Chapter 1
Power Management for Wireless Base Station in Smart Grid Environment: Modeling and Optimization

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The overall contribution of cellular network operators to the entire human CO₂ emissions is estimated at 2.5% in the U.S. [1]. Thereinto, about 60% – 80% originates from wireless base stations (BSs) [7]. As current cellular network architectures are designed to cope with peak load and degraded conditions, underutilization of them occurs most of the time. A recent study [70] shows that the average power consumption of the traditional BS amounts to nearly 850W, with only up to 40W power consumed to transmit from the antennas and the rest wasted even during idle operation. This result indicates that there is a large room for power savings for nowadays’ cellular network.

In this chapter, we consider the problem of power management for wireless BS with renewable power source in smart grid environment. In Section 1.1, we first provide an introduction of green wireless communications with the focus on two closely related research fields, i.e., renewable power source and smart grid. Then, we provide an overview on the power management approaches of wireless BS, which consists of two major directions, i.e., BS power control and smart BS operation. The former is achieved at equipment level, while the latter can be realized at system/network level. Afterwards, we discuss about some challenges and open issues with regard to power management for BS. In Section 1.2, we present the power consumption model of wireless BS. Specifically, power consuming components are first introduced and analyzed. Moreover, we present two power consumption models, one for macro BSs which contains a static power consumption part only, and the other for micro BS which additionally consists of a dynamic power consumption part. The power consumption models of macro BS and micro BS allow to characterize, quantify and compare different deployment strategies when realistic input parameters are available. In Section 1.3, we propose an adaptive power management approach for wireless BS with a renewable power source in smart grid environment. While the main
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Power supply of wireless BS is from electrical grid, an alternative is from solar panel. An adaptive power management approach is used to coordinate among electrical grid and the solar panel, which is energy-efficient and allows for greater penetration of variable renewable power sources in green communication system. With smart grid technology, the adaptive power management can be informed of the instantaneous power price from the electrical grid and adjust power buying accordingly. However, in such an environment, many parameters are uncertain (e.g., generated renewable power, power price from electrical grid, and power consumption of wireless BS which depends on the traffic load). Therefore, the stochastic optimization problem is formulated and solved to achieve the optimal decision of power management. The performance evaluation is performed and clearly shows that with the optimal policy of the proposed adaptive power management, the power cost of the wireless BS can be minimized. We believe that the proposed solution based on the studied communication architecture is a major step towards green wireless communications.

1.1 Power Management for Wireless Base Station

This section focuses on the power management for wireless BS, which is a strategic target for green wireless communications. In the following, we first make an introduction of green wireless communications and its related issues. Then, we provide an overview on the power management approaches of wireless BS, as it is one of the main concerns in wireless cellular network. Finally, we outline some challenges and open issues.

1.1.1 Green Communications in Centralized Wireless Networks

Until now, wireless communication systems have been well developed and optimized in terms of spectrum efficiency [8], transmission reliability [9], and users’ satisfaction [10] from a variety of mobile applications. However, the increasing power cost and higher volume of teletraffic demand have posed new challenge to wireless communication system recently [11]. Owning to economical, environmental and marketing reasons, there is an immediate need for the “green” wireless communications which is a set of concepts, designs, and approaches to improve power efficiency of wireless system, while meeting the quality-of-service (QoS) of mobile applications and services. The advance of green wireless communications will benefit the network operator not only in saving the power cost through better power efficiency per service, but also in providing the environmental responsibility through minimizing the environmental impact (e.g., by using renewable power resource to reduce the CO₂ emission). In addition, wireless communication system has to match its own power demand to the change of power supply side, which will become more dynamic and distributed, known as “smart grid” [1]. Given all these requirements, the issue of power manage-
ment for wireless system becomes increasingly crucial and needs to be addressed accordingly. Over the years, valuable research efforts have been made in wireless industry, aiming for environment-friendly power solutions which lead to green wireless communications. Green wireless communications will contribute to the reduction of our global carbon footprint and enable mutual broader impacts across related fields, among which, renewable power sources [12] and smart grid are attracting growing interests. In the following, we present an introduction of the major concerns related to renewable power sources and smart grid.

1.1.1.1 Renewable Power Sources and Green Wireless Communications

Pushed by the climate change deriving from enormous power consumption as a result of rapid industrial development, renewable power resources are emerging as attractive alternative energy because of their low pollution and sustainable accessibility. In green wireless communications, renewable power resources can be used to replenish the energy of wireless BSs and/or network nodes as replacements of traditional fossil energy. Manufacturers and network operators have started developing and deploying wireless BS with renewable power source [59]. For example, Ericsson and Telecom Italia developed and tested the Eco-Smart solution which uses solar panel to fully power the cell site. Vodafone, China Mobile and Huawei jointly performed various experiments on the renewable power sources including solar panel, wind power generator, and the hybrid system for wireless BS [60]. The experiments focus on the implementation verification, power reliability, and cost reduction. However, renewable power sources (e.g., solar, wind, hydro, geothermal, tidal energy and biomass), are typically featured as weather-driven, uneven geographically distributed, non-scheduled, and relatively unpredictable. Since the amount of renewable power generation is known to be fluctuant and intermittent, efficient power management to match the power replenishment rate with actual power demand becomes one of the primary concerns of the applications of renewable power sources.

In wireless network, power saving often requires a degradation in network performance (i.e., higher latency and lower throughput) [13]. Compromise between power saving and network performance therefore should be well taken care of in the design of efficient power management. A number of interesting works have been carried out to address this issue in applying renewable power sources. Compromise between throughput and power constraints has been studied for a wireless network employing renewable power sources in [61]. Optimal scheduling algorithms were presented to maximize the throughput and total transmission data. More recently, [63] investigated the compromise between power saving and preventing node outage. An energy-aware resource provisioning algorithm was proposed for power provisioning in solar-powered wireless mesh network.

1.1.1.2 Smart Grid and Green Wireless Communications

High-voltage long-distance transmission and large-scale centralized electricity generation are the two basic causes of power inefficiency in traditional electrical
grid system. To deal with this problem, the concept of smart grid has been proposed to improve the power efficiency and reliability of the electrical grid by using information and communications technology (ICT). The key features of smart grid related to the green wireless communications are demand response (DR), demand side management (DSM), decentralized power generation, and price signaling. With DR and DSM, the power generators and consumers can interact to improve the efficiency of power supply and consumption. For example, the operation and power consumption of the deferrable load (e.g., heating and pumping) can be adjusted according to the generator capability. These two concepts will be further introduced in Section 1.3.2. With decentralized power generation, the power generation can be performed by consumers and small power plants (e.g., solar panel and wind turbine). As a result, consumers will be less dependent to the main electrical grid, reducing the power cost and avoiding the impact from power failure. With price signaling, the consumers will be aware of the current power price and the generators can use cheap power price to encourage the consumers to use the electrical power during off-peak period (e.g., night time or weekend). Consequently, the peak load will be reduced which results in lower investment for the infrastructure (e.g., transmission line and substation).

The enabling technologies of interaction between smart grid and wireless communications have attracted a lot of research attentions [64]. On one hand, wireless communications are the key components in smart grid to communicate a variety of data and measurement among power generators, transmission lines, distribution substations, and consumer loads. On the other hand, smart grid can be used to support green wireless communications for the better use of power to provide wireless service to mobile units. This similar concept has been explored in the “green computing” [2]. In a green computing, the data center can schedule the service request (i.e., data processing) according to the power supply from electrical grid. Also, efforts have been made on theoretical analysis. In wireless network, each wireless BS/node powered by smart grid might be selfish in improving its own performance in capacity or QoS. How to improve power saving without adversely affecting capacity and QoS is one of the main concerns. Recent progress in wired distributed computing theory [65] has provided fundamental models for coordinated management and load balancing of wireless BSs underneath smart grid, which has potential for addressing the concern.

1.1.2 Approaches of Power Management for Wireless Base Station

In the past years, cellular network operators have dedicated valuable efforts to streamlining all the network components across BSs [3], mobile units [4, 5], and backhaul networks [6] for environmental as well as economic reasons. The focus of this section is on the power management for BS, as BS is the dominant power consumer in wireless cellular networks. Power management for wireless BS has been extensively studied over the past decades. The existing approaches can be achieved in two ways, BS power control, and smart BS operation. The former
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is done at equipment level, while the latter can be realized at system/network level. In the following, we present an overview of power management approaches that are applicable to wireless BS, which is of great significance towards green communications.

1.1.2.1 BS Power Control

Power control is a necessary feature in wireless cellular networks and the key for the management of interference, energy, and connectivity [14]. With power control, wireless BS transmits and receives at an appropriate power level to minimize the interference as well as satisfy the required QoS. The QoS requirement is mainly to satisfy some received power and signal quality requirements at the receiver side (i.e., mobile unit).

BS power control is often formulated as an optimization problem. According to the optimization variables, the existing approaches of BS power control have mainly three types: Opportunistic BS Power Control which considers only transmit power as optimization variable, Joint BS Power Control and Beamforming which additionally concerns beamforming vectors, and Joint BS Power Control and BS Assignment which considers both transmit power and connectivity in an optimization formation.

The objective of Opportunistic BS Power Control approach is to adjust transmit power and increase transmission rate when channel is in good quality and avoid using the channel when the channel quality is below a threshold. To exploit variations in channel quality, the instantaneous and history information of channel quality are leveraged opportunistically. Opportunistic BS Power Control enables priority in channel access for mobile units. An example of opportunistic BS power control is in cognitive radio network [16], where primary users (users with higher priority) are always able to maintain their signal-to-interference ratio (SIR) requirement. However, because of the variation in channel quality and user mobility, secondary users (users with low priority) have to transmit their data opportunistically without violating the SIR requirement of primary users. Opportunistic BS Power Control that maximizes the total downlink utilities of a cell has been studied in [17, 18]. In Opportunistic BS Power Control, BS schedules the channel and transmit power for selected mobile units to transmit. The most commonly adopted scheduling approaches for BS mainly include proportional fair scheduling [19, 18] and general utility-based scheduling [15].

Joint BS Power Control and Beamforming is the approach of power management in multiple antenna system. With an introduction of multiple-input-multiple-output (MIMO) technology, deploying multiple antennas at both BS and mobile unit provides better diversity in power control. To compromise among hardware limitation of mobile unit, network performance and complexity, beamforming technology with multi-antenna BS and single-antenna mobile unit is advocated [20, 21]. In the downlink, the beamforming vectors spread signals over the antenna array prior to transmission [20]. The beamforming vectors are coupled and must be optimized jointly, which makes Joint BS Power Control
and Beamforming a complicated problem. Approaches to address the problem have been proposed in [25, 26, 27, 28] for fixed SIR requirement, and in [29] for max-min SIR fairness. The key of these solutions is the use of uplink-downlink duality concept [22]. The idea of uplink-downlink duality is that, under the same power constraint, the optimal beamforming vectors in the downlink are also the optimal beamforming vectors in the uplink [22, 23, 24]. This duality theorem leverages the better understood knowledge in uplink beamforming for the downlink problem. Base on the duality theorem, downlink BS power control problems can be transformed into their dual uplink domains and efficiently solved.

BS assignment [31] provides reassignment of BSs, functioning as servers, to mobile units to deal with dynamic connectivity patterns between mobile units and BSs. Joint BS Power Control and BS Assignment aims to determine the BS assignment that minimizes the required transmit power with fixed SIR targets on each link. By jointly considering power and connectivity as network resources to optimize, the performance improvement of wireless cellular network and user experience could be expected. However, the joint optimization is difficult because of the coupling in SIR on each link. For example, the power adjustment caused by the BS assignment for a mobile unit from one BS to another may create greater interference for those mobile units near the latter BS. To overcome the difficulty, solutions have been attempted in [32, 33, 34] by applying the uplink-downlink duality mentioned above.

1.1.2.2 Smart BS Operation

Smart BS operation refers to the BS power management made at the system/network level to alleviate the power inefficiency which results from the fact that nowadays BSs are typically deployed and operated continuously based on peak-hour traffic estimates. Existing efforts addressing the energy-efficient operation of BS mainly includes BS Mode Switching and Cooperative Relaying.

In BS Mode Switching approach, BS can operate in two modes, i.e., active and sleep. This approach is applied in the wireless cellular network where BSs are densely deployed, e.g., urban area. The idea of BS Mode Switching is to dynamically minimize the number of active BSs to meet the traffic variation in the network. The overlapped coverage of the BSs results in small number of the mobile units associated with each BS and high traffic dynamics among BSs [38], which makes it feasible for BS Mode Switching to save power. To achieve this, some BSs are switched off during the periods when they are under-utilized because of low traffic load, leaving their radio coverage and service quality taken care of by the BSs that remain active. A case study in an urban UMTS network shows that, the little amplification in the transmit power of active BSs is negligible compared to the total power consumption saved by BSs switch-off [37]. Thus, wide implementation of BS Mode Switching has the potential to reduce power consumption of wireless cellular network substantially. BS Mode Switching approaches have been proposed for BSs in cooperative 2G/3G networks [39, 41], 2G and HSPA networks [40], and Long Term Evolution (LTE) system [42]. Except for the stud-
ies of BSs in wide area networks, BS Mode Switching approaches for small cell BSs, e.g., femtocell BS and picocell BS, have also been investigated and developed [44, 45]. Moreover, joint consideration of BS Mode Switching problem and mobile unit association for energy-delay tradeoffs with time scale separation has been studied in [43].

The objective of Cooperative Relaying is to minimize the power consumption of wireless cellular network for transmission, subject to the average transmission rate and signal-to-interference-plus-noise ratio (SINR) requirement of mobile unit’s traffic. Cooperative Relaying applies in wireless cellular networks with intra-cell orthogonal medium access control (e.g., TDMA, FDMA, or orthogonal CDMA), and Decode-and-Forward relaying adopted by either mobile units or relay stations (RSs). RSs can be considered as mini BSs which are able to transmit and receive signals from mobile units and have wireline connections to BSs. In the literature, two different types of relaying network architecture have been investigated. One uses a mobile RS as a signal relay between BSs and mobile units [51, 52]. The mobile RSs can also be other mobile equipments with additional features to function as relay. In the other case, RSs are fixed at certain locations in the cell [53, 54, 55]. When a BS needs to transmit signal to mobile units, RSs placed in between are chosen for signal relay. It is proven that Cooperative Relaying solves the problem of asymmetrical coverage [49] and “dead spots” [46], and can increase system coverage [47] and capacity gains [48] as well as reduce path loss and power consumption [50]. With regard to the effect of power consumption saving, case studies have been made in [56] for cooperative broadcasting in dense wireless cellular networks, in [57] by joint power minimization with routing in ad hoc network, and in [58] for a pair of source and destination nodes in a network with a number of RSs.

1.1.3 Open Research Issues

In the previous section, we have provided an overview of the existing approaches of power management for wireless BS. In this section, we outline some open research issues related to advancing the power management for wireless BS. The open research issues are presented accordingly with regard to our previous classification of the BS power management approaches.

The open research issues in BS power control are summarized as follows:

- In Opportunistic BS Power Control, feedback of channel quality measurement is the key to select mobile units to transmit. However, the feedback is sometimes inaccurate and delayed. How to characterize the impact of the limited information from feedback of channel quality remains to be an open issue for Opportunistic BS Power Control.
- Joint BS Power Control and Beamforming can be formulated in two ways, minimization of total transmit power for fixed SIR and maximization of total utility for variable SIR. Existing solutions have solved the former problem by
adding a beamforming vector update to power control algorithms [25, 26, 27, 28]. As for the latter problem, solutions have been attempted only in special cases [29, 30]. Joint Power Control and Beamforming for maximizing a general concave utility function are yet to be fully studied.

- The main challenge in joint BS Power Control and BS Assignment lies in the coupling in SIR on each link, combined with the integer constraints introduced by connectivity variables which is hard to solve. Also, Joint Power Control, Beamforming and BS Assignment has been proposed for further optimizing network performance [35]. The joint optimization problems require more research efforts.

The open research issues in smart BS operation are summarized as follows:

- In BS Mode Switching, frequent mode switching should be prevented, considering factors in implementation, e.g., signal overhead processing, working stability and equipment lifetime. How to achieve the best tradeoff between those factors in implementation and power saving requires further study. Besides, more research efforts on the effects of BS switch-off on coverage are needed, taking the consideration of technological aspects such as cell breathing [36] and antenna tilting [38] into account.

- As for Cooperative Relaying, the channel knowledge is crucial for RS selection. Most of the Cooperative Relaying studies assume perfect channel knowledge at mobile unit and BS side. However, it is hard to acquire accurate knowledge about the channel, e.g., fast fading channels only remain stationary for small durations. Thus, existing Cooperative Relaying approaches would not work well in a real implementation. How to cope with the positioning of relaying when the channel knowledge is inaccurate is a challenge. Another important issue is the incentive mechanism for Cooperative Relaying, which is also associated with implementation. Although from the collective point of view, the total power consumed from relay transmission by the RSs and mobile units is lower than that from direct transmission by BS, a mobile unit will not relay traffic for another one unless it has own benefit from individual point of view. It is necessary to study the mechanism to optimize incentive for mobile unit to participant relaying before implementing the Cooperative Relaying approaches.

1.2 Power Consumption Model of Wireless Base Station

Nowadays, wireless communications are becoming a major worldwide cause of power consumption, with a high impact on carbon dioxide emissions [71]. In wireless cellular networks, the wireless BSs, backhaul routers and data servers are the major power consumers, and hence, the main contributors to CO₂ emissions. Due to spectrum scarcity and high bandwidth requirements of the mobile units, a much more dense wireless BS deployment is expected in future wireless
cellular networks, particularly with regard to traffic coverage. Therefore, significantly increased demand in power consumption for wireless cellular network can be envisioned. This also indicates that environmental problem associated with wireless BS is becoming an important issue in the coming years.

Today’s cellular networks mainly consist of a large amount of conventional macro BSs and a small number of recently adopted micro BSs. Macro BSs are strong in power and usually cover area radius of about 500 meters up to 2500 meters and a degree of coverage of at least 90% in urban areas [73]. The average power consumption of a macro BS is determined by its covered area and the degree of coverage. Comparatively, a micro BS is small-coverage, low-power, lower-cost cellular BS with the target to expand coverage and improve capacity of wireless cellular network [66]. Compared to the macro BS, the area covered by a micro BS generally enjoys much higher average SINR due to advantageous path loss and shorter propagation distance. With the increasing demand of high QoS in wireless cellular network, it is expected that a significant amount micro BSs will be deployed in the future [67].

This section concerns macro and micro BSs in power consumption, specifically, the power consumption models of them are introduced, with a focus on component level. Power consumption is one of the most important figure of metrics to measure energy-efficiency of deployment strategies applied in wireless cellular network. The power consumption models allow to characterize, quantify and compare different deployment strategies when realistic input parameters are available.

1.2.1 Components of Wireless Base Station

A wireless BS is an equipment communicating with the mobile units and the backhaul network. In a wireless BS, there are typically several power consuming components. Figure 1.1 gives an overview of these components. Among these ones, there are components that are parts of sector of wireless BS. These equipments include followings:

- Power amplifier (PA) is responsible for amplifying input power. To maximize PA efficiency, a PA is expected to work in a state in which the peak value of the signal corresponds with the possible peak power of the PA.
- Digital signal processing is responsible for system processing and coding.
- A/D converter converts an input analog voltage or current to a digital number proportional to the magnitude of the voltage or current.
- Transceiver is in charge of receiving and sending of microwave signal to mobile units.
- Signal generator produces microwave signal.
- Antenna is used to transmit or receive microwave signal.
- Feeder is the component to feed the microwave signal to the rest of the antenna structure.
Since the power consumption of A/D converter is less than 5% of a macro BS’s input power [72], it is not considered separately and assumed to be included in the signal processing part. The power consumption of signal processing part is denoted as $P_{SP}$. The transmission part consists of PA, transceiver and signal generator, which totally consume power of $P_{TX}$. The power consumption of antenna and feeder is included into the link budget.

Also, a wireless BS contains equipments that are commonly used by all sectors such as cooling, which is responsible for dissipating the heat generated by the functioning of the components. The power consumption of cooling mainly depends on environmental conditions and is defined as $C_c$. This values is typically between zero (i.e., free cooling) and 40% [72]. Besides, a wireless BS is powered by a power supply and battery backup component. Loss occurs within
this component during power transmission. The power consumption of this component, denoted as $P_{PSBB}$, is typically between 10% and 15% [72] depending on the employed technology.

The main contributors to a BS’s power consumption typically include utilization of PA with corresponding link budget, different methods of cooling, e.g., air conditioning, air circulation and free cooling, site sharing, especially regarding infrastructure, and number of carrier frequencies.

For simplicity in modeling, each component of a wireless BS can be regarded to consume a constant value of power, except for PA, the power consumption of which depends on the input power of antenna. A parameter, $E_{PA}$, is defined as the ratio of transmit power to direct current input power to characterize the power consumption of PA.

1.2.2 Assumptions and Power Consumption Model of Macro Base Station

The power consumption of a BS varies over time, depending on the mode it is working in. Two modes can be distinguished, specifically, a BS can work in an operational or non-operational mode. In an operational mode, there are low traffic and peak traffic modes. Furthermore, a transition time is needed for a BS to switch between different modes, e.g., turning on the power of a BS consumes a dedicated amount of time and power. Since the time spent by BS in each mode is usually greater than all the transition time, it is assumed that the transition time is disregarded in modeling for both macro BS and micro BS.

The power consumption of a BS is composed of two parts, static and dynamic power consumption. The former describes the consumption which already exists in an empty BS, while the latter depends on the dynamic load situation. A recent measurement [70] shows that the power consumption of macro BS is barely relevant to the traffic load. For example, over a period of several days, about 3% and 2% variation in power consumption for a UMTS and a GSM BS is observed, respectively, while the data traffic of both BSs varies between no load and peak load level. Thus, macro BS is characterized and quantified in dependent of the load level. Also, since the amount of dynamic power is negligible, the dynamic power consumption is disregarded and the power consumption of macro BSs is considered to be static.

Considering all the different components of macro BS, the power consumption can be calculated as following,

$$P_{BS,Macro} = N_{Sector} \cdot N_{PAPSec} \cdot \left( \frac{P_{TX}}{E_{PA}} + P_{SP} \right) \cdot (1 + C_C) \cdot (1 + C_{PSBB}).$$

(1.1)

where the parameters are denoted in Table 1.1.
Table 1.1. NOTATION.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
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<tbody>
<tr>
<td>$N_{Sector}$</td>
<td>The number of sectors</td>
</tr>
<tr>
<td>$N_{P_{ApSec}}$</td>
<td>The number of PAs per sectors</td>
</tr>
<tr>
<td>$P_{TX}$</td>
<td>Transmit power</td>
</tr>
<tr>
<td>$E_{PA}$</td>
<td>PA efficiency</td>
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<tr>
<td>$C_c$</td>
<td>Cooling loss</td>
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<tr>
<td>$P_{SP}$</td>
<td>Power consumption for signal processing overhead</td>
</tr>
<tr>
<td>$C_{PS}$</td>
<td>Power supply and battery backup loss</td>
</tr>
<tr>
<td>$P_{MTX}$</td>
<td>Maximum transmit power per PA</td>
</tr>
<tr>
<td>$C_{TX,static}$</td>
<td>Static transmit power</td>
</tr>
<tr>
<td>$P_{SP,static}$</td>
<td>Power for static signal precessing</td>
</tr>
<tr>
<td>$C_{PS}$</td>
<td>Power supply loss</td>
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<tr>
<td>$C_{TX,N_{L}}$</td>
<td>Dynamic transmit power per link</td>
</tr>
<tr>
<td>$P_{SP,N_{L}}$</td>
<td>Dynamic signal processing per link</td>
</tr>
<tr>
<td>$N_{L}$</td>
<td>Number of active connections</td>
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1.2.3 Assumptions and Power Consumption Model of Micro Base Station

It is assumed that a micro BS consists of only one sector which contains one PA. No battery backup and air conditioning are typically needed for power supply and cooling, respectively, in micro BS. Compared to macro BS, the design size of micro BS is much more compact which results in limited transmit power and coverage area. Thus, the power consumption is considerably smaller.

Since the number of mobile units in micro cell is statistically varying, the traffic load variation, thus power consumption is dynamic. Power adaptivity of PA is the key for energy-efficiency in micro cell. For example, for a given mobile unit density, there is a high probability that no one locates in a micro cell, lowering down the transmit power in this case will lead to abundant power saving. Therefore, micro BSs are usually equipped with more efficient PA to cope with the traffic load variation. It is assumed that PA in micro BSs shall be able to adapt their power consumption to traffic load conditions.

Regarding to the property of power adaptivity of PA, the power consumption of micro BS can be modeled as

$$ P_{BS,Micro} = P_{static,Micro} + P_{dynamic,Micro} $$  \hspace{1cm} (1.2)

where $P_{static,Micro}$ and $P_{dynamic,Micro}$ represent static and dynamic power consumption in micro BS, respectively.

Similar to that of macro BS, the static power consumption of micro BS can be calculated as,

$$ P_{static,Micro} = \left( \frac{P_{MTX}}{E_{PA}} \cdot C_{TX,static} + P_{SP,static} \right) \cdot (1 + C_{PS}) $$ \hspace{1cm} (1.3)

where the parameters are denoted in Table 1.1.
Digital part (i.e., digital signal processing) is the main cause for the dynamic part of the power consumption of a micro BS. It is assumed that the digital part scales according to the number of active connections. Thus, the dynamic power consumption can be calculated as

\[
P_{\text{dynamic,Micro}} = \left( \frac{P_{\text{MTX}}}{E_{\text{PA}}} \cdot (1 - C_{\text{TX,static}}) \cdot C_{\text{TX,static}} + C_{\text{TX,NL}} + P_{\text{SP,NL}} \right) \cdot N_{\text{L}} \cdot (1 + C_{\text{PS}}).
\]

where the parameters are denoted in Table 1.1.

### 1.3 Optimization of Power Management in Smart Grid Environment

The fact that current power network (i.e., electrical grid) needs to provision enough generation, transmission and distribution capacities for peak rather than the average demand leads to overplus of power supply and a mass chunk of waste over most of the time, as load demand fluctuates periodically. The smart grid technology has been proposed to address the inefficiency of electrical grid, which has become a social issue due to resource depletion and increase in power cost. Smart grid is an auto-balancing, self monitoring electrical grid that integrates various generation concepts and technologies [74]. In smart grid, consumers adjust their consumption based on their demand and market information to optimize the use of power sources and minimize the negative impact on environment (e.g. CO\(_2\) emission).

One of the strategical approaches to improve efficiency and reducing power waste is to match the supply [69]. However, with the steady rise in the proportion of renewable power sources, power supply nowadays is also becoming highly time-varying, which makes matching the supply increasingly challenging. To address the challenge, we study a green communication system model where wireless BS is provisioned with a combination of electrical grid and renewable power source. Taking into account the real-time availability of a partly unpredictable supply, we design a reliable and efficient DR program, called adaptive power management, with the purpose of facilitating the adoption of renewable power resource generation by matching the load demand to an ever-changing power supply.

#### 1.3.1 System Model

The system model of adaptive power management for wireless BS is shown in Figure 1.2. The components in this system model are presented as following:

- **Wireless BS**: Wireless BS or access point is a centralized device used to provide wireless services to mobile units. As introduced before, wireless BS is the main
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Renewable power is provided from natural resources such as sunlight and wind which are replenishable. As a result, the variable cost of renewable power is usually cheaper than that from electrical grid. However, owning to the unpredictable availability of natural resources, the amount of power generated is typically highly time-varying. Therefore, renewable power source is considered to be an alternative power supply of electrical grid. The maximum amount of power (i.e., capacity) generated from renewable power source is denoted by $R \text{ kW}$ (kilowatt).

- **Electrical grid:** Electrical grid is an interconnected network composed of power lines and distribution substations for electricity delivery from generators to consumers. Electrical grid acts as the main source of power supply to the wireless BS. The power supplied from electrical grid is charged at a price per kWh (kilowatt-hours).

- **Renewable power source:** Renewable power is provided from natural resources such as sunlight and wind which are replenishable. As a result, the variable cost of renewable power is usually cheaper than that from electrical grid. However, owning to the unpredictable availability of natural resources, the amount of power generated is typically highly time-varying. Therefore, renewable power source is considered to be an alternative power supply of electrical grid. The maximum amount of power (i.e., capacity) generated from renewable power source is denoted by $R \text{ kW}$ (kilowatt).

- **Power storage:** Battery is the power storage device for wireless BS. Battery can be charged by the power from the renewable power source when it is available or from the electrical grid when the power price is low. Battery has a limited maximum capacity for power storage denoted by $B \text{ kW}$. Note that the power stored in a battery can decrease even without consumption. This is

Figure 1.2 System model of adaptive power management for wireless base station in smart grid.
referred to as the self-discharge phenomenon [76]. The self-discharge rate per time unit is denoted by $L$.

- **Adaptive power management controller:** Adaptive power management controller is implemented with a DR program to make decision on power supply from renewable power source and electrical grid to the battery and wireless BS. The design goal of the adaptive power management controller is to make optimal decision to minimize power cost, subject to the constraint that the power demand of wireless BS should be met. The details of how to realize the optimal decision making will be presented later in this section.

While the electrical grid is owned by the utility company, wireless BS, power storage, renewable power source, and adaptive power management controller belong to the network operator with the objective to minimize power cost. The information to be exchanged and maintained among above components to support adaptive power management for wireless BS includes following: price of power from electrical grid, the amount of power generated from renewable power source, battery storage, and power consumption of wireless BS. These information is required to be measured and reported periodically to the adaptive power management controller. We assume that the communications infrastructure to transfer these information are available, as this communication capabilities will become norm in future smart grids [75]. To enable information exchange in this case, broadband access (e.g., ADSL) and local area network (e.g., Ethernet) can connect the adaptive power management controller with the electrical grid and renewable power source as well as wireless BS.

Adaptive power management can be considered as a DR program, the main aim of which is to provide incentive to mobile units to defer their power consumption from peak periods to off-peak periods. In the environment of the system model under consideration, adaptive power management has ability to control the power buying (i.e., consumption) from electrical grid and from renewable power source given the varied price and the amount of renewable power generation. In addition, adaptive power management controller will defer power buying when the price is high (e.g., peak hour) and shift the consumption (e.g., charging battery) to the off-peak duration such as nighttime. The micro BS is considered in which its power consumption depends on the traffic load (i.e., dynamic power consumption is significant compared to static consumption). The model described in (1.2) is used.

### 1.3.2 Demand Response for Wireless BS in Smart Grid

An important feature of smart grid is that consumers work as an integral part of the power system, participating in system operation and management. With the aim to balance the power consumption from peak to off-peak period, reducing the cost of infrastructure to accommodate peak demand, it is critical for smart grid to enable the power consumers (e.g., wireless BS) to adjust their own power.
consumption. In this context, two concepts, DR and DSM, are basically perceived as the solutions to achieve the aim.

DR refers to the short-term changes targeted for the critical hours during a period (e.g., a day/year), when the demand is high or when the reserve margin is low, while DSM is the long-term changes in power consumption or customer behavior achieved by demand-side efforts. By enabling mobile units to take actions in response to the supply conditions, both DR and DSM turn electrical grid from a vertically controlled structure into a collaborative environment where the grid system is not only governed by the generation side, but also affected by the participating mobile units.

This section focuses on DR scheduling and implementation in smart grid system. Under smart grid, the objective of DR is to average out the load shape, shifting as much the flexible demand as possible away from peak period into less stressful periods (i.e., through a power storage). This requires careful balancing of the relationship between the electrical grid operators and mobile units. The advantage of DR is twofold. First, it alleviates the maximum power generation capacity required by a utility in order to avoid instability of electrical grid, occurrences of equipment failures, blackouts or brownouts. Second, by shaping the power usage to remain relatively constant over time, it avoids repeating to start and stop power generating units.

The management of DR in smart grid involves four main participants: power balancing authority which orders (i.e., offers or requests DR), DR aggregator which integrates individual DR resources, distribution utility/system operator which operates the distribution grid where DR events are happening, and power consumers that are subscribed to the DR programs. In the system model introduced in Section 1.3.1, adaptive power management controller is a combination of power balancing authority and DR aggregator, while electrical grid and wireless BS work as distribution utility/system operator and power consumer, respectively.

The scheduling process of DR management is initiated from the balancing authority, the order from whom is signaled to DR aggregators covering the whole or part of grid territory. DR aggregators compare the order with the DR availability and select the participant units by considering each one’s compliance factor which is statistically calculated. Then expected DR actions can be determined by DR aggregators and is returned to the balancing authority as a feedback.

According to the party which initiates the demand reduction, DR programs can broadly be of three types: Incentive-Based DR, Rate-Based DR and Demand Reduction Bid.

- Incentive-based DR is initiated by the utility or DR aggregator to provide incentive (i.e., reward), for wireless BS to decrease their power consumption during peak periods. Through shifting load from peak to off-peak periods, wireless BS can release the demand stress they place on the electrical grid. In
turn, the participated wireless BS could receive discounted charge or separate incentive reward.

- Rate-Based DR charges the price of electricity on a real-time basis and let wireless BS voluntarily respond to the varying electricity price. Under this type of DR programs, the wireless BS would have to pay high price for peak periods and low price for off-peak periods.

- Demand Reduction Bid is to encourage wireless BS to reduce load demand at prices for which they are willing to be curtailed. The bid is initiated and sent from wireless BS to the utility or DR aggregator, normally with the information of the amount of demand reduction and the price asked for.

In the following section, we introduce an adaptive power management approach for wireless BS in smart grid environment, which can be regarded as an Incentive-based DR program.

1.3.3 Optimization Formulation of Power Management

The challenge of adaptive power management for wireless BS rests with the uncertainty in the smart grid environment and system. To address this issue, stochastic optimization problem can be formulated and solved to realize the best decision making of power buying for the adaptive power management controller. The general objective is to minimize the cost, while the demand is met.

1) Uncertainty: A variety of uncertainties exist for the power management for wireless BS, which are listed as following.

- **Renewable power source**: Due to the weather-driven nature of renewable power resources, the amount of power generated from renewable power sources such as solar and wind generators is highly time-varying [77]. For example, the solar energy depends on the amount of sunlight. Unpredictable factors in weather, like cloud and rain, can reduce the amount of generated power.

- **Power price from electrical grid**: The power price from electrical grid fluctuates within a certain range depending on the instantaneous system conditions (e.g., demand) of the electrical grid [78], which is unpredictable. For example, power price can be high in a certain time interval (i.e., peak hour), which needs to be informed to the consumers instantly (i.e., by price signaling feature in smart grid).

- **Traffic load of wireless BS**: The traffic load is random because of the following two reasons. First, the connection arrival (i.e., newly initiated and handoff units) can be varied (e.g., due to the mobility) which results in a random number of ongoing connections $N$ in a wireless BS [79]. Second, the connection demand of a wireless BS varies depending on the usage condition (e.g., special event which results in peak load). As a result, the power consumption which can be calculated from the power consumption model introduced in Section 1.2.3 is also random.
The uncertainty can be represented by the “scenario” which is the realization of random variable. The scenario takes value from the corresponding space which is commonly assumed to be finite discrete set. For example, during a certain time interval, the power price can be taken from a set of 20 and 30 cents per kWh (i.e., off-peak and peak hour prices, respectively). The scenario can be also defined over multiple intervals. For example, with four intervals in one day, the first scenario can be defined as {20, 20, 30, 20} cents per kWh for the power prices in the morning (6:00 – 12:00), afternoon (12:00 – 18:00), evening (18:00 – 24:00), and at night (0:00 – 6:00), respectively. Alternatively, the second scenario can be defined as {20, 30, 30, 20} cents per kWh, which means in this case peak-hour price is offered in the afternoon and evening.

With multiple random parameters, the scenario is defined as a composite value of generated renewable power, power price from electrical grid, and power consumption of wireless BS. For example, one scenario denoted by \( \omega \) is defined as follows: For morning, afternoon, evening, and night, the generated renewable powers are \{200, 300, 0, 0\} W, the power prices are \{20, 20, 30, 20\} cents per kWh, and power consumption are \{200, 250, 300, 200\} W, respectively. A possible way to obtain the scenarios is to extract from historical data, e.g., the traffic load history and the corresponding power price from electrical grid. Meanwhile, the weather forecast can be used to determine the scenario of generated renewable power.

The probability distribution associated with the scenario of generated renewable power, power price from electrical grid, and power consumption of wireless BS can be estimated. Given the observation period (e.g., 90 days), the number of days for the observed scenario can be counted. The corresponding probability can be then calculated by dividing this number of days of a certain period by the duration of the observation period (i.e., 90 days). For example, if the number of days for the power price scenario \{20, 20, 30, 20\} is 27 days, while the number of days for scenario \{20, 30, 30, 20\} is 63 days, then the probabilities for the first and second power price scenarios are \( \frac{27}{90} = 0.3 \) and \( \frac{63}{90} = 0.7 \), respectively. The same method can be applied for the scenarios of generated renewable power and power consumption.

2) Stochastic Programming Formulation: The optimization problem based on multi-period linear stochastic programming can be formulated and solved to obtain the decision of adaptive power management controller under uncertainty. Stochastic programming is an extension of the deterministic mathematical programming, and can be used to model the optimization problem with uncertainty of parameters [80]. An advantage of stochastic programming is that it does not have a strong assumption on the complete knowledge of the parameters. Instead, stochastic programming incorporates the probability distribution of random parameters, which can be statistically estimated, into the optimization formulation. A feasible policy for the possible cases (i.e., scenarios) can be obtained form the optimal solution of stochastic programming. This optimal solution or policy which is a mapping from scenario to the decision can mini-
mize the expectation of the objective (i.e., cost). To get the optimal solution of stochastic programming, equivalent deterministic mathematical program can be formulated and efficiently solved by the standard methods (e.g., interior point method). For example, linear stochastic programming problem can be transformed into the deterministic linear programming problem and solved to obtain the optimal solution.

Although other approaches (e.g., Markov decision process, robust optimization, and chance-constrained programming) are also able to cope with the optimization problem with uncertainty, they are not necessarily suitable for the cost optimization of adaptive power management for wireless BS. For Markov decision process, the stochastic process of the random parameters must have Markov property, i.e., the state (i.e., scenario) of the random parameter depends on the current state rather than past one. This Markov property may not be held in many situations in smart grid environment (e.g., power price from electrical grid). For robust optimization, the solution is obtained only for the worst case scenario with which performance can be unrealistically poor due to the consideration of extreme case. For chance-constrained programming, with optimal solution, the constraint violation will be bounded by the threshold. However, only complex analysis exists for the basic probability distribution (e.g., normal distribution).

Therefore, stochastic programming becomes the best approach for the adaptive power management since this approach can be used to obtain the optimal solution which ensures that all constraints will be met. The efficient method can be applied to obtain the optimal solution for possible scenarios in which the expectation of cost given uncertainty is minimized.

For the optimization model, we consider a $T$-time-interval decision horizon, with the length of each time interval to be one hour. Within a time interval, the power price from electrical grid is constant. Then, the multi-time-interval stochastic programming model for adaptive power management can be formulated as following,

$$\min_{x_{t,\omega}} \sum_{t=1}^{T} \mathbb{E}(x_{t}P_t + s_{t}L) = \sum_{t=1}^{T} \sum_{\omega \in \Omega} Pr(\omega)(x_{t,\omega}P_{t,\omega} + s_{t,\omega}L)$$

subject to

$$s_{t,\omega} + x_{t,\omega} + R_{t,\omega} = s_{t+1,\omega} + C_{t,\omega} + y_{t,\omega}, \quad t = 1, \ldots, T-1, \omega \in \Omega$$

$$s_{1,\omega} = B_1, \quad s_{T,\omega} = B_T$$

$$x_{t,\omega} \geq 0, \quad s_{t,\omega} \geq 0, \quad y_{t,\omega} \geq 0, \quad t = 1, \ldots, T, \quad \omega \in \Omega$$

The objective and constraints of the optimization formulation defined above are introduced accordingly as follows:

- (1.5) is an objective to minimize the expected cost due to power buying from electrical grid and battery loss due to self discharging over the entire decision
horizon (i.e., $t = 1, \ldots, T$). $s_{t,\omega}$ represents the amount of power stored in battery at the beginning of time interval $t$ in scenario $\omega$. $x_{t,\omega}$ and $P_{t,\omega}$ are denoted as the amount of power buying from electrical grid and the power price during time interval $t$ in scenario $\omega$, respectively. $E(\cdot)$ is the expectation which is over all scenarios in space $\Omega$ given the corresponding probability $Pr(\omega)$ of scenario $\omega \in \Omega$.

- (1.6) is a constraint to balance of power input and output of a time interval $t$. The power input of a time interval $t$ includes the power stored $s_{t,\omega}$ at the beginning of time interval $t$, power buying $x_{t,\omega}$ and generated renewable power $R_{t,\omega}$ during time interval $t$. The power output of a decision time interval $t$ includes the power remained in battery $s_{t+1,\omega}$ at the end of time interval $t$ (i.e., at the beginning of time interval $t + 1$), the power consumption of wireless BS in the current time interval $C_{t,\omega}$, and excess power $y_{t,\omega}$. Note that the excess power is used to represent the amount of power input exceeding the power consumption and battery capacity.

- (1.7) is a constraint of power storage that the power in the battery must be lower than or equal to the capacity $B$.

- (1.8) denotes the initial and termination condition constraints, where $B_1$ and $B_T$ are the power storage in battery at the first and last time intervals, respectively.

- (1.9) states the constraint of non-negative value of power.

The above multi-time-interval stochastic programming model can be transformed into a linear programming problem, which can be solved by applying the standard method of linear programming solution [80]. The solution value, denoted by $x^*_{t,\omega}$, is the amount of power buying from electrical grid at time interval $t$ given scenario $\omega$. When the realization of the scenario of generated renewable power, power price, and power consumption is observed, this solution is applied.

### 1.3.4 Performance Evaluation

1) **Parameter Setting**: An adaptive power management for a micro BS is considered with the parameter setting of the micro BS similar to that in [72]. The static power consumption is 194.25W, while the dynamic power consumption coefficient is 24W per connection. The transmission range of micro BS is 100 meters in which the transmit power calculated as in [72] is applied to ensure the reliable connectivity of the mobile units. The maximum number of connections of the micro BS is 25.

We consider the solar panel as a renewable power source. The capacity of the solar panel is 450Wh. The battery capacity is 2kWh. The initial and termination power levels of battery are assumed to be 500W. The self-discharge rate of the battery is 0.1% per hour. We consider the randomness of the power price, generated renewable power, and the traffic load of the micro BS. For power price, two
scenarios are considered, i.e., peak and off-peak hour prices, whose average power prices are 20 and 12 cents per kW.h, and the corresponding probabilities are 0.6 and 0.4, respectively. For renewable power source, two scenarios are considered, i.e., clear sky and cloudy, whose average generated power from 6 : 00 – 18 : 00 are 292 kWh and 150 kWh, and the corresponding probabilities are 0.6 and 0.4, respectively. For traffic load of the micro BS, five scenarios are considered, i.e., heavy uniform, medium uniform, light uniform, heavy morning, and heavy evening, and the corresponding probabilities are 0.1, 0.1, 0.2, 0.2, and 0.4, respectively. For heavy uniform, medium uniform, and light uniform scenarios, the traffic load is uniform and the mean connection arrival rates are 0.56, 0.22, and 0.15 connections per minute, respectively. For heavy morning and heavy evening scenarios, the connection arrival is peak during 8 : 00 – 11 : 00 and 17 : 00 – 21 : 00, whose mean connection arrival rates is 0.8 connections per minute, respectively. The adaptive power management scheme is optimized for 24-hour time interval.

2) Numerical Results: Figure 1.3 shows the different average power over the optimization period. In this case, the renewable power source (i.e., solar panel) can generate power only when the sunlight is available. Therefore, the adaptive power management controller has to optimize the power storage in the battery and the power buying from electrical grid to meet the requirement of the micro BS. We observe that the battery is charged with the renewable power. The power is bought from electrical grid occasionally for the micro BS (e.g., when the renewable power and storage power are unavailable between 23 : 00–05 : 00) or to charge the battery (e.g., at 08 : 00). Given the average power shown in
Figure 1.3, the power cost of this micro BS with adaptive power management is 9.19 dollars per month.

For comparison purpose, we consider a simple power management scheme in which the power is bought from electrical grid when renewable power is unavailable. In this case, the power storage in battery is maintained to be constant (i.e., 1kW). The power cost per month of this simple power management scheme is 14.7 dollars per month. Clearly, the proposed adaptive power management scheme achieves lower cost and lower power consumption from electrical grid. Even though the cost saving for one micro BS may be marginal (i.e., 5.51 dollars per month or about 37.48%), this cost saving can be significant when micro BSs experience wide deployment. Furthermore, the reduction of power demand from electrical grid which is mostly generated from traditional fossil fuel (e.g., coal and oil) will help to decrease the CO₂ emission, which is the main aim of green wireless communications.

![Figure 1.4](image)

**Figure 1.4** Power cost per month under different battery capacity.

Then, we study the impact of the battery capacity to the power cost. Figure 1.4 shows the power cost per month under different battery capacity and different renewable power source capacity. With the increase of battery capacity, the adaptive power management controller can store more power when the power price is low, i.e., when renewable power generates or when the power price from electrical grid is cheap. As a result, the power cost per month decreases. However, when a certain value of capacity is reached, the power cost becomes constant because all generated renewable power or the power with cheap price from electrical grid can be stored in the battery and sufficient for the future demand. Consequently, further increasing the battery power capacity over this...
threshold will not help to reduce power cost, while the cost of battery will be higher.

In addition, as expected, the power cost buying from electrical grid decreases as the capacity of renewable power source increases (Figure 1.4). However, it is also important to note that the cost of increasing the capacity of renewable power source cannot be ignored. For example, the average price of solar panel with capacity of 150W is 230 dollars. Therefore, the optimal deployment of battery capacity and renewable power source capacity is an important issue and require further studies in the future work.

![Image](average_power Battery Storage.png)

**Figure 1.5** Average buying power and battery storage under different connection arrival rates.

Next, we investigate the effect of traffic load of micro BS to the power consumption. Figure 1.5 shows the average power stored in a battery and power buying from electrical grid under different connection arrival rates. As expected, when the connection arrival rate increases, the micro BS consumes more power. However, with the renewable power source, the consumed power can be supplied partly from electrical grid. However, the power of battery storage increases as the traffic load decreases due to higher power consumption.

Then, the impact of threshold in connection admission control (CAC) to the QoS performance and power cost is investigated. With the guard channel CAC [81], the threshold is used to reserve the channels for handoff connections, since the mobile units are more sensitive to the dropping of handoff connection than the blocking of new connection. With guard channel CAC, the new connection is accepted if the current number of ongoing connections is less than the threshold, and will be rejected otherwise. As expected, as the threshold becomes larger, more new connections are accepted and can perform data transmission.
Consequently, the new connection blocking probability decreases (Figure 1.6). However, handoff connection dropping probability increases, since less channels are reserved. We observe that as the threshold increases, there will be more ongoing connections with micro BS due to more accepted new connections. Therefore, the power consumption increases, and the amount of power cost saving (compared to that without CAC) decreases (Figure 1.6). This result can be used to optimize the parameter (i.e., threshold) of CAC. For example, if the objective is to minimize the handoff connection dropping probability and maximize the power cost saving subject to the new connection dropping probability to be less than 0.1. Then, the threshold should be set to 20.

From above results, it is clear that, given various uncertainty including renewable power generation, power price, and traffic load of the wireless BS, the proposed adaptive power management can make optimal decisions to minimize the cost of power consumption. The optimization formulation will be useful for the design of the resource management of the wireless system in green wireless communications.

1.4 Summary

The growing concern of a global environmental change raises a revolution on the way of utilizing power. In wireless industry, green wireless communications have recently gained increasing attention and are expected to play a major role in reduction of electrical power consumption. In particular, actions to promote
power saving of wireless communications with regard to environmental protection are becoming imperative. The renewable power source and smart grid emerge as two major research fields that are closely associated with and push the promotion of green wireless communications. With the integration of these state-of-the-art green technologies and computing technologies, future wireless communication systems will become more smart, autonomous and open. To counter this trend, we contribute a study on power management for wireless BS in smart grid environment.

First, an introduction of green wireless communications has been given. Then, for understanding and optimizing an operation of wireless BS, the power consumption model of macro and micro BSs have been presented. Finally, the adaptive power management approach for wireless BS with a renewable power source in smart grid environment has been introduced. With an stochastic optimization method, the power cost of wireless BS can be minimized while meeting demand of mobile units.
References


