Chapter 1
Smart Grids and Green Wireless Communications

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Nomenclature

AMI	Advanced metering infrastructure
AP	Access point
BS	Base station
CR	Cognitive radio
D2D	Device to device
DR	Demand response
DSM	Demand-side management
EE	Energy efficiency
EH	Energy harvesting
FQL	Fuzzy Q-learning
FSL	Fuzzy SARSA learning
GA	Genetic algorithm
GHG	Greenhouse gas
HetNet	Heterogeneous network
HPPP	Homogeneous Poisson point process
ICT	Information and communications technology
IoT	Internet of things
LTE-A	Long-term evolution advanced
M2M	Machine to machine
MNO	Mobile network operator
NE	Nash equilibrium
OPEX	Operational expenditure
PLC	Power line communications
PSM	Power saving mode

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QoS	Quality of service
RES	Renewable energy source
RPS	Renewable power supplier
SEP	Smart energy profile
SG	Smart grid
SGFAN	Smart grid field area network
SGHAN	Smart grid home area network
SGNAN	Smart grid neighborhood area network
SGWAN	Smart grid wide area network
SINR	Signal to interference and noise ratio
UDN	Ultradense network
UE	User equipment
UMTS	Universal mobile telecommunications system
WSN	Wireless sensor network

1.1 Introduction

In a traditional electric grid, the main causes of power inefficiency are high-voltage, long-distance transmission, and large-scale centralized electricity generation [1]. To improve the power efficiency and reliability of the grid, the concept of smart grids (SGs) has been proposed by using information and communications technology (ICT). Demand response (DR), decentralized power generation, demand-side management (DSM), and price signaling are the key characteristics of a SG associated with green wireless communications. With DR and DSM, both power generators and consumers can interact to optimize the process of power supply and consumption. The power generation may be performed by small distributed power plants (e.g., small wind turbines and solar panels) and consumers using decentralized design. Therefore, this could help consumers to be less dependent on the main electrical grid. With price signaling, the consumers will know about the present power price. Moreover, the generators can encourage consumers to consume electrical energy when the demand is low, i.e., during the off-peak period, by giving them a lower price for electricity during those times. This will result in a lower investment for the infrastructure as the peak load will be reduced.

In recent years, the integration of wireless communications and SGs has attracted a significant research attention [2]. On one hand, wireless communication technologies will play an essential role in the revolution of SGs by communicating a variety of data and measurement over all nodes of the electrical grid. On the other hand, for a better power usage when providing a wireless service to mobile units, SGs can be used to support green wireless communications. In wireless networks, each wireless base station (BS) powered by a SG might be selfish in optimizing its own operation in terms of capacity or quality of service (QoS). In this chapter, how to design energy-efficient communication infrastructures without negative effects on the performance is one of the main concerns. Indeed, the problems of power management, cost-function analysis, optimal network design, energy-harvesting (EH), and energy-efficient strategies are considered for green-powered communication networks in a SG environment and, in particular, we attempt to focus on efficient interaction between the RPS's random green power generations and the BS's dynamic of energy consumption via minimization of an energy-based cost function, considering the D2D and M2M impacts on efficient utilization of energy and bandwidth. In general, due to the unlimited growth of service demands and high load traffic, a green wireless communication system is considered with the aim of decreasing energy consumption of heterogeneous networks (HetNets). This system provides a proportion of required energy of BSs by employing some renewable power suppliers (RPSs), while user equipment (UE) and sensor nodes especially benefit from short device-to-device (D2D) and machine-to-machine (M2M) links as a promising technique to design energy-efficient HetNets.

1.2 Demand-Response Power Consumption Model

To meet today's rapid proliferation of data traffic, the cellular network operators are recently installing more and more BSs. As a result, the daily power cost adds up to a huge bit of the operational expenditure (OPEX). Therefore, the need for cellular operators to implement new energy-efficient solutions is critical in order to lower their energy costs [3–6]. In general, energy-efficient solutions can be employed by managing either the power supply or the data-traffic demand. On the supply side, energy-harvesting technologies, such as wind turbines and solar panels, at the BSs are considered as one of the most commonly adopted solutions. Using energy-harvesting devices, BSs can consume clean and affordable renewable energy to decrease or even substitute the energy purchased from the grid. It is clear that the power grid, as a reliable energy source to BSs, is still required. This is because the renewable energy is not always available when needed, and it is mainly distributed in both time and space in a random way. As a result, different BSs are hard to solely rely on the uncertain supply to power their units.

Power grid, in addition to being a reliable energy supply, can offer new capabilities for the BSs' cost-saving with its ongoing transformation from conventional grid to SG. A SG differs from the conventional grid in that it allows two-way data and energy flows between the grid and end users by deploying smart meters at end users, rather than a one-way flow. Energy cooperation in cellular networks, which allows the BSs to trade and share their harvested energy to support the nonuniform data traffic in a cost-effective way, will then be possible through the two-way delivery of energy-information flow in SG. On the demand side, to lower the energy consumption, different methods have been proposed across various layers of protocols for data transmission. Among these methods, communication cooperation, which enables the BSs to share the wireless resources and shift the traffic loads with each other, is the most appealing. However, the use of renewable energy sources at BSs

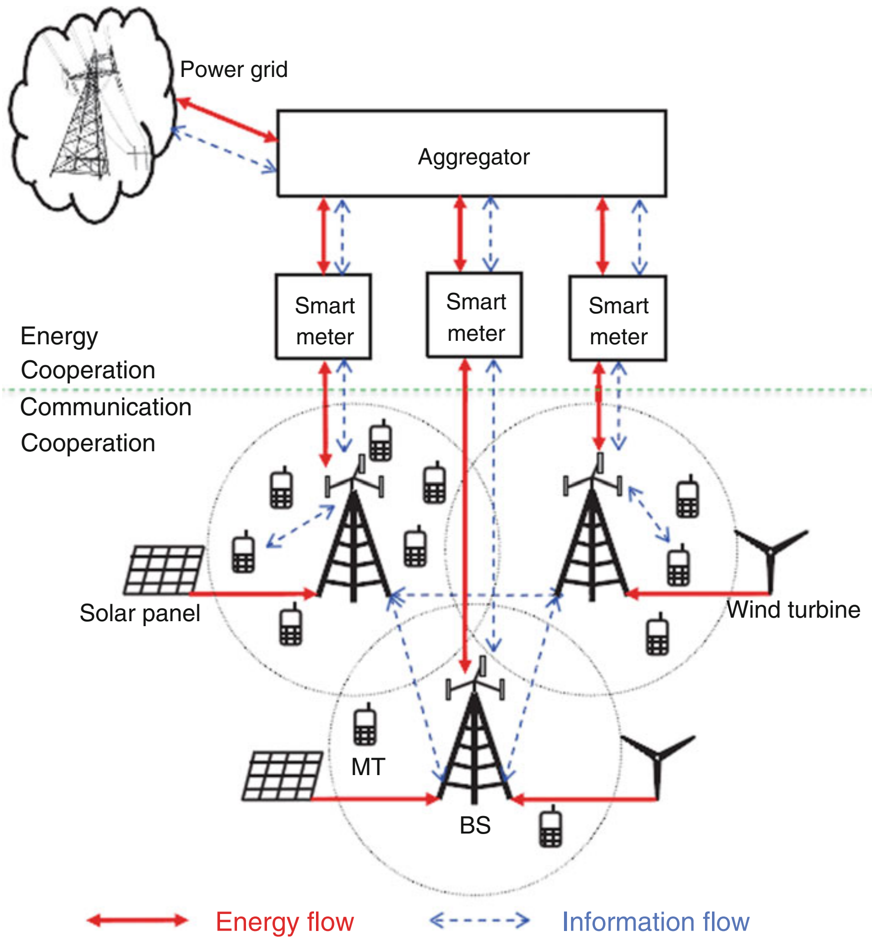


Fig. 1.1 A general model for integrated smart grids and green wireless communications [3]

would lead to a variety of new problems and challenges in the current communication cooperation design: the conventional design to save energy may no longer be cost-effective. In fact, although renewable energy is unreliable in supplying energy, in general it is way cheaper than the energy purchased from the grid and thus BSs should maximally harvest renewable energy to lower cost. However, under the energy-saving design, the harvested energy at BSs may not be efficiently exploited when serving a time-variant traffic load. To tackle this issue, the design of novel cost-aware communication cooperation schemes is desirable. This can be done by taking into consideration the cost differences between conventional and renewable energy sources [3]. In Fig. 1.1, we can see the general energy and communication cooperation model for cellular networks at the power supply and the communication demand layers, respectively.

1.3 Energy-Efficient Communication Infrastructures

In wireless networks, consisting of battery-powered nodes such as sensor nodes or mobile phones, energy efficiency (EE) has always been under consideration. However, until recently, the EE of network equipment powered from mains such as switches, routers, and BSs has not been caught in the spotlight of attention [7]. With the growing number of subscribers and their ever-increasing energy demands, electricity bills of service providers have been skyrocketing. Therefore, to reduce the energy consumption of core and access network equipment, significant efforts have been made in both academic and industrial projects. Besides the energy costs, the high level of greenhouse gas (GHG) emissions coming from the communication networks is expected to increase the expenses and costs of the operators with the forthcoming carbon taxes and caps. To lower energy costs and electricity bills, the communication infrastructure can employ the price-following demand management of SG. Indeed, on one side, the way energy-efficient communication technologies are implemented is influenced by SG-driven schemes. On the other side, SG is impacted from EE techniques as it involves dense communications.

In terms of communication coverage and functionality, we can roughly divide the SG into three interconnected communication networks: SG home area network (SGHAN), SG neighborhood area network (SGNAN), and SG wide area network (SGWAN). SGHAN basically corresponds to a network of signal-controlled appliances, consumer devices, and energy management devices. This will enable connected devices to send/receive signals from meter, displays, and other home management devices. Indeed, SGWAN covers home area monitoring, regulation, control, and management. SGNAN is applicable for distributed generation and distribution automation, and it is related to a group of houses possibly fed by the same transformer. SGWAN shelters SGHAN and SGNAN for monitoring and control of the entire communication network. SGWAN is a gigantic network covering the management of generation, transmission, distribution, and utilization of the entire grid. The communication facility for the electricity distribution systems is also formed by a SG field area network (SGFAN), which operates as a bridge between customer premises and substations. Since the geographical scale of a SGFAN is similar to SGNAN, similar communication techniques can be considered for both of them. A variety of communication technologies can be used to implement these network domains. For example, because of their wide-coverage fiber-optic, universal mobile telecommunications system (UMTS), long-term evolution (LTE)/ LTE-advanced (LTE-A) can be more applicable for SGWAN, while IEEE 802.11 and IEEE 802.15.4 power line communications (PLC) could be more appropriate for SGNAN and SGHAN. The authors in [8] present a profound research on routing protocols and applications in the related fields. Generally, wireless communications have a broad range of applications in the SG including demand management, substation, meter data collection, and power line monitoring and protection. In the following subsections, wireless technologies that are applied in SGWAN, SGNAN, and SGHAN are described, respectively.

1.3.1 Energy-Efficient SGWAN

The EE, in wireless communications, is generally defined as the ratio of the total achievable data rate to the total power consumption, and it is quantified by the "bits-per-joule" metric [7]. The EE of OFDMA as the common multiple access scheme for 3G, 4G, and WIMAX networks has been studied in several works. Note that 3G, 4G, and WIMAX stand as strong candidates for SGWAN. An energy-efficient rate adaptation and resource allocation approach has been presented in [9]. Multiple input multiple output (MIMO) is another technique that is common in 3G, 4G, and WIMAX. In MIMO, higher throughput is often achieved at the cost of using more antennas and therefore higher circuit power consumption. The authors in [10] propose a selective model of active antennas in order to improve EE for MIMO according to the daily profile of traffic loads. In a SG environment, the implications of adaptively changing the number of antennas have been explored. Note that the effects of this adaptive approach on the performance of SG applications still remain as an essential challenge.

Finally, according to the IEEE 802.22 standard, cognitive radio (CR) is a technology that allows unlicensed users to access the blank frequency bands. Based on the concept of CR, underutilized resources that are facing scarcity are being used by unlicensed secondary users opportunistically when the primary users (licensed user) are idle, i.e., when the channels are not occupied by primary users. Thus, the spectrum is maximized and the channels are vacated before the primary users arrive since they have higher priority. The authors in [11] have suggested a CR network that senses not only the radio-frequency bands but also the SG resources. Under real-time pricing, the operating cost of the CR network is optimized. More specifically, BSs manage their power consumptions over the related cells according to the electricity costs. Although the main focus of those studies has not been energy conservation, they are providing a combinational model of CR networks and SG concepts. To this end, EE of CR has been investigated in [12]. The effects of EE techniques on the QoS of SG data and other related challenges in energy-efficient communications have been discussed in [7] as well.

1.3.2 Energy-Efficient SGNAN

SGNAN, one of the important fields, carries large volumes of data that come from heterogeneous data sources and supports a large number of devices. Indeed, 3G, 4G, and WIMAX can also be exploited in the SGNAN as they are strong candidates for SGWAN. In addition, promising deployments for urban SGNANs are offered by the IEEE 802.11 family of standards. Recently, power saving mode (PSM) has been adopted by several IEEE 802.11 standards in their operations. PSM is utilized by IEEE 802.11b and IEEE 802.11s to enable sleep mechanisms for wireless nodes when they are not in active mode, i.e., when they are not transferring data. IEEE

802.11b is also preferred for SGHANs because it is widely used for residential premises, while IEEE 802.11s, the mesh standard, is defined as a promising solution for electric vehicle networks. In [13], the authors consider an admission control scenario for electric vehicles to study the performance of IEEE 802.11s. In fact, PSM can be used for SGNAN communications; however, one bottleneck of the PSM is the extra delay which is the common issue in all sleep/wake-up mechanisms [14]. Because of this, it is necessary to further explore the impacts of PSM on the SG operation [7].

1.3.3 Energy-Efficient SGHAN

In general, ZigBee is considered a widely adopted protocol for home automation and smart energy standards in SGHANs. Recently, there exist different types of ZigBee-certified products for home automation. Some of the leading smart meter vendors have manufactured ZigBee-enabled smart meters. In addition, smart energy profile (SEP) has been developed by ZigBee Alliance to support the needs of smart metering and advanced metering infrastructure (AMI) and connects utilities and household devices. Indeed, ZigBee is a new technology of short-range, low complexity, low power consumption, low-cost, and duplex wireless communications that is based on the IEEE 802.15.4 standard. Initially, ZigBee was defined for power-constrained sensor networks; thus, EE is an intrinsic property of ZigBee. The authors in [15] propose to use a ZigBee-based wireless sensor network (WSN) for demand management in the SGHAN. Another strong candidate for wireless SGHAN communications is Wi-Fi. The use of Wi-Fi-enabled sensors in the SG has been researched in [16]. Particularly, it is expected that newly emerging ultralow-power Wi-Fi chips increase the adoption of Wi-Fi for WSNs and increase their interoperability at SGHAN. There is abundant literature relating to energy saving and EE in WSNs; however, those works are out of the scope of this chapter because they are independent of SG concepts such as demand management and dynamic pricing. Besides ZigBee and Wi-Fi, cellular technologies are also able to provide data-transmission links among residential premises distributed over small cells. To lower the energy consumption of the transmitters in SGHAN, femtocells and indoor picocells can be used as they are more energy-efficient than macrocells [17]. It should be noted that the total power consumption of a cellular network can be reduced by up to 60% in urban areas using the joint deployment of macro- and residential picocells. Moreover, the growth of small cell density and ultradense networks (UDNs) will increase the EE [18]. As a result, implementing small-cell-based SGHANs provides energy-efficient wireless communications [7].

1.4 Green Communications Model to Support Smart Grids

As already stated, due to the rapid growth of subscribers and the traffic loads, power consumption of the networks is rising [19]. Indeed, the main issues in correspondence to the rise in the number of sensors and devices need to be responded through an improvement in EE. The traditional networks provide capacity enhancement by focusing on the transmission power. However, such strategy is not always applicable from the economic perspective of the mobile network operators (MNOs). Therefore, modernization of cellular networks with green strategies is one of the most important goals which is realized by the 5G networks and the networks thereafter. This goal is met by reducing the power consumption which is not related to information transmission directly. The 5G green strategies which allow minimization of power consumption can be observed in Fig. 1.2.

Since the highest proportion of energy is consumed by the BSs, some practical strategies should be investigated in order to reduce power consumption and achieve the desired demand response without ignoring the acceptable QoS [20]. Meanwhile, employing renewable energy sources (RESs) has been suggested to reduce the overall grid energy consumption of HetNets, where the user equipment and machines are respectively allowed to use D2D and M2M communications to improve the capacity with little amount of energy in the presence of managing the interference [21]. In D2D communications, UEs are able to transmit information via direct links not through the BS, which offloads the traffic load of the core network. D2D users can either utilize different time/frequency resources from cellular ones (overlay mode) or reuse the same resources with them and transmit simultaneously (underlay mode) [22]. Considering environmental conditions and dependence on location and weather, the amount of supplied power of renewable power suppliers (RPSs) is variable. In addition, the reservation capacity of RPSs is limited. Thus, a proper controlling mechanism is essential for efficient power allocation. In addition,

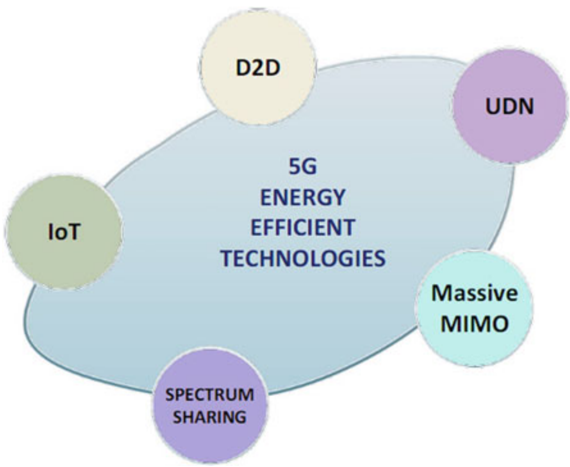


Fig. 1.2 Energy-efficient technologies for green wireless communications [19]

minimizing the cost function of both supply cost of RPSs and energy reservation cost of BSs is the other main criterion in the system design [23]. This system provides a proportion of the required energy of BSs by employing some RPSs, while UEs especially benefit from short D2D links as a promising technique to design energy-efficient HetNets. Indeed, according to our presented model, BSs are jointly powered via a renewable energy source and the electric grid (EG).

As stated, the factor of EE is critical to obtain the maximum performance of cellular networks, according to power consumption of the whole system. Prior researches have considered various conditions and applied different technologies to get a desirable level for EE. Due to the high power consumption of BSs, [20] presents an online algorithm where a BS is able to switch between on and off states based on traffic load. In order to manage and minimize power consumption of the BS, employing RPSs has been developed and some of the famous operators like Huawei and Ericson have started exploiting this technology to provide energy for the BS via these sources [24]. Some beneficial optimal strategies for BS's transmission were considered to reduce the amount of energy demand while considering the QoS requirements [25]. Due to the time-variant energy demands of a BS, article [5] showed that BSs are able to determine the amount of both used and reserved energies. Considering undeniable cost, the recent research in [26] presented a stochastic programming approach in order to minimize energy cost regarding BS's storage and utilizing RPSs. Ref. [23] proposes a new noncooperative game model to achieve an optimal strategy for decentralized allocating energy and minimize the cost of BS for reservation and RPS for supply based on the interaction between them. Indeed, using an M/M/G make-to-stock queue model, the impact of QoS on the energy supply rate of RPS and energy storage level was discussed. On the other hand, D2D communications in wireless cellular networks have attracted researcher's attention. D2D communication is a promising technique for improving the system performance with respect to reducing power consumption of BSs and increasing the whole network throughput. To get this aim, in [27] D2D communications and HetNets have been presented together for designing a future generation of systems in order to maximize the amount of spectrum reusing. Mobile association, as an important factor in choosing access points (APs) with the aim of balancing load distribution and providing the best performance, has been analyzed in [28]. Some practical strategies have also been investigated to provide energy-efficient resource allocation for D2D-aided networks. In [29], authors introduce a method for managing resources by employing a novel model called coalition game. A resource allocation technique based on the game and matching theory has also emerged to get maximum EE of users [30]. Energy harvesting (EH), as an efficient solution to overcome the limitation problem of battery capacity and lifetime, has been promoted recently which enables users to get the required energy from RPSs [31]. This will reduce the amount of power consumption of BSs. In [21], to perform the joint optimization of power control and resource allocation problem in a D2D-aided network using EH technology, authors provided an energy-efficient stable matching algorithm. In [32], an energy-efficient mobile association has been investigated to maximize the EE of networks by solving a joint optimization problem of AP selection, switching mode, and power control.

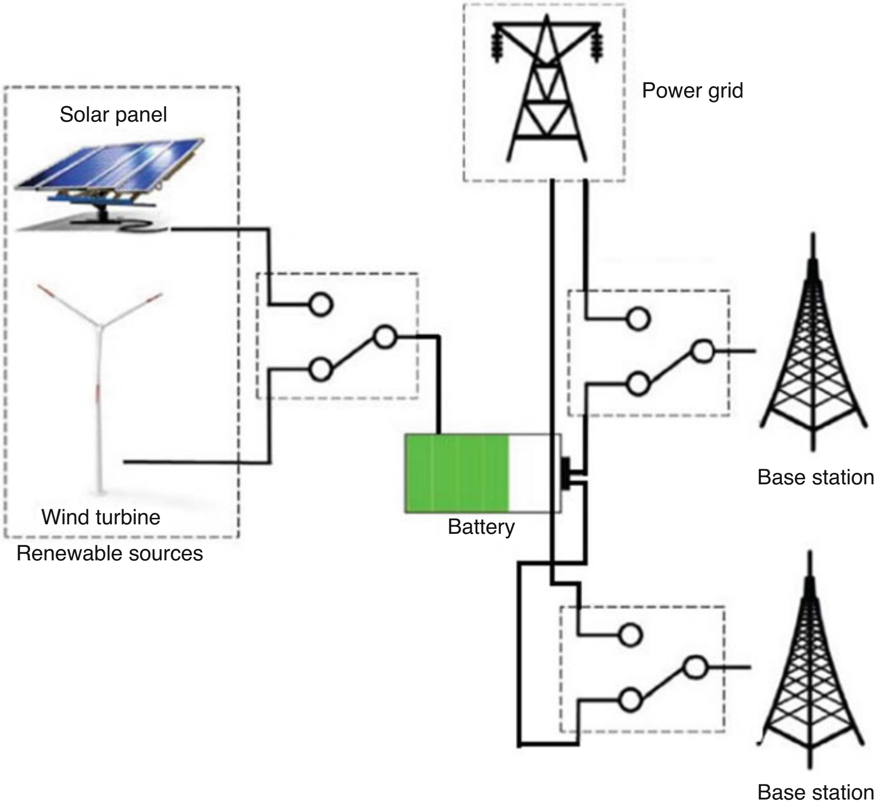


Fig. 1.3 Green-powered communication base stations

Moreover, we provide a green cellular model in which the BSs are jointly powered via RES and EG power sources. Indeed, we present the efficient interaction between the RPS's green power generations and the BSs' dynamic of power consumption via minimization of an energy-based cost function, considering the cache-enabled D2D impacts on efficient utilization of energy and bandwidth. The network performance takes into consideration the downlink (DL) connections as well. In this scenario, the system components are described in detail that refer to the renewable-energy-powered BSs and the power supplier consisting of EG and RPS (Fig. 1.3). The output power of the supplier is considered as random variable with mean η_s^0 (energy per time). Considering the finite capacity of the RPS, η_s is defined as the amount of supply rate of the RPS based on the RPS's production model in the BS's point of view $\left(\eta_s < \eta_s^0\right)$. Indeed, we analyze the power consumption of the BS in a wireless system that involves both static and dynamic parts such that it is related to the type of BS. In addition, estimation of the connection demands over a cell is possible due to the usage history. The connection demand is modeled as a stochastic homogeneous Poisson point process (HPPP) with rate λ_c (the number of connection demands/unit time). Providing connection demand is due to the order of arrival connections that follows the first-come-first-served model, and E is defined as a unit of consuming energy of a BS in each connection in the DL mode. The energy storage unit of the BS should be charged by the green energy in order to respond to the D2D-aided network demands and provide mobile services. Thus, if the stored energy of the BS is not enough to achieve a desired QoS, the BS will compensate this shortage by requesting and reserving power from the RPS and consequently paying a specific price for each unit energy. The methods of reserving energy from RPS depend on the condition of renewable power production. As a result, the BSs are responsible for paying the cost C_{r} per unit time due to the holding energy in storage unit according to the desired energy level α.

Users in the HetNet can request popular contents from neighboring users through D2D communication, whereas they can also request contents from the BSs by the traditional cellular communication [33, 34]. Users may request files from a set of m files, named "library." We assume the BSs are aware of the stored files and channel state information of the users and control the D2D communications. For example, a user node u establishes a link with a certain BS when the user node u requests a file from the "library" of size m. Then, BS searches the requested file in the certain area where the user is located at the center point. If the file is found, BS allocates a frequency sub-band f_{D2D} for the D2D link between the user u and the user storing the file. Otherwise, user u receives the file through the traditional cellular network. Here, we also assume that users follow PPP with average intensity λ_{U}; that is, the probability that l users exist in the area S is

$$f(l;S) = \frac{\left(|S|\lambda_{\mathrm{U}}\right)^{l}}{l!}\mathrm{e}^{-|S|\lambda_{\mathrm{U}}} \tag{1.1}$$

where$|S|$ means the area of district S. Denote the probability that a user stores the file i as p_i. Therefore, the file i is distributed with the PPP model with average intensity $\lambda_{UD}p_i$. Also, let r_d be a random variable representing the distance between the reference user requesting file i and the nearest user storing the file i. When $r_d > d$, there exists no user with file i in the area S ($|S| = \pi d^2$). Thus, the probability of the reference user successfully establishing a D2D link to deliver the desired file is

$$Pr(r_d \leq d) = 1 - Pr(r_d > d) = 1 - f(0;S) = 1 - \mathrm{e}^{-\pi d^2 \lambda_{UD} p_i} \tag{1.2}$$

Obviously, only users without file i try to send the request to get file i. As a result, averagely, there are $\lambda_{\mathrm{U}}\left|\acute{S}\right|(1 - p_i)$ users who may request file i in the network. $\left|\acute{S}\right|$ is the area of the cellular system. The probability that users cache the ith ranked file can be expressed as (Zipf distributions) [35]

$$p_i = \frac{(1/i)^{r_c}}{\sum_{j=1}^{m}(1/j)^{r_c}} \quad i = 1, 2, \ldots, m \tag{1.3}$$

where $r_c \geq 0$ is a parameter named skew coefficient and characterizes the distribution by controlling the relative popularity. Let q_i denote the probability that file i is requested by a user; the user request probability also follows the Zipf distribution [35]. Based on the above explanations, the number of activated D2D links for delivering file i is

$$n_i = \lambda_U |\acute{S}|(1 - p_i)q_i\left(1 - e^{-\pi d^2 \lambda_{UD} p_i}\right) \tag{1.4}$$

and the expected number of active D2D links for all files can be given by

$$N_{D2D} = \sum_{i=1}^{m} \lambda_U |\acute{S}|(1 - p_i)q_i\left(1 - e^{-\pi d^2 \lambda_{UD} p_i}\right) \tag{1.5}$$

A cellular link with the reference user is set up if establishing a D2D communication link is a failure. It implies that a traditional cellular link has to be established if the reference receiver cannot find the corresponding user who stores the desired file within the maximum transmission range of D2D links (d). Thus, the expected number of cellular links for all files (or the expected number of users who obtain their desired files from the cellular network) is

$$N_{Cellular} = \sum_{i=1}^{m} \lambda_U |\acute{S}|(1 - p_i)q_i\left(e^{-\pi d^2 \lambda_{UD} p_i}\right) \tag{1.6}$$

1.5 Energy-Cost Analysis

Considering one time unit for each connection with one unit energy consumption, in the presence of a backlogged access where the BS is not able to provide the desired energy level α for the UE's demand, the BS energy storage should be charged to α units via RPS. Thus, the process of reserving energy follows the energy inventory strategy [23] in order to avoid placing energy replenishment by the BS without paying attention to connection arriving. Scheduling the process of a queuing system has impressive effects on improving QoS. In our model, where the backlogged access occurs, the UE has to wait for a while and this leads to QoS deterioration. As a result, a cost δ will be assigned to the system. This cost is divided into two parts and is devoted to the BS and RPS with a fraction $\delta \in [0, 1]$. We define parameter C_b as the average number of backlogged accesses, C_r as the average energy reservation level, and C_η as the operation cost for the RPS which is considered because of load factor variation of the RPS (i.e., the relation of the service demand rate and the service supply rate as $\rho = \lambda_c/\eta_s < 1$). Indeed, the RPS is able to distribute energy among several BSs. The mean cost per unit time for both the BS and RPS is respectively formulated as

$$C_{\mathrm{BS}}(\alpha, \eta_s) = \varepsilon \cdot C_r - \epsilon R_{\mathrm{D2D}} + \delta C_b \tag{1.7}$$

and

$$C_{\mathrm{RPS}}(\alpha, \eta_s) = (1 - \delta) C_b + \xi C_\eta \tag{1.8}$$

where ε, ϵ, and ξ are the cost coefficients, and R_{D2D} is defined as a saving energy reward for D2D communications over a cell which may lead to data traffic offloading from the BSs. In order to analyze and optimize the cost functions of the RPS and the BS, we will utilize an M/M/G queue to determine C_r and C_b with the help of α and η_s. Thus, we investigate a model based on the noncooperative strategic game [36] with predefined assumptions, in a way that the BS and the RPS are the players of this game with the strategies α and η_s, respectively. A queuing policy will be followed in our model which is based on the BS that is considered as a single-server queue with specified demand rate λ_c and service rate η_s. Here we assume N_c as a continuous random variable that is geometrically distributed with mean $\rho/(1 - \rho)$ or exponentially distributed with parameter $\beta = (1 - \rho)/\rho = (\eta_s - \lambda_c)/\lambda_c$ and shows the stationary number of waiting connections. It is straightforward to express the average cost functions as $C_r = E[\alpha > N_c]$, $C_b = E[\alpha < N_c]$ and also the average D2D reward function as $R_{\mathrm{D2D}} = E[N_{\mathrm{D2D}} < \alpha < N_c]$.

A wireless network based on a queuing system with heavy traffic condition has a large ρ, meaning that there is a shortage of green energy production. Since there are several entities (i.e., BSs) with rate λ_b which request power from the RPS, the load factor can be defined as $C_\eta = \lambda_b/\left(\eta_s^0 - \eta_s\right) - \lambda_b/\eta_s^0 = \lambda_b \eta_s/\eta_s^0\left(\eta_s^0 - \eta_s\right)$ that represents the operation cost (the average power supply cost) of the RPS. Recall that η_s^0 is the maximum power generation rate of the RPS and η_s is the provided power for the BS by the RPS. Thus, a Poisson process is introduced with rate $\eta_s^0 - \eta_s$ that defines the rest of the supply capacity of the RPS. Load factor is an important parameter for a queuing system in order to determine the average queue length. When load factor arrives 1, it means that the average queue length will get to infinity and finally leads to loss QoS totally. Here, we attempt to express average cost of the BS and the RPS while they are normalized and investigated in terms of the α and β (normalized energy supply rate). Therefore, the average cost of the BS and the RPS are respectively given as follows:

$$C_{\mathrm{BS}}(\alpha, \beta) = \alpha - \frac{1 - e^{-\alpha\beta}}{\beta} - \epsilon R_{\mathrm{D2D}} + \delta \frac{e^{-\alpha\beta}}{\beta} \tag{1.9}$$

$$C_{\mathrm{RPS}}(\alpha,\beta) = (1-\delta)\frac{\mathrm{e}^{-\alpha\beta}}{\beta} + \frac{\lambda_{\mathrm{c}}(\beta+1)}{\eta_{\mathrm{s}}^{0} - \lambda_{\mathrm{c}}(\beta+1)} \tag{1.10}$$

The mentioned demand-response system operates over periodic intervals during which network parameters such as the power production capacity and connection demand rate can be estimated. However, smart grid monitoring systems are able to extract the required network characteristics from history record and atmospheric parameters [23]. It should be noted that fixed power prices are assumed in this model. Therefore, no matter whether the RPS has storage or not, it should respond to the power demands from the BS rather than storing the energy. Indeed, the BSs' action to choose a strategy α corresponds to set a power replenish order to the RPS. Therefore, at the start of the game, the BS should have charged its energy storage to an inventory of α energy units through the existing EG or the RPS. Once the game starts, the RPS attempts to supply the energy with the service rate β and the BS serves the users with the renewable energy, thereby striking a balance between the power consumption and maintaining the QoS. Generally, in a distributed game-theoretic formulation, both BS and RPS attempt to select their individual strategies α and β so that their own cost functions are minimized. It means that the BS will opt α to reach a minimum value for $C_{\mathrm{BS}}(\alpha,\beta)$, assuming that the RPS selects β to minimize $C_{\mathrm{RPS}}(\alpha,\beta)$; similarly, the RPS will simultaneously assign a value for β to minimize $C_{\mathrm{RPS}}(\alpha,\beta)$, assuming the BS uses α to minimize $C_{\mathrm{BS}}(\alpha,\beta)$. Thus, a pair of strategies (α^*,β^*) is a Nash equilibrium (NE) if neither the BS nor the RPS can gain from a one-sided deviation from their strategies, i.e.,

$$\alpha^* = arg\min_{\alpha} C_{\mathrm{BS}}(\alpha,\beta^*) \tag{1.11}$$

and

$$\beta^* = arg\min_{\beta} C_{\mathrm{RPS}}(\alpha^*,\beta) \tag{1.12}$$

Since the existence of the NE is guaranteed as [23], the conventional best response dynamics [36, 37] can be exploited to converge to the NE. Therefore, the RPS and the BS can adopt a plan about the strategies at the start of the game. Further, the performance of the demand-response strategies is evaluated for the RPS and BSs over a HetNet with a specific power consumption profile. Indeed, a model based on the noncooperative strategic game is considered with predefined assumptions, in a way that the BS and the RPS are the players of this game with the strategies α and β, respectively. Then, the D2D communication is exploited to reduce the cost values for the RPS and BSs formulated in this section in order to determine the D2D impacts on efficient utilization of energy.

In the first set of results (Figs. 1.4, 1.5, and 1.6) presented here, the power demand and related cost values for the RPS and $N = 20$ BSs are evaluated according to the specific network power-consumption profile. Later (in Fig. 1.7), the D2D impacts on

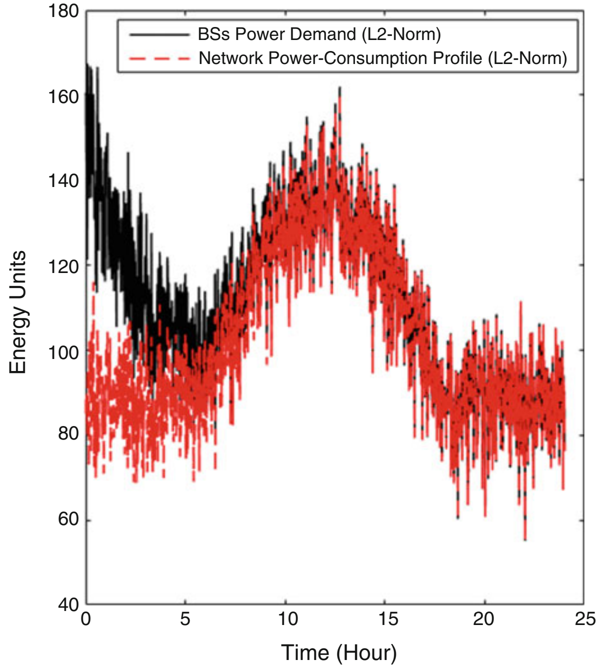


Fig. 1.4 BSs' power demand according to a power-consumption profile

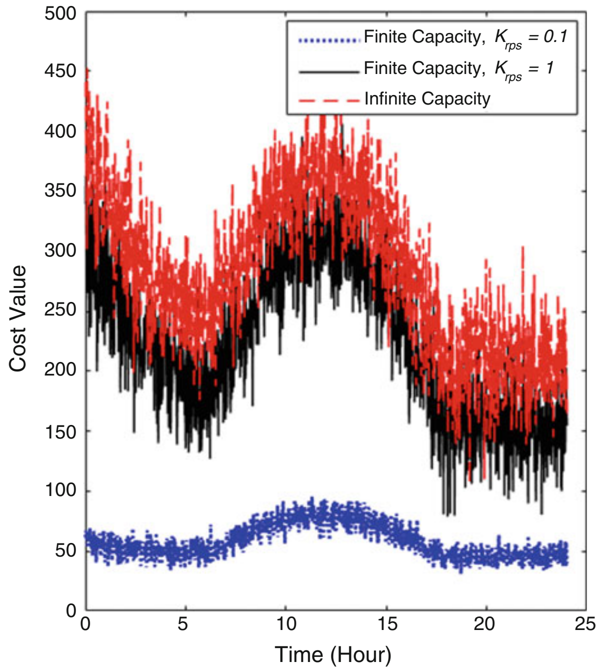


Fig. 1.5 The cost values for the RPS (L2-norm)

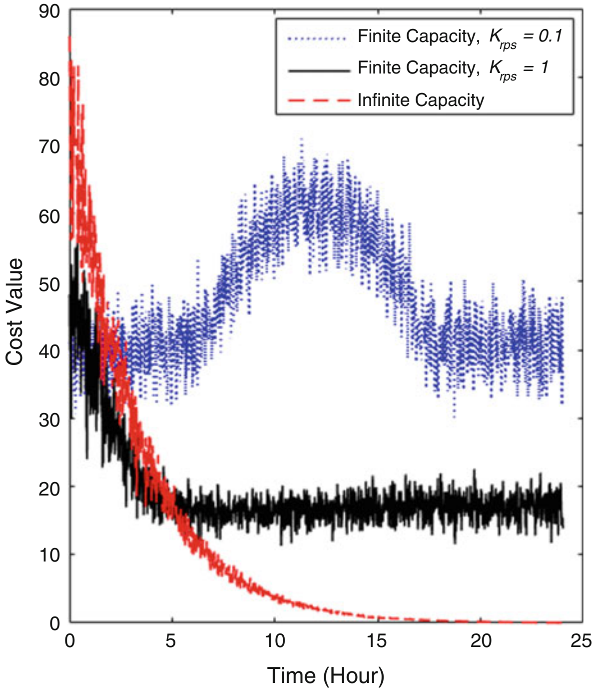


Fig. 1.6 The cost values for the BSs (L2-norm)

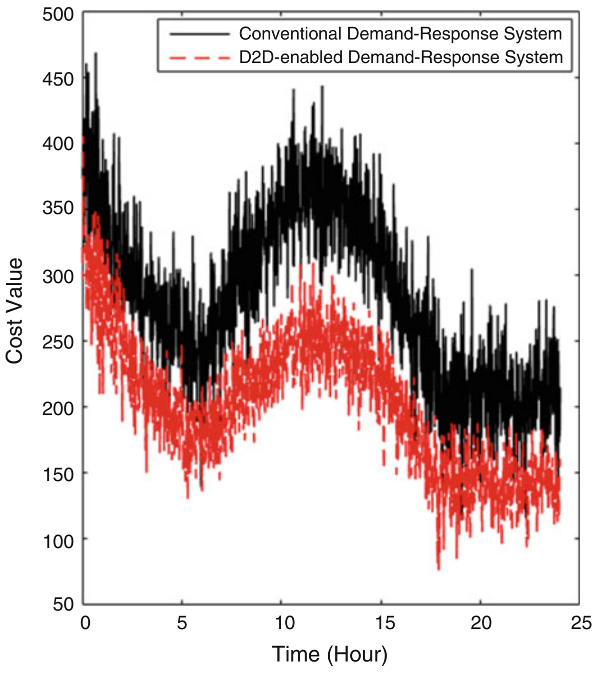


Fig. 1.7 The cost evaluation (L2-norm) for a perfect RPS over the conventional or D2D-enabled demand-response systems

efficient utilization of energy are analyzed. Here, the energy threshold is defined as $k_{\mathrm{rps}} \cdot E_{\mathrm{Req}}$ to indicate the maximum service capacity provided by the RPS. Note that E_{Req} is assumed to be the average energy demand ordered by the BSs. Moreover, k_{rps} is the service coefficient ($0 < k_{\mathrm{rps}} < \infty$). Clearly, lower values for k_{rps} mean that the RPS has finite capacity in response to the received energy demands. Furthermore, in the case of $k_{\mathrm{rps}} \to \infty$, there is no energy constraint (i.e., infinite capacity); thus maximum cost values can be expected in the RPS side. Indeed, the RPS should acquire the exact energy demand information from the BSs. Meanwhile, the traffic offloading effects of the D2D communication can be observed in Fig. 1.7, where the cost values are reduced for the D2D-enabled network compared to the conventional demand-response system.

1.6 Energy-Optimized Wireless Communications

1.6.1 Wireless Cellular Networks

In the literature—see, e.g., [38–45]—the EE of single-tier (macro-tier) cellular networks has been widely discussed and researched. The authors in [40, 45] suggest using the dynamic BS operation, i.e., adopting a dynamic off/on switching for BSs based on a real network traffic profile. However, both the randomness and the spatial distribution of the network traffic have been ignored. More recently, the cellular network has become multitiered with cells providing overlapping coverage [46, 47]. This is due to the emergence of low-cost small cells. Because of the increased overlapping areas and high fluctuations of traffic demand (both in time and over space) in cellular networks, optimal sleep/wake-up schemes can be designed either for small cells or for the coverage-overlapped macro-BSs (MBSs) [48, 49].

The studies mentioned above consider models such as hexagonal and Manhattan model network [50]. In other words, they only focus on ideal and non-tractable network deployment models. Here, the non-tractability issue is in accordance with signal to interference and noise ratio (SINR) distribution. However, dense and unplanned deployment of small cells over space have called for more tractable models. Using tractable models, key performance metrics can be evaluated quickly without the need to perform complex and time-consuming ray tracing and simulations. A tractable network deployment is modeled by the authors in [51, 52] with the aid of stochastic geometry [53–56]. More specifically, they propose to independently switch off each BS with a fixed probability. However, the HetNet deployment has not been considered in their work. Authors in [35, 57, 58] have studied sleep/wake-up schemes in stochastic geometry-based HetNets. Both dynamic (i.e., traffic load-based) and random sleeping strategies for MBSs have been presented in [35]. To design the optimal sleeping mechanism for MBSs, they consider EE maximization. The authors in [57, 58] also study random sleep/wake-up schemes for BSs. In [57], based on minimizing BS energy consumption, the optimal switch-off probability for

MBSs is determined. Also, in [58], based on maximizing EE with the constraint for coverage probability, the optimal switch-off probability for small cell BSs is derived.

Compared with the dynamic BS sleep/wake-up strategies, the random sleep/wake-up schemes have the advantages of less operational cost and low computational complexity. However, they are not adaptable to the dynamic nature of realistic cellular networks. The basic concepts about dynamic BS operation issues have also been summarized in [42]. They, however, lack the ability to learn the uncertain wireless network environment. Many factors such as intracell and intercell interference, location uncertainty, SINR requirements, and traffic load can be considered for characterizing uncertainty. The use of learning-based mechanisms in wireless networks is not new. For example, in [59–62], in order to optimize range expansion bias, sleep/wake-up scheduling, and transmit power, two learning-based techniques known as regret-based learning and Q-learning have been applied. Another learning-based technique developed in [63] plays a key role for BS energy conservation in cellular radio access networks (RANs). More specifically, they use Markov decision processes with knowledge transferring to formulate and model the BS operations under a variant traffic load. Note that the state of the surrounding environment and available actions to the agents are commonly represented by discrete sets in all lookup-table-based learning-based approaches (such as Q-learning and state-action-reward-state-action [SARSA]). This may lead to inaccuracies and subjectivity in the agent's behavior and consequently the system performance, particularly when the input variables are continuous or the number of state-action pairs is large. To deal with this issue, a fuzzy logic controller is usually combined with Q-learning and SARSA. The combination of the fuzzy logic controller with Q-learning and SARSA is known as fuzzy Q-learning (FQL) and fuzzy SARSA-learning (FSL) [64], respectively. This will help agents (BSs) to better and faster adjust their actions bringing in a considerable benefit in terms of precision and the learning period. Nevertheless, FSL might be somewhat faster than FQL. This is because FQL does not learn the same policy as it follows, i.e., in FQL, the policy is updated dependent on the best possible future scenario, rather than what actually happens after an action is taken (as is the case in FSL) [64, 65]. However, this will lead to a better performance of FQL, while FSL appears to be not flexible enough for uncertain and changing environments and to get stuck in local maxima. Therefore, in general and particularly for uncertain wireless environments, it is believed that the policy learnt by FQL is able not only to satisfy the system constraints, but also to achieve a higher level of system performance in terms of EE.

The unavoidable coverage holes caused by switching some BSs off is one of the key bottlenecks of applying sleep/wake-up mechanisms. Because of this reason, several schemes, such as user association [38, 43, 52] and power control [20, 35, 39, 40, 45], have been suggested to counter the coverage voids. For instance, a fixed power control policy is proposed in [35], where it is assumed that the power of all active BSs is increased equally without considering the channel conditions of the switched off cell users. A perfect power control strategy taking into account power levels at other cells is considered by the authors in [20], which can consequently manage the interference between neighboring cells. Different from these studies, in

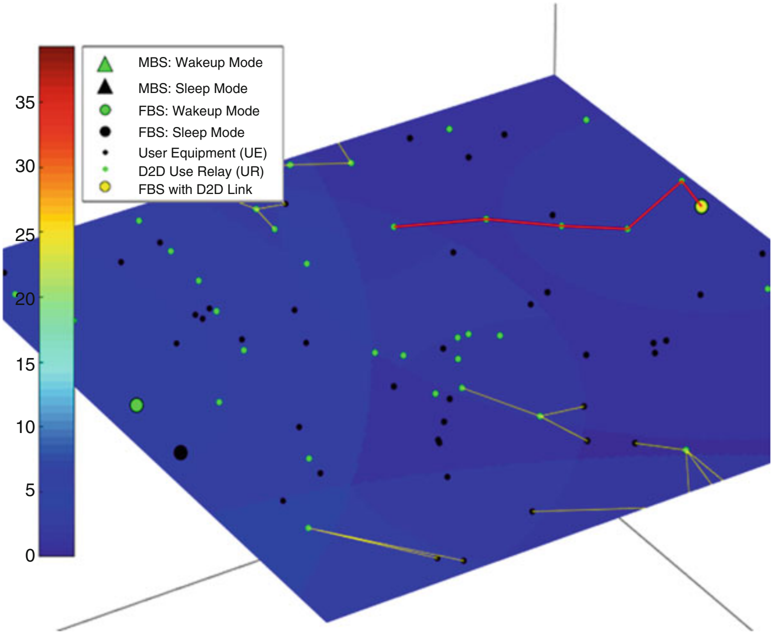


Fig. 1.8 Coverage simulations for learning based on D2D-enabled HetNets (zoomed-in view) [32]

[32], a D2D-enabled FQL scheme is used to fill the coverage holes resulting from switching some BSs off (see Fig. 1.8).

1.6.2 Wireless Sensor Networks

Here, a hierarchical sensor network is considered that means some fusion centers collect reports from the neighboring sensors in the area and send the information to the BS [15, 16, 62]. Indeed, the network is cluster-based in which the cluster heads (CHs) or sinks have a more prominent role than the other sensors. It should be noted that each cluster consists of several nodes and a head node. Generally, the WSN architecture is n-tier ($n > 1$), and WSNs are widely used in a two-tier network format. Thus, we consider a two-tier heterogeneous WSN that includes a number of clusters and several BSs. In this two-tier network, the lower tier consists of nodes of different clusters, while the CHs and the BSs compose the upper tier (see Fig. 1.9).

Sensors, which form the network's lower tier, are responsible for sensing and sending the collected data to the CHs or sinks in their own area. CHs have the ability to collect and transmit the received data to the BS. The BS receives the data from the sinks and, according to its analysis, obtains the full sense of the network. In the defined network model, the cluster can also play the role of the relay and transfer the messages to the BS in multiple hopes. As mentioned before, the energy of BSs is

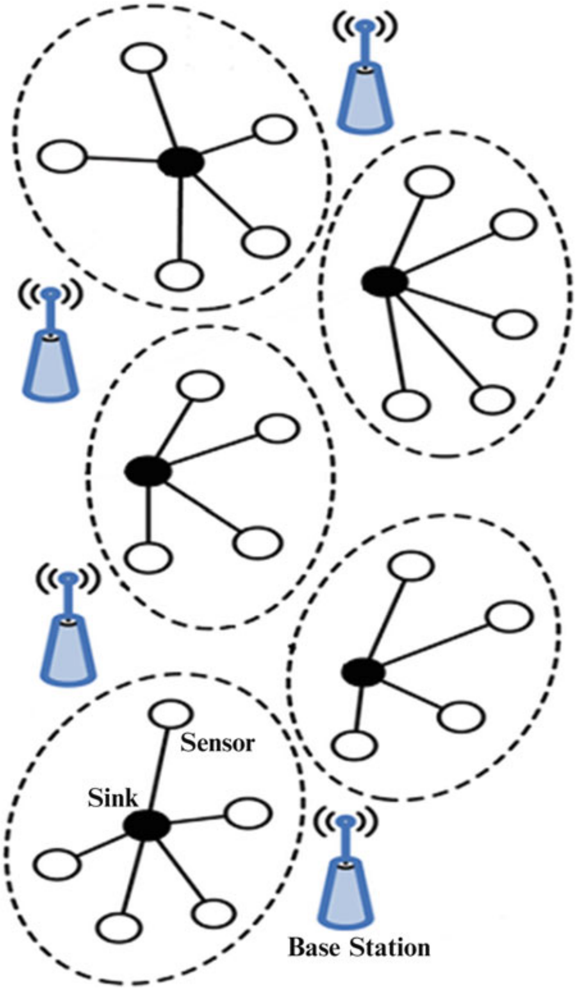


Fig. 1.9 Wireless sensor network with BSs, sinks, and mobile sensors

considered limited. Therefore, the energy consumption of the BSs is our concern and it is clear that in order to decrease power consumption and prolong the lifetime of the two-tier WSN, power management mechanisms should be exploited more precisely. In order to understand the sleep and wake-up mechanisms, it is first necessary to recognize the differences between the different modes of power saving that can be given by a small cell. We describe this concept in terms of "depth." The greater the depth, the higher the power saving, and the deeper the sleep, the more time it takes to

Table 1.1 Different operation modes

Operation mode	Power consumption
On/wake-up	100%
Standby	50%
Sleep	10%
Off	0

wake up. Power consumption is considered as a percentage of total power consumption in each mode. It is assumed that a BS is the most energy consuming when it is turned on. In addition, BS power consumption varies according to different traffic, but we consider the average of the network performance. Therefore, the instantaneous power changes have not been considered for traffic variations in the BS power consumption model. It should be noted that, in this section, sleep/wake-up mechanisms are simply used to control the power consumption of BSs by putting them in different operation modes (see Table 1.1). Indeed, this section addresses the problem of designing of a smart sleep and wake-up mechanism using the genetic algorithm (GA), as a nature-inspired optimization approach, to manage the operation modes of the BSs according to the time-variant profile for the daily traffic load.

In addition, simulation results are presented to analyze the performance of the smart sleep and wake-up mechanism. The impact of network topology and parameters (e.g., density of BSs, CHs, and the related locations) can be investigated according to the comprehensive network simulations (Fig. 1.10). All simulations are performed using Monte Carlo runs. Here, as mentioned before, GA, as a nature-inspired optimization approach, makes the opportunity to design optimal and practical solutions for WSNs. Therefore, the GA-based optimization is performed in the simulations that focuses on a centralized management process to adopt the operation modes of BSs according to the time-variant profile for the daily traffic load. By controlling the operation modes of the densely deployed BSs over the WSN, EE of the network converges to the optimal level as can be observed in Fig. 1.11. Here, L2-norm of the operation modes for the BSs also converges versus iterations that verify the network stability in the steady phase of the GA (Fig. 1.12). In addition, the optimal operation modes for the BSs can be finally considered to form the optimal network configurations as in Fig. 1.13

Indeed, a practical GA-based strategy can also be adopted to obtain the optimal BSs' positions for the two-tiered HetNet. Then, we demonstrate the L2-norm of BSs' positions (Fig. 1.14) and the network EE curve (Fig. 1.15) versus a sufficient number of iterations. We then show the optimal network topology obtained according to the optimal numerical results for the BSs' positions (Fig. 1.16). As mentioned before, the GA-based optimization executes over several generations in order to determine the best set of solutions (i.e., the optimal BS positions) and generally finishes at the best convergence, that is, when the best fit occurs according to the convergence criteria. Results show that convergence can be obtained for the network EE as the number of iterations increase, and this clearly confirms the network stability in the steady phase of the GA.

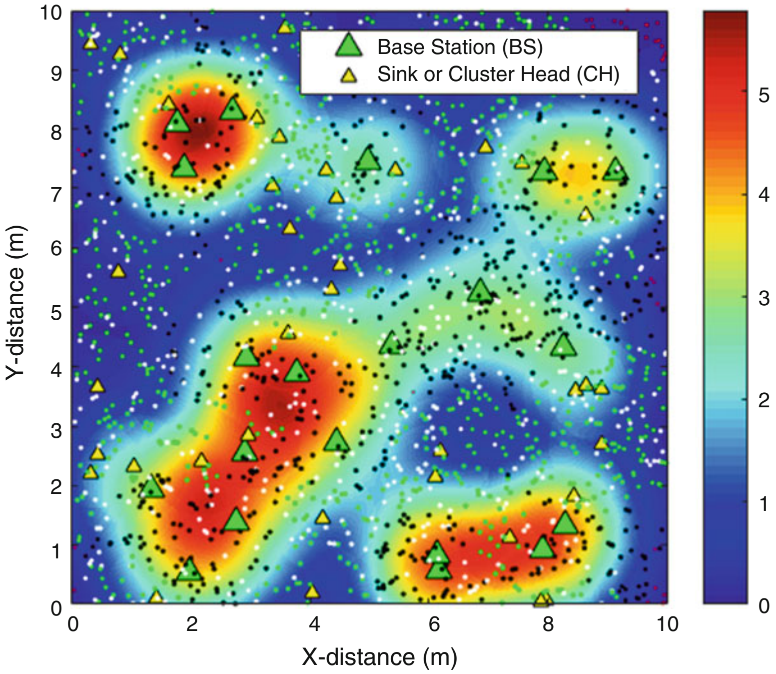
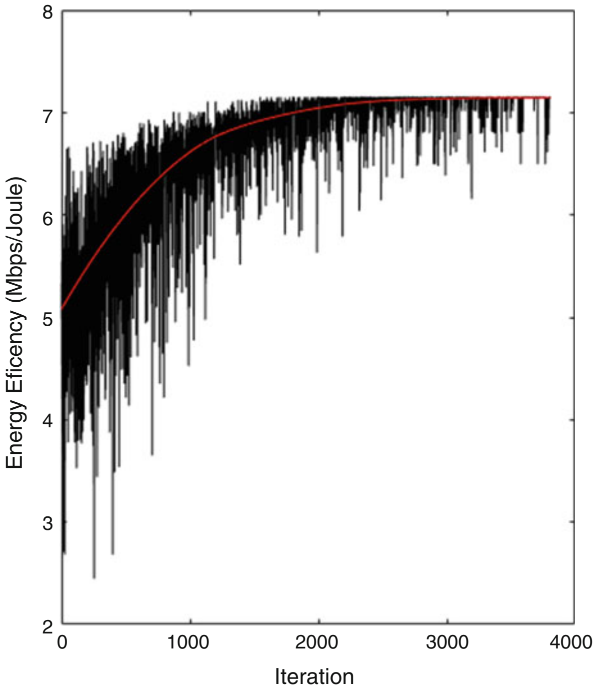


Fig. 1.10 Coverage map for conventional power configurations

Fig. 1.11 Network energy efficiency versus iterations



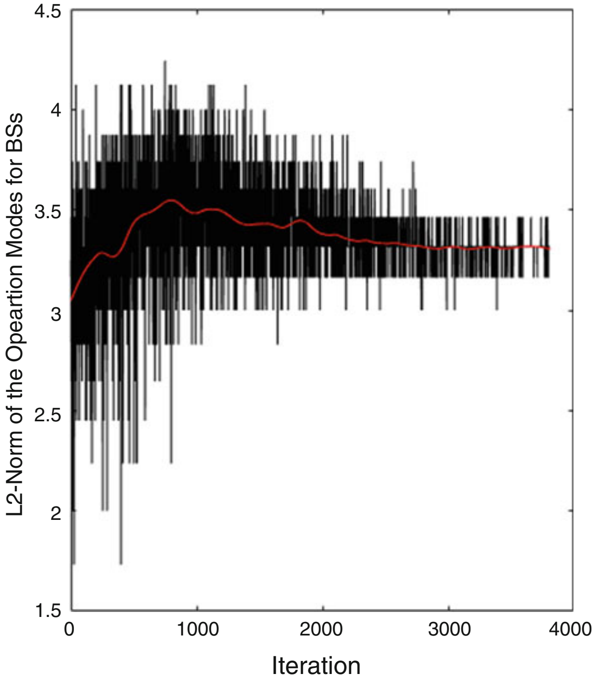


Fig. 1.12 L2-norm of the operation modes for the BSs versus iterations

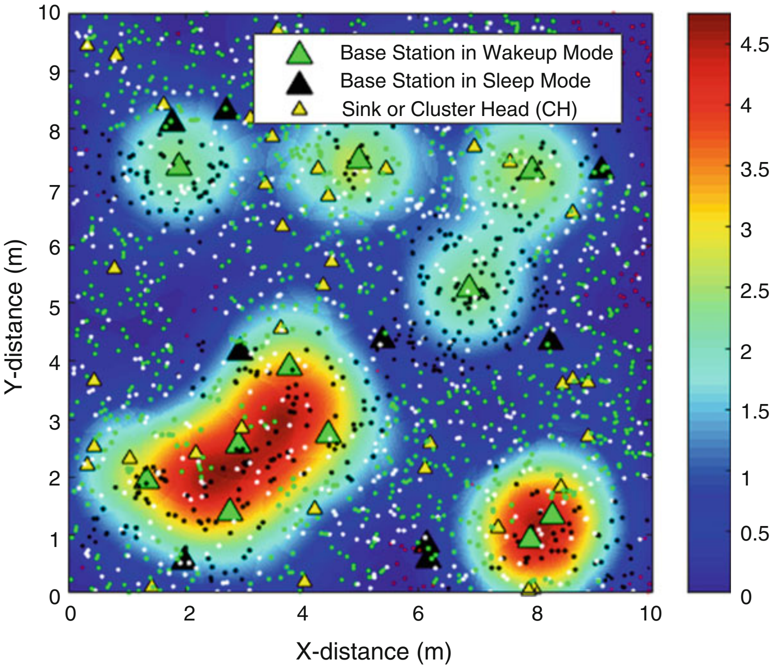


Fig. 1.13 Coverage map for GA-based optimal power configurations

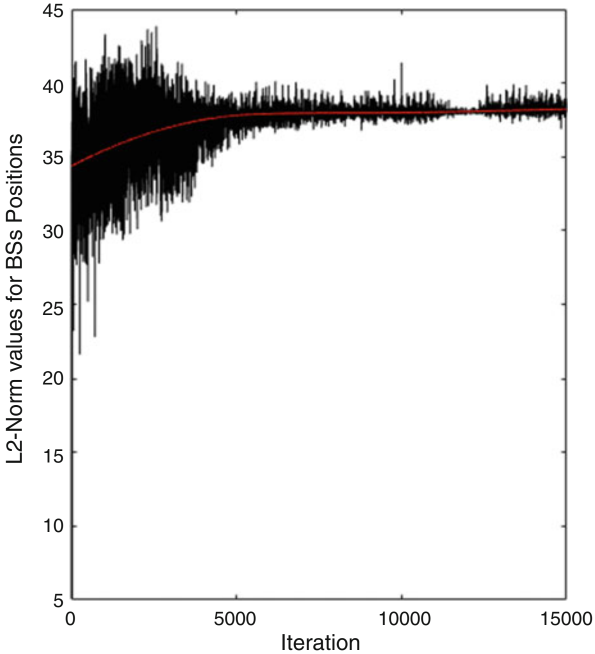


Fig. 1.14 L2-norm of the BSs' positions versus iterations

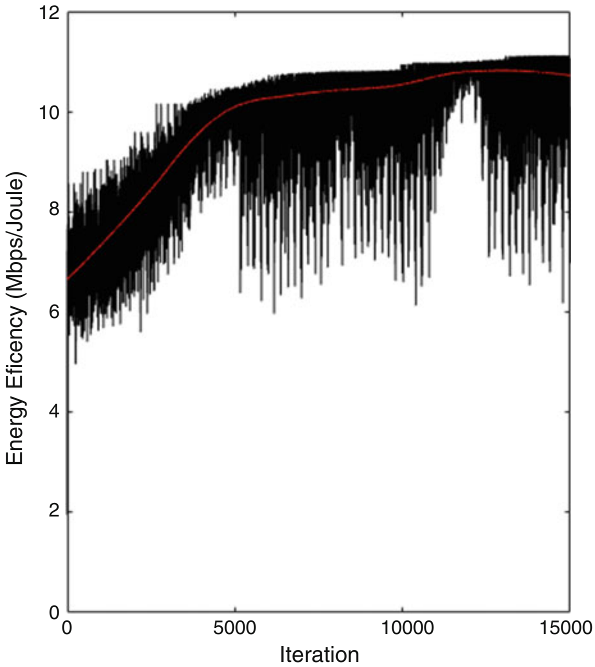


Fig. 1.15 Network energy efficiency versus iterations

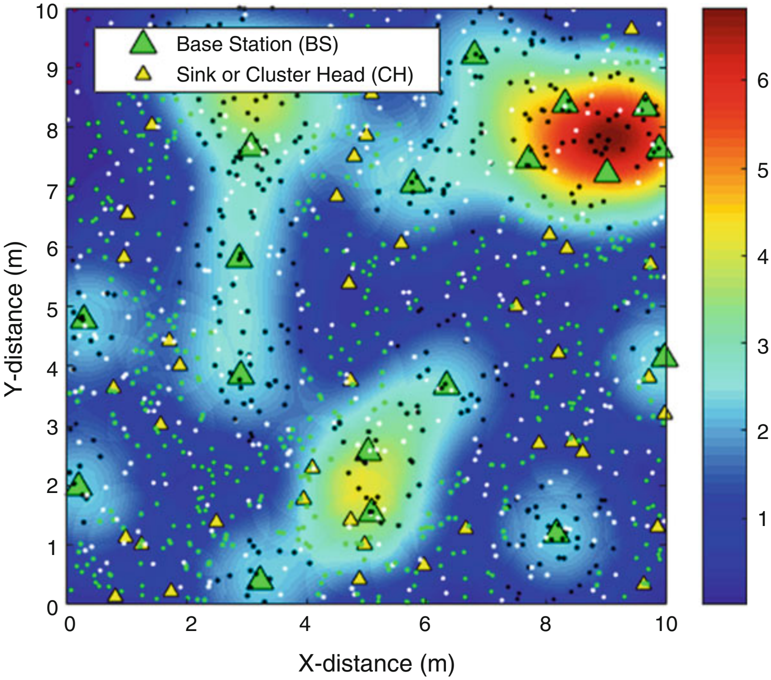


Fig. 1.16 Optimal topology for the wireless sensor network

1.7 Energy Harvesting and Self-Powered Technologies

Generally, the EH has been utilized for quite a long time for bike dynamos or solar panels. Today, it is widely applied to application fields, such as smart cities, automotive vehicles, and security systems. Development inside the areas of big data and IoT and thus the spread of battery-based sensor systems are real power-driving advances in EH and self-powered systems [66, 67]. The most well-known power sources utilized for EH are mechanical and thermal energy and sunlight-based radiations. Recent advances in ultralow-power technologies have accelerated the improvement of self-powered monitoring gadgets for a wide scope of utilizations consisting of SGs, structural health monitoring, and biomedical telemetry [68–71]. A self-powered wireless sensor, which gains surrounding energy for driving its hardware, is among the promising techniques for supporting a maintenance-free sensor network in SGs. The worldwide EH market demonstrates a stunning development: somewhere in the range of 2015 and 2019, it could sum at 21.9% and peak at 28% in 2019 (Fig. 1.17). Governments and public initiatives are the main drivers for EH market development. Public actors utilize EH as a key apparatus for gathering the rising energy request and saving power. The imperative to confront the issue of climate change as a worldwide challenge will fuel the development of the market amid the coming 5 years.

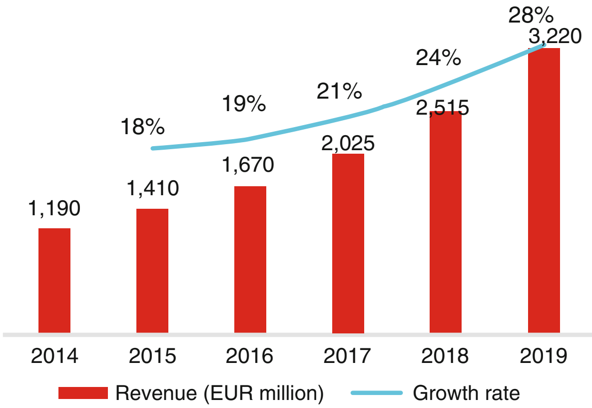


Fig. 1.17 Global energy-harvesting market 2014–2019

In fact, EH supports SGs by powering WSNs that are fundamental to provide connectivity between devices. A huge number of sensors are required to monitor and manage SG processes and the sensors should be powered. Ordinarily, batteries were utilized to enable the sensing nodes but they have a restricted lifetime, and in a network with a huge number of wireless sensors, replacement of the batteries will not be applicable. It should be noted that EH-powered sensors need less maintenance and are easier to arrange than batteries and also more comfortable to manage in mobile sensing strategies. To sum up, development of IoT and energy-efficient communication infrastructures for SGs is driving interest for wireless and battery-less sensors which will be increasingly more powered by EH. Indeed, EH wireless solutions find increasing applications in SGs due to their low-cost installation and maintenance. In addition, EH-based wireless technology is the reliable communication strategy to provide connectivity among thousands of nodes in SGs.

Here, a practical smart scenario for mobile sensors is considered to investigate the power-saving impacts of EH on wireless sensor networks. In addition, to evaluate whether this strategy can help to accelerate the EH process in mobile sensors, we conduct a series of simulations. It should be noted that the simulated environment is configured according to the conventional WSN parameters, and then we present the simulation results corresponding to the conventional EH model (Fig. 1.18a) and a FQL-based EH model (Fig. 1.18b), respectively. After that, a simple definition to evaluate the EH effectiveness over the network is presented. Here, the EH rate (EHR) is formulated as $k_{\mathrm{EH}} \cdot \left(d_{\mathrm{EH}}^{0}/d_{\mathrm{EH}}^{t}\right)^2$ to indicate any improvement in acceleration of the charging process for all mobile sensors deployed over the network. Note that d_{EH}^{t} is assumed to be the mean distance between mobile sensors and power stations (PSs) at the time of t. Moreover, k_{EH} is the EH coefficient ($1 \leq k_{\mathrm{EH}}$). From the results (Fig. 1.19), one can observe the performance degradation in the case of partial PS-state information (where the mobile sensors are moving toward PSs based on partial location information of PSs obtained via M2M communications), for average EHR, as expected. It is assumed that the exact information of PS locations can be accessible for all mobile sensors when the perfect case is performed.

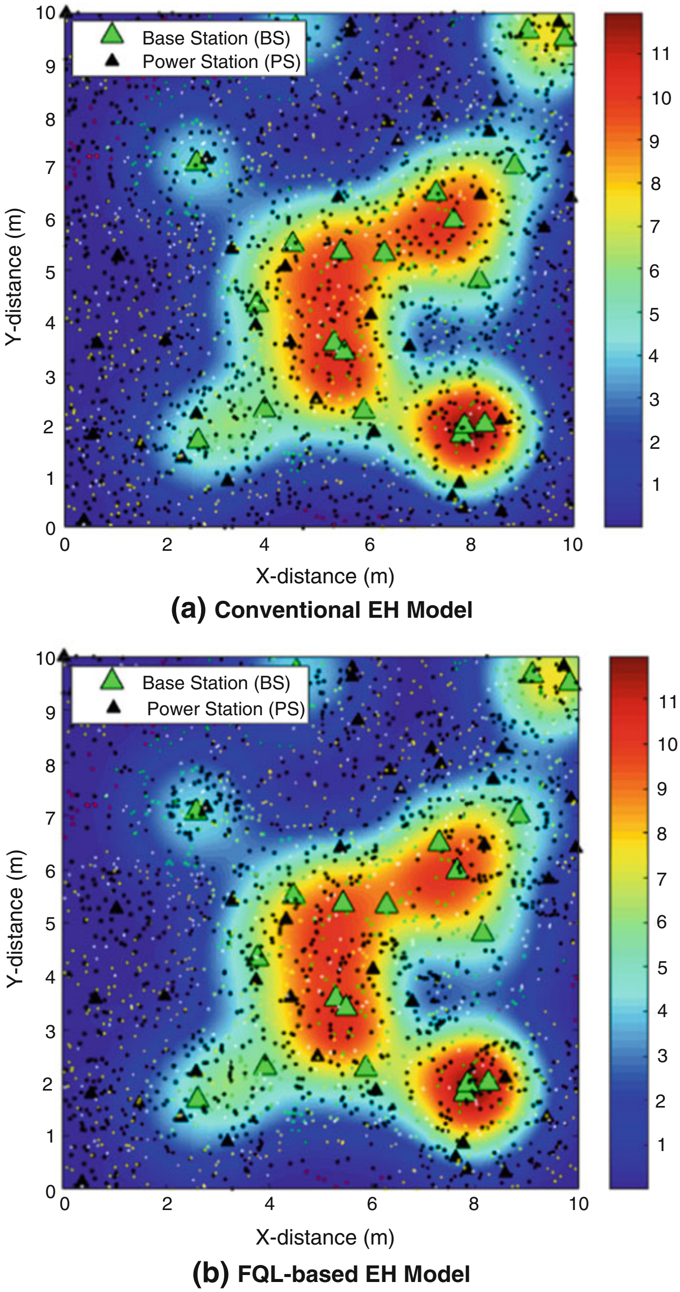


Fig. 1.18 Coverage map for the wireless powered sensor network. (**a**) Conventional EH model. (**b**) FQL-based EH model

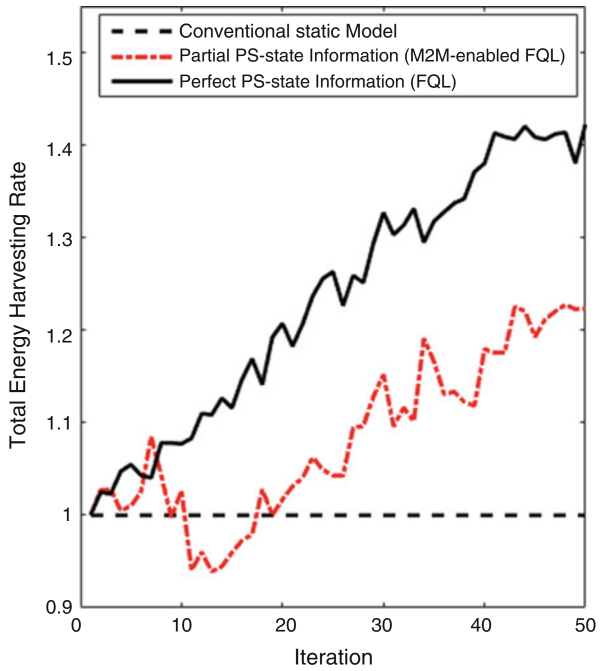


Fig. 1.19 EH rate for static and dynamic sensor scenarios

1.8 Conclusion

The electric power grid is experiencing extraordinary changes that have changed it from a hierarchical system to a distributed, user-based SG. Realizing the vision of the SG is dependent upon energy-efficient communication infrastructures that can empower rapid and reliable data transmission in the grid. Undoubtedly, wireless communication systems play a key role in realizing a lot of the SG features, for example, DR, AMI, electric vehicle, storage units, and microgrid control. Thus, a plenty of strategies for SG communications have been proposed that rely on wireless communications and PLC technologies. The incorporation of ICTs in the grid clearly raises security hazards that must be controlled based on cyber-physical protocols. Indeed, this chapter presented profound contributions in the broad area of SG communications along with various scenarios through computer simulation. Table 1.2 summarizes the general topics to prepare a comprehensive perspective on the recent studies in this area.

Table 1.2 Major topics and the latest research developments on smart grid green communications

Topics	References
Communication architectures for AMI	[72, 73]
Networking methods for realizing new SG capabilities	[74, 75]
Communication-based procedures for DR, demand-side, and power management	[76, 77]
Big data analyses for SGs	[78, 79]
Integrated storage units and electric vehicles in SGs	[80, 81]
Multiple access schemes for SG communications	[82, 83]
PLC challenges in the SG	[84, 85]
Cross-layer design and SG service integration	[86, 87]
Secure and private protocols in the SG	[88, 89]
Resilient communication solutions for SGs	[90, 91]
Cyber-physical models for smart power management	[92, 93]
Nature-inspired optimal algorithms for SGs	[94, 95]
Hybrid wired and wireless architectures for power communications	[96, 97]
Encoding and modulation techniques for PLC and wireless communications in the grid	[98, 99]
Routing and congestion strategies in PLC systems	[100, 101]
Optimal designs for decentralized power sources and microgrids	[102, 103]
Control and communications synergies in the SG	[104, 105]
Green-powered systems for wireless communications	[23, 106]
Device-to-device communications in the SG	[107, 108]
Coexistence of SG communication technologies	[109, 110]
SG-enabled cellular communication networks	[111, 112]
Economic approaches for improving SG communications and energy efficiency	[113, 114]
Optimal positioning for SG communication nodes	[115, 116]
Standard measurements and experimental evaluations for SG communication systems	[117, 118]

References

1. E. Hossain, V.K. Bhargava, G. Fettweis, *Green Radio Communication Networks* (Cambridge Univ. Press, Cambridge, UK, 2012)
2. B. Heile, Smart grids for green communications [industry perspectives]. IEEE Wireless Commun. **17**(3), 3–6 (2010)
3. J. Xu, L. Duan, R. Zhang, Cost-aware green cellular networks with energy and communication cooperation. IEEE Commun. Mag. **53**(5), 257–263 (2015)
4. J. Wu, S. Rangan, H. Zhang, *Green Communications: Theoretical Fundamentals, Algorithms, and Applications* (CRC Press, Boca Raton, 2012)
5. T. Han, N. Ansari, Powering mobile networks with green energy. IEEE Wireless Commun. **21** (1), 90–96 (2014)
6. S. Bu, F.R. Yu, Y. Cai, X.P. Liu, When the smart grid meets energy-efficient communications: green wireless cellular networks powered by the smart grid. IEEE Trans. Wireless Commun. **11**(8), 3014–3024 (2012)
7. M. Erol-Kantarci, H.T. Mouftah, Energy-efficient information and communication infrastructures in the smart grid: a survey on interactions and open issues. IEEE Commun. Surv. Tut. **17** (1), 179–197 (2015)

8. N. Saputro, K. Akkaya, S. Uludag, A survey of routing protocols for smart grid communications. Comput. Networks J. **56**(11), 2742–2771 (2012)
9. G. Miao, N. Himayat, Y. Li, D. Bormann, Energy efficient design in wireless OFDMA, in *IEEE International Conference on Communications* (2008), pp. 3307–3312
10. C.-B. Kim, G.d.V. Chae, R.W. Heath Jr., A cross-layer approach to energy efficiency for adaptive MIMO systems exploiting spare capacity. IEEE Trans. Wireless Commun. **8**(8), 4264–4275 (2009)
11. J. Huang, H. Wang, Y. Qian, C. Wang, Priority-based traffic scheduling and utility optimization for cognitive radio communication infrastructure-based smart grid. IEEE Trans. Smart Grid **4**(1), 78–86 (2013)
12. L. Li, X. Zhou, H. Xu, G.Y. Li, D. Wang, A. Soong, Energy-efficient transmission in cognitive radio networks, in *IEEE Consumer Communications and Networking Conference* (Jan. 2010), pp. 1 and 5
13. M. Erol-Kantarci, J.H. Sarker, H.T. Mouftah, Communication-based plug-in hybrid electrical vehicle load management in the smart grid, in: *IEEE Symposium on Computers and Communications* (June 2011)
14. M.N. Alam, R. Jantti, J. Kneckt, J. Nieminen, Performance analysis of the IEEE 802.11s PSM, J. Comput. Networks Commun. **2012**, 14 p (2012)
15. M. Erol-Kantarci, H.T. Mouftah, Wireless sensor networks for cost-efficient residential energy management in the smart grid. IEEE Trans. Smart Grid **2**(2), 314–325 (2011)
16. L. Li, X. Hu, C. Ke, K. He, The applications of WiFi-based wireless sensor network in internet of things and smart grid, in *IEEE Conference on Industrial Electronics and Applications (ICIEA)* (June 2011), pp. 789–793
17. V. Chandrasekhar, J. Andrews, A. Gatherer, Femtocell networks: a survey. IEEE Commun. Mag. **46**(9), 5967 (2008)
18. F. Richter, A.J. Febske, G.P. Fettweis, Energy efficiency aspects of base station deployment strategies in cellular networks, in *Proceedings of IEEE VTC 09-Fall*, Anchorage, AK (Sept. 2009)
19. P. Gandotra, R.K. Jha, S. Jain, Green communication in next generation cellular networks: a survey. IEEE Access **5**, 11727–11758 (2017)
20. S. Kokkinogenis, G. Koutitas, Dynamic and static base station management schemes for cellular networks, in *IEEE Global Communications Conference (GLOBECOM)* (2012), pp. 3443–3448
21. Z. Zhou, C. Gao, C. Xu, T. Chen, D. Zhang, S. Mumtaz, Energy-efficient stable matching for resource allocation in energy harvesting-based device-to-device communications. IEEE Access **5**, 15184–15196 (2017)
22. S. Shalmashi, E. Björnson, M. Kountouris, K.W. Sung, M. Debbah, Energy efficiency and sum rate tradeoffs for massive MIMO systems with underlaid device-to-device communications. EURASIP J. Wireless Commun. Network. **1**, 175 (2016)
23. D. Li, W. Saad, I. Guvenc, A. Mehbodniya, F. Adachi, Decentralized energy allocation for wireless networks with renewable energy powered base stations. IEEE Trans. Commun. **63**(6), 2126–2142 (2015)
24. J. Gozalvez, Green radio technologies [mobile radio]. IEEE Veh. Technol. Mag. **1**, 9–14 (2010)
25. C.K. Ho, R. Zhang, Optimal energy allocation for wireless communications with energy harvesting constraints. IEEE Trans. Signal Process. **9**, 4808–4818 (2012)
26. D. Niyato, X. Lu, P. Wang, Adaptive power management for wireless base stations in a smart grid environment. IEEE Wireless Commun. **6**, 44–51 (2012)
27. G. Yu, L. Xu, D. Feng, R. Yin, G.Y. Li, Y. Jiang, Joint mode selection and resource allocation for device-to-device communications. IEEE Trans. Commun. **11**, 3814–3824 (2014)
28. Q. Ye, B. Rong, Y. Chen, M. Al-Shalash, C. Caramanis, J.G. Andrews, User association for load balancing in heterogeneous cellular networks. IEEE Trans. Wireless Commun. **6**, 2706–2716 (2013)

29. D. Wu, J. Wang, H. Rose Qingyang, Y. Cai, L. Zhou, Energy-efficient resource sharing for mobile device-to-device multimedia communications. IEEE Trans. Veh. Technol. **5**, 2093–2103 (2014)
30. Z. Zhou, K. Ota, M. Dong, C. Xu, Energy-efficient matching for resource allocation in D2D enabled cellular networks. IEEE Trans. Veh. Technol. **6**, 5256–5268 (2017)
31. U. Saleem, H.K. Qureshi, S. Jangsher, M. Saleem, Transmission power management for throughput maximization in harvesting enabled D2D network, in *2016 IEEE Symposium on Computers and Communication (ISCC)* (2016), pp. 1078–1083
32. S. Xiao, X. Zhou, D. Feng, Y.-W. Yi, G.Y. Li, W. Guo, Energy-efficient mobile association in heterogeneous networks with device-to-device communications. IEEE Trans. Wireless Commun. **8**, 5260–5271 (2016)
33. F.H. Panahi, F.H. Panahi, G. Hattab, T. Ohtsuki, D. Cabric, Green heterogeneous networks via an intelligent sleep/wake-up mechanism and D2D communications. IEEE Trans. Green Commun. Network. **2**(4), 915–931 (2018)
34. F.H. Panahi, F.H. Panahi, G. Hattab, T. Ohtsuki, D. Cabrici, Green heterogeneous networks via an intelligent power control strategy and D2D communications, in *2017 IEEE 28th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*, Montreal, QC (2017), pp. 1–8
35. Y.S. Soh, T.Q. Quek, M. Kountouris, H. Shin, Energy efficient heterogeneous cellular networks. IEEE J. Sel. Areas Commun. **31**(5), 840–850 (2013)
36. Z. Han, D. Niyato, W. Saad, T. Başar, A. Hjørungnes, *Game Theory in Wireless and Communication Networks: Theory, Models, and Applications* (Cambridge University Press, Cambridge, 2011)
37. M.J. Osborne, A. Rubinstein, *A Course in Game Theory* (MIT Press, Cambridge, 1994)
38. H. Tabassum, U. Siddique, E. Hossain, M.J. Hossain, Downlink performance of cellular systems with base station sleeping, user association, and scheduling. IEEE Trans. Wireless Commun. **13**(10), 5752–5767 (2014)
39. E. Oh, B. Krishnamachari, Energy savings through dynamic base station switching in cellular wireless access networks, in *2010 IEEE Global Telecommunications Conference GLOBECOM 2010* (Dec 2010), pp. 1–5
40. L. Chiaraviglio, D. Ciullo, M. Meo, M.A. Marsan, Energy-efficient management of umts access networks, in *2009 21st International Teletraffic Congress* (Sept 2009), pp. 1–8
41. A.J. Fehske, F. Richter, G.P. Fettweis, Energy efficiency improvements through micro sites in cellular mobile radio networks, in *2009 IEEE Globecom Workshops* (Nov 2009), pp. 1–5
42. Z. Niu, Y. Wu, J. Gong, Z. Yang, Cell zooming for cost-efficient green cellular networks. IEEE Commun. Mag. **48**(11), 74–79 (2010)
43. K. Son, H. Kim, Y. Yi, B. Krishnamachari, Base station operation and user association mechanisms for energy-delay tradeoffs in green cellular networks. IEEE J. Sel. Areas Commun. **29**(8), 1525–1536 (2011)
44. J. Wu, S. Zhou, Z. Niu, Traffic-aware base station sleeping control and power matching for energy-delay tradeoffs in green cellular networks. IEEE Trans. Wireless Commun. **12**(8), 4196–4209 (2013)
45. M.A. Marsan, L. Chiaraviglio, D. Ciullo, M. Meo, Optimal energy savings in cellular access networks, in *2009 IEEE International Conference on Communications Workshops* (June 2009), pp. 1–5
46. L. Saker, S.E. Elayoubi, R. Combes, T. Chahed, Optimal control of wake up mechanisms of femtocells in heterogeneous networks. IEEE J. Sel. Areas Commun. **30**(3), 664–672 (2012)
47. S.E. Elayoubi, L. Saker, T. Chahed, Optimal control for base station sleep mode in energy efficient radio access networks, in *Proceedings of IEEE INFOCOM 2011* (Apr. 2011), pp. 106–110
48. W.C. Liao, M. Hong, Y.F. Liu, Z.Q. Luo, Base station activation and linear transceiver design for optimal resource management in heterogeneous networks. IEEE Trans. Signal Process. **62** (15), 3939–3952 (2014)

49. M. Oikonomakou, A. Antonopoulos, L. Alonso, C. Verikoukis, Cooperative base station switching off in multi-operator shared heterogeneous network, in *2015 IEEE Global Communications Conference (GLOBECOM)* (Dec 2015), pp. 1–6
50. A.N.F. Iqbal, M. Javed, Interference-aware multipath routing in wireless mesh network. EURASIP J. Wireless Commun. Netw. **140**, 1 (2014)
51. E. Altman, C. Hasan, M.K. Hanawal, S.S. Shitz, J.M. Gorce, R. El-Azouzi, L. Roullet, Stochastic geometric models for green networking. IEEE Access **3**, 2465–2474 (2015)
52. Y.S. Soh, T.Q.S. Quek, M. Kountouris, Dynamic sleep mode strategies in energy efficient cellular networks, in *2013 IEEE International Conference on Communications (ICC)* (June 2013), pp. 3131–3136
53. F.H. Panahi, T. Ohtsuki, Stochastic geometry based analytical modeling of cognitive heterogeneous cellular networks, in *2014 IEEE International Conference on Communications (ICC)* (2014), pp. 5281–5286
54. F.H. Panahi, T. Ohtsuki, Stochastic geometry modeling and analysis of cognitive heterogeneous cellular networks. EURASIP J. Wireless Commun. Network. **2015**(1), 141 (2015)
55. G. Hattab, D. Cabric, Joint resource allocation and user association in multi-antenna heterogeneous networks, in *IEEE GLOBECOM* (Dec. 2016)
56. F.H. Panahi, T. Ohtsuki, Inter-tier interference mitigation in multi-antenna HetNets: a resource blanking approach, in *IEEE GLOBECOM* (Dec. 2016)
57. J. Peng, P. Hong, K. Xue, Stochastic analysis of optimal base station energy saving in cellular networks with sleep mode. IEEE Commun. Lett. **18**(4), 612–615 (2014)
58. C. Liu, B. Natarajan, H. Xia, Small cell base station sleep strategies for energy efficiency. IEEE Trans. Veh. Technol. **65**(3), 1652–1661 (2016)
59. M. Simsek, M. Bennis, I. Guvenc, Enhanced intercell interference coordination in hetnets: single vs. multiflow approach, in *IEEE Globecom Workshops* (Dec 2013), pp. 725–729
60. M. Simsek, M. Bennis, A. Czylwik, Dynamic inter-cell interference coordination in hetnets: a reinforcement learning approach, in *IEEE GLOBECOM* (Dec. 2012)
61. S. Samarakoon, M. Bennis, W. Saad, M. Latva-aho, Opportunistic sleep mode strategies in wireless small cell networks, in *IEEE ICC* (2014), pp. 2707–2712
62. D. Ye, M.Z. Au, A self-adaptive sleep/wake-up scheduling approach for wireless sensor networks. IEEE Trans. Cybern. **48**(3), 979–992 (2018)
63. R. Li, Z. Zhao, X. Chen, J. Palicot, H. Zhang, Tact: a transfer actor-critic learning framework for energy saving in cellular radio access networks. IEEE Trans. Wireless Commun. **13**(4), 2000–2011 (2014)
64. H. Arabnejad, C. Pahl, P. Jamshidi, G. Estrada, A comparison of reinforcement learning techniques for fuzzy cloud auto-scaling, in *Proceedings of the 17th IEEE/ACM International Symposium on Cluster, Cloud and Grid Computing* (IEEE Press, 2017), pp. 64–73
65. S. Chettibi, S. Chikhi, Adaptive maximum-lifetime routing in mobile ad-hoc networks using temporal difference reinforcement learning. Int. J. Evol. Syst. **5**(2), 89–108 (2014)
66. A.S. Adila, A. Husam, G. Husi, Towards the self-powered Internet of Things (IoT) by energy harvesting: trends and technologies for green IoT, in *Second IEEE International Symposium on Small-scale Intelligent Manufacturing Systems (SIMS)* (2018), pp. 1–5
67. P. Kamalinejad et al., Wireless energy harvesting for the internet of things. IEEE Commun. Mag. **53**(6), 102–108 (2015)
68. J. Han, J. Hu, Y. Yang, Z. Wang, S.X. Wang, J. He, A nonintrusive power supply design for self-powered sensor networks in the smart grid by scavenging energy from ac power line. IEEE Trans. Ind. Electron. **62**(7), 4398–4407 (2015)
69. B. Fateh, M. Govindarasu, V. Ajjarapu, Wireless network design for transmission line monitoring in smart grid. IEEE Trans. Smart Grid **4**(2), 1076–1086 (2013)
70. J.L. Wardlaw, I. Karaman, A.I. Karsilayan, Low-power circuits and energy harvesting for structural health monitoring of bridges. IEEE Sensors J **13**(2), 709–722 (2013)

71. S.Y. Tang, S. Chakrabartty, A 5nw quasi-linear cmos hot-electron injector for self-powered monitoring of biomechanical strain variations. IEEE Trans. Biomed. Circuits Syst. **10**(6), 1143–1151 (2016)
72. K. Yu, M. Arifuzzaman, Z. Wen, D. Zhang, T. Sato, A key management scheme for secure communications of information centric advanced metering infrastructure in smart grid. IEEE Trans. Instrum. Measur. **64**(8), 2072–2085 (2015)
73. Qi Wang, A. A. Gebremariam, R. Palacios-Trujillo, F. Granelli, Power saving strategy in advanced metering infrastructure for high-density residential community, in *2015 IEEE 20th International Workshop on Computer Aided Modelling and Design of Communication Links and Networks (CAMAD)*, Guildford (2015), pp. 201–206
74. M. Akerele, I. Al-Anbagi, M. Erol-Kantarci, A fiber-wireless sensor networks QoS mechanism for smart grid applications. IEEE Access **7**, 37601–37610 (2019)
75. S. ivanadBirajdar, M. Mungekar, A centralized microgrid protection using wireless communication network, in *2018 International Conference on Current Trends towards Converging Technologies (ICCTCT)*, Coimbatore (2018), pp. 1–4
76. A. Jindal, G. S. Aujla, N. Kumar, R. Prodan, M. S. Obaidat, DRUMS: demand response management in a smart city using deep learning and SVR, in *2018 IEEE Global Communications Conference (GLOBECOM)*, Abu Dhabi, United Arab Emirates (2018), pp. 1–6
77. D. Bian, D. Shi, M. Pipattanasomporn, M. Kuzlu, S. Rahman, Mitigating the impact of renewable variability with demand-side resources considering communication and cyber security limitations. IEEE Access **7**, 1379–1389 (2019)
78. Y. Simmhan et al., Cloud-based software platform for big data analytics in smart grids. Comput. Sci. Eng. **15**(4), 38–47 (2013)
79. Z. Asad, M.A. Rehman Chaudhry, A two-way street: green big data processing for a greener smart grid. IEEE Syst. J. **11**(2), 784–795 (2017)
80. Y.Q. Xing, J.X. Jin, Y.L. Wang, B.X. Du, S.C. Wang, An electric vehicle charging system using an SMES implanted smart grid. IEEE Trans. Appl. Supercond. **26**(7), 1–4 (2016)
81. V. Calderaro, V. Galdi, G. Graber, G. Graditi, F. Lamberti, Impact assessment of energy storage and electric vehicles on smart grids, in *2014 Electric Power Quality and Supply Reliability Conference (PQ)*, Rakvere (2014), pp. 15–18
82. K.M. Rabie, B. Adebisi, E.H.G. Yousif, H. Gacanin, A.M. Tonello, A comparison between orthogonal and non-orthogonal multiple access in cooperative relaying power line communication systems. IEEE Access **5**, 10118–10129 (2017)
83. R.H.Y. Louie, W. Hardjawana, Y. Li, B. Vucetic, Distributed multiple-access for smart grid home area networks: compressed sensing with multiple antennas. IEEE Trans. Smart Grid **5** (6), 2938–2946 (2014)
84. D. Sharma, A. Dubey, S. Mishra, R.K. Mallik, A frequency control strategy using power line communication in a smart microgrid. IEEE Access **7**, 21712–21721 (2019)
85. G. Artale et al., A new low cost coupling system for power line communication on medium voltage smart grids. IEEE Trans. Smart Grid **9**(4), 3321–3329 (2018)
86. Y. Dong, M.J. Hossain, J. Cheng, V.C.M. Leung, Dynamic cross-layer beamforming in hybrid powered communication systems with harvest-use-trade strategy. IEEE Trans. Wireless Commun. **16**(12), 8011–8025 (2017)
87. G.A. Shah, V.C. Gungor, O.B. Akan, A cross-layer QoS-aware communication framework in cognitive radio sensor networks for smart grid applications. IEEE Trans. Ind. Inform. **9**(3), 1477–1485 (2013)
88. P. Gope, B. Sikdar, An efficient data aggregation scheme for privacy-friendly dynamic pricing-based billing and demand-response management in smart grids. IEEE Internet Things J. **5**(4), 3126–3135 (2018)
89. J. Ni, K. Zhang, X. Lin, X.S. Shen, Balancing security and efficiency for smart metering against misbehaving collectors. IEEE Trans. Smart Grid **10**(2), 1225–1236 (2019)

90. Y. Kim, J. Lee, G. Atkinson, H. Kim, M. Thottan, SeDAX: a scalable, resilient, and secure platform for smart grid communications. IEEE J. Sel. Areas Commun. **30**(6), 1119–1136 (2012)
91. S. Xu, Y. Qian, R. Qingyang Hu, Reliable and resilient access network design for advanced metering infrastructures in smart grid. IET Smart Grid **1**(1), 24–30 (2018)
92. H. Georg, S.C. Müller, C. Rehtanz, C. Wietfeld, Analyzing cyber-physical energy systems: the INSPIRE cosimulation of power and ICT systems using HLA. IEEE Trans. Ind. Inform. **10**(4), 2364–2373 (2014)
93. C. Tham, T. Luo, Sensing-driven energy purchasing in smart grid cyber-physical system. IEEE Trans. Syst. Man Cybern. Syst. **43**(4), 773–784 (2013)
94. M.K. Mishra, S.K. Parida, A game theoretic approach for demand-side management considering generation, storage and the combinatorial nature of load scheduling, in *2018 International Conference and Utility Exhibition on Green Energy for Sustainable Development (ICUE)*, Phuket, Thailand, (2018), pp. 1–8
95. M. Çinar, A. Kaygusuz, Optimization algorithms used for self-healing of smart grids, in *2018 International Conference on Artificial Intelligence and Data Processing (IDAP)*, Malatya, Turkey (2018), pp. 1–5
96. T. Holden, J. Yazdani, Hybrid security for hybrid vehicles exploring smart grid technology, powerline and wireless communication, in *2011 Second IEEE PES International Conference and Exhibition on Innovative Smart Grid Technologies*, Manchester (2011), pp. 1–5
97. F. Salvadori, C.S. Gehrke, A.C. de Oliveira, M. de Campos, P.S. Sausen, Smart grid infrastructure using a hybrid network architecture. IEEE Trans. Smart Grid **4**(3), 1630–1639 (2013)
98. L.T. Berger, A. Schwager, P. Pagani, D.M. Schneider, MIMO power line communications. IEEE Commun. Surv. Tut. **17**(1), 106–124 (2015)
99. M. Sayed, T.A. Tsiftsis, N. Al-Dhahir, On the diversity of hybrid narrowband-PLC/wireless communications for smart grids. IEEE Trans. Wireless Commun. **16**(7), 4344–4360 (2017)
100. C. Vlachou, A. Banchs, P. Salvador, J. Herzen, P. Thiran, Analysis and enhancement of CSMA/CA with deferral in power-line communications. IEEE J. Sel. Areas Commun. **34**(7), 1978–1991 (2016)
101. S. Yoon, D. Kang, S. Bahk, Multichannel CSMA/CA protocol for OFDMA-based broadband power-line communications. IEEE Trans. Power Deliv. **28**(4), 2491–2499 (2013)
102. Y. Han, K. Zhang, H. Li, E.A.A. Coelho, J.M. Guerrero, MAS-based distributed coordinated control and optimization in microgrid and microgrid clusters: a comprehensive overview. IEEE Trans. Power Electron. **33**(8), 6488–6508 (2018)
103. A. Parisio, E. Rikos, L. Glielmo, A model predictive control approach to microgrid operation optimization. IEEE Trans. Control Syst. Technol. **22**(5), 1813–1827 (2014)
104. B. Wang, M. Sechilariu, F. Locment, Intelligent DC microgrid with smart grid communications: control strategy consideration and design. IEEE Trans. Smart Grid **3**(4), 2148–2156 (2012)
105. C. Lo, N. Ansari, Decentralized controls and communications for autonomous distribution networks in smart grid. IEEE Trans. Smart Grid **4**(1), 66–77 (2013)
106. Y. Chia, S. Sun, R. Zhang, Energy cooperation in cellular networks with renewable powered base stations. IEEE Trans. Wireless Commun. **13**(12), 6996–7010 (2014)
107. Z. Fan, R.J. Haines, P. Kulkarni, M2M communications for E-health and smart grid: an industry and standard perspective. IEEE Wireless Commun. **21**(1), 62–69 (2014)
108. W. Chin, Y. Lin, H. Chen, A framework of machine-to-machine authentication in smart grid: a two-layer approach. IEEE Commun. Mag. **54**(12), 102–107 (2016)
109. R. Ma, H. Chen, W. Meng, Dynamic spectrum sharing for the coexistence of smart utility networks and WLANs in smart grid communications. IEEE Network **31**(1), 88–96 (2017)
110. R. Ma, S. Chen, H. Chen, W. Meng, Coexistence of smart utility networks and WLANs in smart grid systems. IEEE Trans. Wireless Commun. **15**(12), 8313–8324 (2016)
111. H. Al Haj Hassan, A. Pelov, L. Nuaymi, Integrating cellular networks, smart grid, and renewable energy: analysis, architecture, and challenges. IEEE Access **3**, 2755–2770 (2015)

112. X. Lu, W. Wang, J. Ma, An empirical study of communication infrastructures towards the smart grid: design, implementation, and evaluation. IEEE Trans. Smart Grid **4**(1), 170–183 (2013)
113. G. Wen, X. Yu, Z. Liu, W. Yu, Adaptive consensus-based robust strategy for economic dispatch of smart grids subject to communication uncertainties. IEEE Trans. Ind. Inform. **14** (6), 2484–2496 (2018)
114. M. Erol-Kantarci, H.T. Mouftah, Energy-efficient information and communication infrastructures in the smart Grid: a survey on interactions and open issues. IEEE Commun. Surv. Tut. **17** (1), 179–197 (2015)
115. B. Appasani, D.K. Mohanta, Optimal placement of synchrophasor sensors for risk hedging in a smart grid. IEEE Sens. J. **17**(23), 7857–7865 (2017)
116. P. Kong, C. Liu, J. Jiang, Cost-efficient placement of communication connections for transmission line monitoring. IEEE Trans. Ind. Electron. **64**(5), 4058–4067 (2017)
117. C. Wiezorek et al., Multi-location virtual smart grid laboratory with testbed for analysis of secure communication and remote co-simulation: concept and application to integration of Berlin, Stockholm, Helsinki. IET Gener. Transm. Distrib. **11**(12), 3134–3143 (2017)
118. W. Song, D. De, S. Tan, S.K. Das, L. Tong, A wireless smart grid testbed in lab. IEEE Wireless Commun. **19**(3), 58–64 (2012)