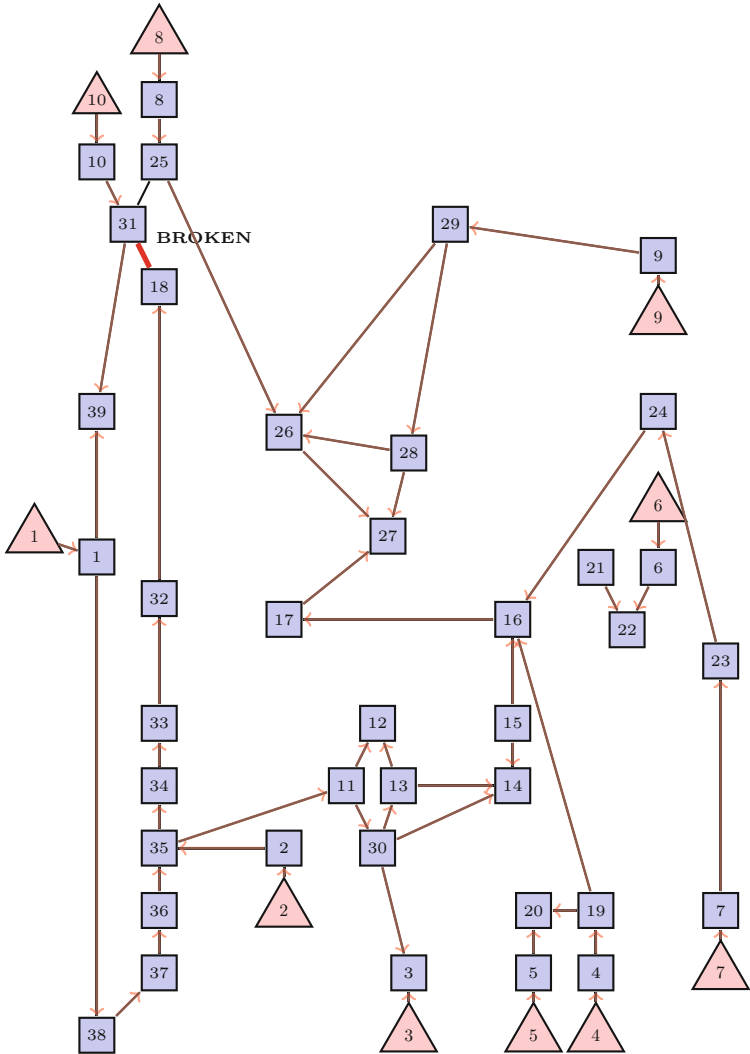


Fig. 2.2 IEEE 38-Bus standard test network

References

1. M.H. Amini et al., ARIMA-based demand forecasting method considering probabilistic model of electric vehicles parking lots, in *Proceedings of IEEE Power and Energy Society General Meeting*, 2015, pp. 1–5
2. M.H. Amini, J. Frye, M.D. Ilic, O. Karabasoglu, Smart residential energy scheduling utilizing two stage mixed integer linear programming, in *IEEE 47th North American Power Symposium (NAPS 2015)*, Charlotte, NC, 4–6 Oct 2015
3. A. Mohsenzadeh, M.-R. Haghifam, Simultaneous placement of conventional and renewable distributed generation using multi objective optimization, in *Proceedings of IEEE, Integration of Renewables into Distributed Grid Workshop, CIRED*, 2012
4. A. Papavasiliou, S.S. Oren, Supplying renewable energy to deferrable loads: algorithms and economic analysis, in *Proceedings of IEEE Power and Energy Society General Meeting, Minneapolis, Minnesota*, July 2010, pp. 1–8
5. A.R. Di Fazio, G. Fusco, M. Russo, Enhancing distribution networks to evolve toward smart grids: the voltage control problem, in *Proceedings of IEEE 52nd Annual Conference on Decision and Control (CDC)*, Firenze, Dec 2013, pp. 6940–6945
6. V. Kekatos, G. Wang, A.J. Conejo, G.B. Giannakis, Stochastic reactive power management in microgrids with renewables. *IEEE Trans. Power Syst.* **99**, 1–10 (2014)
7. S.E. Shafiei et al., A decentralized control method for direct smart grid control of refrigeration systems, in *Proceedings of IEEE 52nd Annual Conference on Decision and Control (CDC)*, Firenze, Dec 2013, pp. 6934–6939
8. G. Cavararo, R. Carli, S. Zampieri, A distributed control algorithm for the minimization of the power generation cost in smart micro-grid, in *Proceedings of IEEE 53rd Annual Conference on Decision and Control (CDC)*, Los Angeles, CA, Dec 2014, pp. 5642–5647
9. S. Kar, G. Hug, J. Mohammadi, J.M.F. Moura, Distributed state estimation and energy management in smart grids: a consensus+innovations approach. *IEEE J. Sel. Top. Sign. Proces.* **99**, 1–16 (2014)
10. S.S. Iyengar, K.G. Boroojeni, *Oblivious Network Routing Algorithms and Applications* (MIT Press, Cambridge, 2015)
11. U.S. Department of Energy, The smart grid: an introduction, 2008
12. S.S. Iyengar, K.G. Boroojeni, N. Balakrishnan, *Mathematical Theories of Distributed Sensor Networks* (Springer Publishing Company, Incorporated, Berlin, 2014)
13. A. Zidan, E.F. El-Saadany, A cooperative multi-agent framework for self-healing mechanisms in distribution systems. *IEEE Trans. Smart Grid* **3**(3), 1525–1539 (2012)
14. R.E. Brown, Impact of smart grid on distribution system design. in *Proceedings of IEEE Power and Energy Society General Meeting*, Pittsburgh, PA, July 2008, pp. 1–4
15. B.H. Chowdhury, S. Rahman, A review of recent advances in economic dispatch. *IEEE Trans. Power Syst.* **5**(4), 1248–1259 (1990)
16. V. Pappu, M. Carvalho, P. Pardalos, *Optimization and Security Challenges in Smart Power Grids* (Springer, Berlin, 2013)
17. J. Zhu, *Optimization of Power System Operation* (Wiley, New York, 2014)
18. N. Padhy, Unit commitment-a bibliographical survey. *IEEE Trans. Power Syst.* **19**(2), 1196–1205 (2004)
19. A. Papavasiliou, S.S. Oren, Supplying renewable energy to deferrable loads: algorithms and economic analysis, in *Proceedings of IEEE Power and Energy Society General Meeting*, Minneapolis, MN, July 2010, pp. 1–8
20. K.G. Boroojeni et al., Optimal two-tier forecasting power generation model in smart grids. *Int. J. Inf. Process.* **8**(4), 79–88 (2014)
21. Y. Liu, N. Ul Hassan, S. Huang, C. Yuen, Electricity cost minimization for a residential smart grid with distributed generation and bidirectional power transactions, in *IEEE Innovative Smart Grid Technologies (ISGT)*, Washington, DC, Feb 2013, pp. 1–6

22. A.I. Selvakumar, K. Thanushkodi, A new particle swarm optimization solution to nonconvex economic dispatch problems. *IEEE Trans. Power Syst.* **22**(1), 42–51 (2007)
23. M.H. Amini, B. Nabi, M.-R. Haghifam, Load management using multi-agent systems in smart distribution network, in *Proceedings of IEEE Power and Energy Society General Meeting*, Vancouver, BC, Canada, July 2013, pp. 1–5
24. J. Lavaei, D. Tse, B. Zhang, Geometry of power flows and optimization in distribution networks. *IEEE Trans. Power Syst.* **29**(2), 572–583 (2014)
25. M.J. Sanjari, H. Karami, H.B. Gooi, Micro-generation dispatch in a smart residential multi-carrier energy system considering demand forecast error. *Energy Convers. Manag.* **120**, 90–99 (2016)
26. E. Kellerer, F. Steinke, Scalable economic dispatch for smart distribution networks. *IEEE Trans. Power Syst.* **99**, 1–8 (2014)
27. M. Carrion, J. Arroyo, A computationally efficient mixed-integer linear formulation for the thermal unit commitment problem. *IEEE Trans. Power Syst.* **21**(3), 1371–1378 (2006)
28. A. Botterud, Z. Zhi, J. Wang et al., Demand dispatch and probabilistic wind power forecasting in unit commitment and economic dispatch: a case study of Illinois. *IEEE Trans. Sustainable Energy* **4**(1), 250–261 (2012)
29. Z. Li, Q. Guo, H. Sun, J. Wang, Sufficient conditions for exact relaxation of complementarity constraints for storage-concerned economic dispatch. *IEEE Trans. Power Syst.* **99**, 1–2 (2015)
30. S.K. Khator, L.C. Leung, Power distribution planning: a review of models and issues. *IEEE Trans. Power Syst.* **12**(3), 1151–1159 (1997)
31. S.S. Iyengar, K.G. Boroojeni, *Oblivious Network Routing: Algorithms and Applications* (MIT Press, Cambridge, 2015)
32. A. Gupta, M.T. Hajiaghayi, H. Racke, Oblivious network design, in *SODA '06: Proceedings of the 17th Annual ACM-SIAM Symposium on Discrete Algorithm* (ACM, New York, 2006), pp. 970–979
33. A.J. Wood, B.F. Wollenberg, *Power Generation, Operation, and Control* (Wiley, New York, 2012)
34. J. Fakcharoenphol, S.B. Rao, K. Talwar, A tight bound on approximating arbitrary metrics by tree metrics, in *Proceedings of the 35th STOC*, 2003, pp. 448–455
35. MATLAB version 8.5. Miami, Florida: The MathWorks Inc, 2015
36. University of Washington Electrical Engineering, Power systems test case archive (2015). Online Available: <http://www.ee.washington.edu/research/pstca/>
37. R.D. Zimmerman, C.E. Murillo-Sanchez, R.J. Thomas, MATPOWER: steady-state operations, planning and analysis tools for power systems research and education. *IEEE Trans. Power Syst.* **26**(1), 12–19 (2011)

Smart Grids: Security and Privacy Issues

Boroojeni, K.G.; Amini, M.H.; Iyengar, S.S.

2017, XIV, 113 p. 26 illus., 25 illus. in color., Hardcover

ISBN: 978-3-319-45049-0