# Advances in Energy Harvesting Communications: Past, Present, and Future Challenges

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***Abstract*—Recent emphasis on green communications has generated great interest in the investigations of energy harvesting communications and networking. Energy harvesting from ambient energy sources can potentially reduce the dependence on the supply of grid or battery energy, providing many attractive benefits to the environment and deployment. However, unlike the conventional stable energy, the intermittent and random nature of the renewable energy makes it challenging in the realization of energy harvesting transmission schemes. Extensive research studies have been carried out in recent years to address this inherent challenge from several aspects: energy sources and models, energy harvesting and usage protocols, energy scheduling and optimization, implementation of energy harvesting in cooperative, cognitive radio, multiuser and cellular networks, etc. However, there has not been a comprehensive survey to lay out the complete picture of recent advances and future directions. To fill such a gap, in this paper, we present an overview of the past and recent developments in these areas and highlight a number of possible future research avenues.**

***Index Terms*—Energy harvesting, cooperative networks, cognitive radio networks, multi-user interference networks, cellular networks.**

## I. INTRODUCTION

WITH unprecedented growth in wireless data services, the demands for power are constantly increasing, leading to a battery depletion problem for wireless nodes/devices [1]. Recent advance in green technology has attracted a lot of attention from both academic and industrial research communities to consider a new paradigm shift of power supply by decreasing the use of fossil fuels while increasing more renewable energy sources in wireless communications and networking.

To achieve this, energy harvesting has been proposed as a viable solution that enables wireless nodes to scavenge energy physically or chemically from natural or man-made phenomena [2], [3]. For example, the physical effects like motion, vibration, pressure and electromagnetic radiation can be applied to harness energy from the environment or the body, and convert the harvested energy to electrical energy. As another example, sunlight can be converted into electricity by applying the chemical effect of photovoltaics. Also the thermoelectric effect, in which charge carriers in materials are diffused from the hot side to the cold side due to the temperature gradient, can be used to generate electricity.

Energy harvesting provides us with many promising advantages and unique features for future wireless communications that cannot be offered by conventional battery or grid power-operated communications, including self-sustainable capability, reduction of carbon footprint, truly wireless nodes without requiring battery replacement and tethering to electricity grids, easy and fast deployment in any toxic, hostile or inaccessible environments, etc. Hence, we can expect that energy harvesting in wireless networks is gaining more and more popularity in wide applications ranging from remote environmental monitoring, consumer electronics, to biomedical implants. It was reported by IDTechEx that the energy harvesting market was amounted up to \$0.7 billion in 2012, and the market growth was expected to quadruple by 2024 [4]. Furthermore, energy harvesting is particularly applicable to wireless sensor networks. The amounts of required energy are different for different types of wireless networks. Typical power requirement for wireless sensor nodes ranges from 100 $\mu$W to 100 mW, which is much less than that for other commercial mobile devices; for example, smart phone is on the orders of 20 mW $\sim$ 1.3 W. Thanks to the great achievements in low-power radio transceivers, many low-power wireless sensors that consume several microwatts have been developed, and more recently, the researchers in [5] have come up with a way to design picowatt radio chip. The combination of low-power wireless nodes and energy harvesting communications creates unprecedented opportunities in many emerging applications, e.g., internet of things (IoT), that were impossible in the past.

Various types of energy sources can be utilized to supplement energy supplies such as solar, wind, vibration, motion, electromagnetic (EM) wave [6]–[22]. The main difference between these renewable energy sources and the conventional non-rechargeable battery supply lies in the fact that the scavenging power is time-varying and limited in most circumstances, which stipulates a new design constraint on energy usage in the time axis. As a result, there is a need to revisit power management policies in all of the existing wireless communication systems

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so that energy expenditure can efficiently adapt to the dynamics of energy arrivals during the energy harvesting period.

In the past few years, there have been significant research progress on energy harvesting communications, and the main focus is on the development of energy harvesting models, protocols and transmission schemes in point-to-point communication systems [35]–[118]. Recently, considerable research efforts have been extended toward energy harvesting networking like cooperative networks, cognitive radio networks, multiuser interference networks, cellular networks [139]–[190]. The optimization of the entire energy harvesting network becomes a more difficult task due to the inclusion of multiple nodes.

In addition to data transmission, different network topologies pose various design considerations, and the energy consumption in achieving these particular application purposes cannot be ignored. In cooperative networks, relay nodes need to determine the signal relaying power in order to provide the desired link reliability from the source to the destination nodes. In cognitive radio networks, secondary users need to be aware of primary users' activity via spectrum sensing. To avoid the waste of the harvested energy, the interference among users is required to be appropriately managed in multi-user environments. In cellular networks, harmony of harvested energy and grid power in a hybrid energy source should also be addressed to ensure the user's quality-of-service (QoS). More recently, energy harvesting has fostered a new line of research, say energy cooperation and sharing, which permits nodes to share harvested energy with each other.

A couple of surveys related to energy harvesting have been conducted [19], [21], [23]–[34]. In [23], fundamental limits of energy harvesting communications are introduced from information-theoretic perspectives. Paper [24] summarizes the recent contribution in energy harvesting communications, whereas only few literatures related to energy harvesting networks are discussed. A survey in [25] mainly focuses on offline scheduling schemes, but online scheduling schemes are ignored, for energy harvesting communications. The works of [19], [21], [26]–[28] primarily cover the design topics of wireless-powered energy harvesting communications. Energy harvesting wireless networks have been also studied in literatures, e.g., cooperative networks in [29], cognitive radio networks in [30], multiuser interference networks in [31], cellular networks or small cells in [32]–[34]. However, the fragments of the broad area of energy harvesting communications and networking are reviewed in each individual work, and the amount of research devoted to energy harvesting networking has been rapidly increasing more recently.

While extensive studies are in progress on energy harvesting techniques, it is worth reflecting upon the current achievements in order to shed light on the future research trends. The goal of this survey article is to provide a comprehensive overview of the past development as well as the recent advances in research areas related to energy harvesting communications and networking. The rest of this paper is organized as follows. In Section II, we overview various energy sources and models. Energy harvesting and usage protocols are presented in Section III. We review the energy scheduling problems and optimization frameworks of the existing works in Section IV and various design issues in energy harvesting communications in Section V. The state-of-the-art research results in energy harvesting networking are discussed in Section VI. Section VII describes two application systems. We point out possible directions of future research in Section VIII and conclude this paper in Section IX.

## II. Energy Sources and Models

In this section, we will first introduce several essential types of energy harvesting sources in our daily life and discuss the characteristics, amount and applications for these energy sources. After that, energy harvesting models are reviewed, which allows us to realize how to model the harvested energy for the design of energy harvesting techniques and algorithms in the subsequent sections.

### A. Types of Energy Harvesting Sources

As shown in Fig. 1 and Table I, the energy harvesting sources can be generally divided into four types: solar/light, thermoelectric power, mechanical motion and electromagnetic radiation. Energy harvesting for wireless communications mainly considers ambient energy sources, e.g., solar, wind, motion, vibration and interference signals. While ambient sources enable environmentally friendly energy supplies, the main disadvantage is that they may not guarantee QoS in wireless applications due to the uncertainty in time, location, and weather conditions. To ensure the reliability, dedicated energy sources, e.g., power stations, are alternatives to supply energy on demand, and they afford to consistently recharge wireless nodes with QoS constraints. However, a clear disadvantage, in comparison with the ambient sources, is that the deployment of the dedicated sources incurs additional cost which increases with the performance requirement. Depending on the ways to scavenge energy physically and chemically, each kind of energy sources has unique characteristics in terms of predictability, controllability and magnitude, and detailed descriptions of all these energy sources are provided as follows.

*1) Solar/Light Energy Sources:* One of the most popular ambient energy sources is visible sunlight/light, and it is well studied and exploited in a wide variety of applications [3]–[7]. The light radiation is converted into electricity through photovoltaic cells. For outdoor environments, the solar power is an obvious energy source for self-sustainable devices during the daytime. While a potentially infinite amount of energy is provided by the sunlight, the energy available to a device could fluctuate dramatically even within a short period in practice, and the energy harvested level is influenced by many sophisticated factors, such as the time of the day, the seasonal weather patterns, the physical conditions of the environment, the characteristics of photovoltaic cells used, to name but a few [8]. Typically, the amount of solar-powered energy is in the order of $100\,\mathrm{mW/cm^2}$ in the daytime, but the disadvantage is that it disappears at night. Also, the solar radiation is dynamic, uncontrollable and only partially predictable in some stationary circumstances, but unpredictable in general cases. For indoor environments, any illumination can be applied as

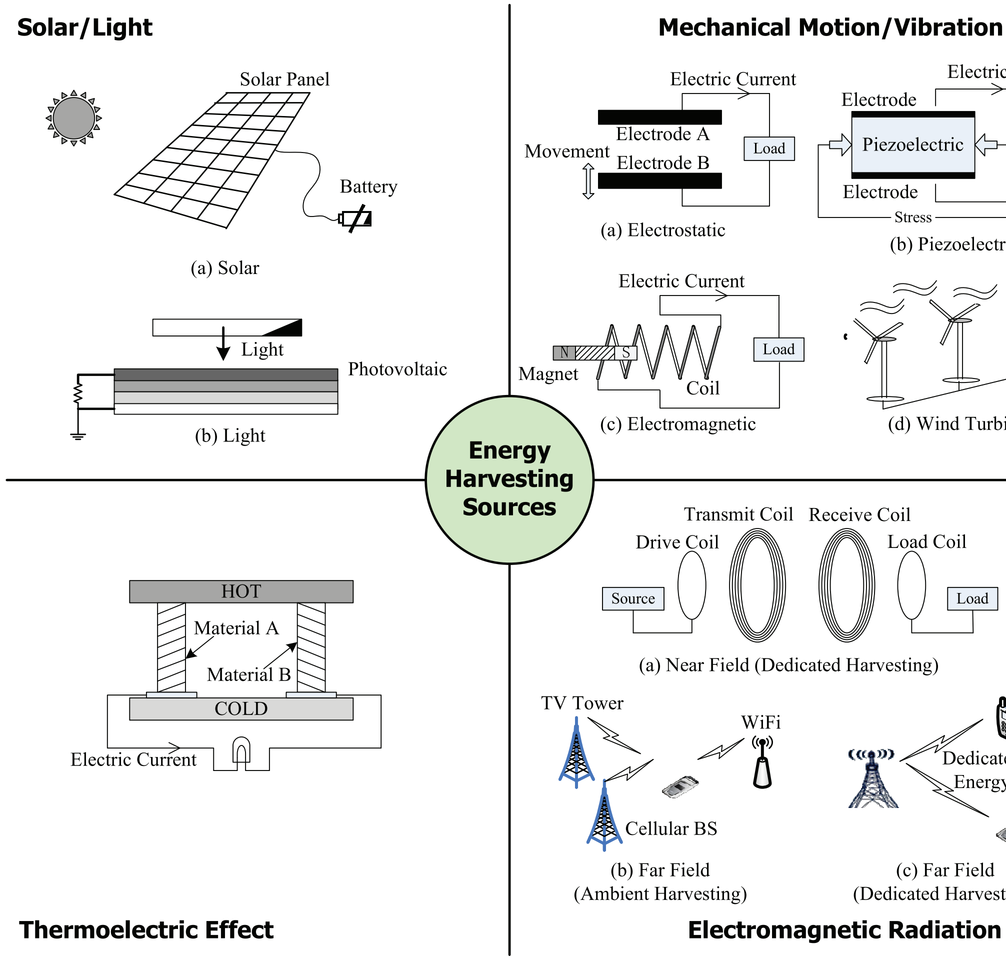


Fig. 1. Types of energy sources.

TABLE I
VARIOUS ENERGY SOURCES, CHARACTERISTICS, AMOUNT, AND APPLICATIONS

| Energy Source | Types | Characteristics | Amount | Applications |
|---|---|---|---|---|
| Solar [3]–[7] | Solar/light | Uncontrollable, partially predictable | 100 mW/cm$^2$ | Outdoor, wireless sensors, cellular base stations |
| Illumination [9], [10] | Solar/light | Partially controllable, predictable | 10 $\mu$W/cm$^2$ $\sim$ 100 $\mu$W/cm$^2$ | Indoor, wireless sensors |
| Thermal [6], [7], [11] | Thermoelectric | Uncontrollable, unpredictable | 10 $\mu$W/cm$^2$ $\sim$ 1 mW/cm$^2$ | Human body, wearable, consumer devices |
| Wind [15], [16] | Motion/vibration | Uncontrollable, unpredictable | 100 mW at wind speeds 2 m/s $\sim$ 9 m/s | Outdoor, wireless sensors, cellular base stations |
| Car engine [2], [14], [17] | Motion/vibration | Controllable, predictable | 30 mW | Vehicle, wireless sensors |
| Blood vessel [2], [14], [17] | Motion/vibration | Controllable, predictable | 1 $\mu$W | Human body, wearable devices |
| Knee bending [2], [14], [17] | Motion/vibration | Controllable, predictable | 7 W | Portable, wearable devices |
| EM induction [20] | Electromagnetic radiation | Controllable, predictable | high efficiency $\geq$ 80 % | Portable devices (distance: $<$ 1 m) |
| Ambient RF [20] | Electromagnetic radiation | Uncontrollable, unpredictable | 0.2 nW/cm$^2$ $\sim$ 1 $\mu$W/cm$^2$ | Wireless sensors, RFID (distance: $\sim$ 10 m) |
| Dedicated RF [28] | Electromagnetic radiation | Partially controllable, partially predictable | 5 $\mu$W at transmit power 4 W, distance 15 m | Wireless sensors, portable devices, power stations (distance: $<\sim$ km) |

the light energy source, while its power density is much lower than that of the solar power and depends on the illumination density as well as the distance between energy sources and energy harvesters [9], [10]. Specifically, its value ranges from 10 $\mu$W/cm$^2$ to 100 $\mu$W/cm. The efficiency achieved by commercial photovoltaic cells is around 8%, which is approximately one-third of the outdoor solar conversion efficiency. Besides, the artificial illumination is only available for a limited period of time, e.g., office hours, depending on the indoor environmental conditions. Although these challenges make the harvested energy relatively small, the indoor light is the most common energy source in most office and residential environments.

*2) Thermoelectric Energy Sources:* The thermoelectric effect can be used to harvest energy [6], [7], [11]. Specifically, a circuit voltage can be stimulated between two conductors with different materials when their junctions are kept at different temperatures. In reality, such a temperature gradient can come out of human bodies or machine conditions. The power densities of thermoelectric sources are primarily determined by the thermoelectric properties and the temperature difference of materials, and they are relatively low and merely range from $10\,\mu\mathrm{W/cm}^2$ to $1\,\mathrm{mW/cm}^2$. Wearable technologies including health monitors, smart watches, fitness bands, and shoes are growing in popularity. Thermoelectric sensors attached to human body, e.g., clothes, are capable of generating electricity by sensing the temperature difference between body and environment. The devices with thermoelectric energy sources have the advantages of long life and reliable with low maintenance, but the energy conversion efficiency is low. At temperature gradient of 5 °C, the harvested power level is around $60\,\mu\mathrm{W/cm}^2$ [2].

*3) Mechanical Motion/Vibration Energy Sources:* Electric power can also be produced by extracting energy from mechanical motion and vibration through transduction methods, including electrostatic, piezoelectric and electromagnetic [3]–[7]. In the electrostatic method, the mechanical motion or vibration can cause the distance change and voltage variation between two electrodes of a capacitor, generating the current in a circuit. In the piezoelectric method, power is obtained by means of piezoelectric materials, while in the electromagnetic method, relative motion between a magnet and a metal coil can stimulate an AC current in the coil, which is referred to as Faraday's law of induction. Generally speaking, the motion and vibration can arise from random and uncontrollable natural effects, e.g., wind and liquid flow [3], [7], [12], [13], or partially controllable human actions, e.g., blood pressure, heart beating, and heel striking [14]. Different motion and vibration energy sources result in different power densities, which can span a wide range of values. It is worth mentioning that when the intensity of the sun is too low to produce sufficient energy, the wind power is a good alternative for the solar power because they often complement to each other in time. In the daytime, an area tends to be windier with less sunlight if the sky is cloudier. Moreover, in many areas, the solar energy is strong in summer, whereas the wind energy gets high in winter. At wind speeds between 2 m/s and 9 m/s, a wind turbine is capable of generating around 100 mW of power [15], [16].

The kinetic energy is a popular energy source for wearable applications. In general, a vibrational microgenerator can generate $4\,\mu\mathrm{W/cm}^2$ and $800\,\mu\mathrm{W/cm}^2$ from human motion (5 mm motion at 1 Hz) and machine-driven motion (2 nm motion at 2.5 kHz), respectively [2]. With different types of generators, the energy harvesting from running shoes is investigated by Paradiso *et al.* of the MIT Media lab, and it is concluded in [17] that the piezoelectric sole, heel and electromagnetic generators can produce around 2 mW, 8 mW and 250 mW, respectively, depending on user's gait and weight. In addition, the vibration of a car engine, the fluctuating pressure in a blood vessel and the bending of the knee can produce output power up to 30 mW, $1\,\mu$W, and 7 W, respectively [2], [17].

*4) Electromagnetic Radiation Energy Sources:* Harvesting energy from EM radiation has attracted more and more attention due to the broadcast nature of wireless communications [3]–[7], [18], [19]. According to short-distance or long-distance applications, the electromagnetic energy sources can be divided into two categories: near-field and far-field. In near-field applications, EM induction and magnetic resonance methods are usually exploited to generate electric power and to wirelessly recharge devices within a distance of a wavelength. Thus, this kind of methods pertains to the dedicated energy sources which are predictable and controllable, and the energy transfer efficiency in near-field applications is higher than 80% [20].

In far-field applications up to a few kilometers, the EM radiation, appearing in the form of radio frequency (RF)/microwave signals, can be received by antennas and then converted to power by rectifier circuits [21], [22]. The RF/microwave sources could be ambient EM radiations from the surroundings or beamforming signals emitted by a known transmitter [32], [27]. The possible sources of the ambient radiations include WiFi access points, TV broadcast stations, amplitude modulation (AM)/ frequency modulation (FM) radio transmitters, and cellular base stations. Although the ambient RF energy is freely available and sufficient in urban areas, it becomes few in suburbs. The amount of harvested energy is uncontrollable and the power level could be as low as $-40\,\mathrm{dBm}$ [20]. On the other hand, the dedicated RF energy sources like cellular power towers are capable of providing on-demand energy supply with QoS constraints. While the power densities at the receiving antennas depend on the power of available sources and the signal propagation distance, this kind of energy is often controllable and predictable if an intended energy harvesting receiver is static. The harvested energy, by contrast, could be random if the receiver is in motion. Considering the power consumption and size (yielding different antenna apertures) of popular mobile devices, a power station transmitting tens of watts can power sensors, smartphones, laptops at a distance less than 15 m [28].

### *B. Energy Harvesting Models*

Energy harvesting models play vital roles in designing energy scheduling and evaluating the performance of energy harvesting wireless communications. Fig. 2 shows the classification of various energy harvesting models, and Table II summarizes the advantages, disadvantages and applications of various models. Based on the availability of non-causal knowledge about energy arrivals at the transmitters, the models adopted in the literature is primarily divided into two classes: deterministic models [35]–[38] and stochastic models [39]–[57], along with other special models [47], [60]–[63].

*1) Deterministic Models:* In deterministic models, full knowledge of energy arrival instants and amounts is known in advance by the transmitters [35]–[38]. The advantage and disadvantage of this model are given as follows. By assuming that the non-causal energy state information (ESI) is acquired

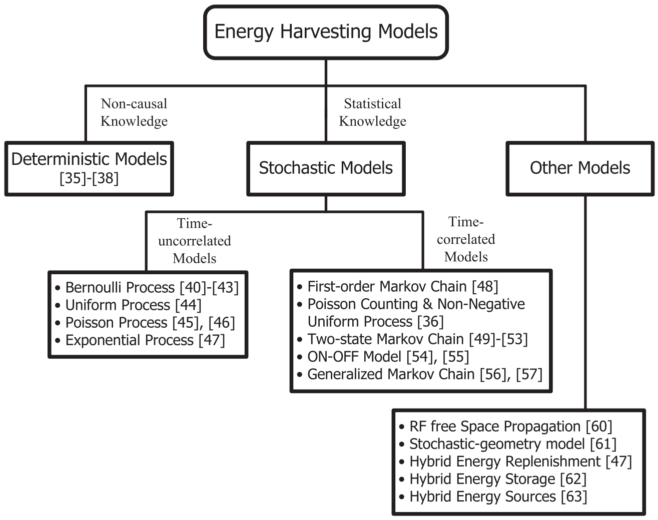


Fig. 2. Classification of energy harvesting models.

perfectly, deterministic models are useful to characterize the optimal energy scheduling strategies, to provide insights into designing some suboptimal approaches which only require the causal ESI, and to benchmark the fundamental performance limits of energy harvesting systems. Nonetheless, the success of the energy management utilizing this model heavily depends upon on accurate energy profile prediction over a somewhat long time horizon, and modeling mismatch often occurs when the prediction interval becomes enlarged. Hence, the deterministic models are suitable for the applications with the energy sources whose power intensities are predictable or vary slowly.

*2) Stochastic Models:* Recent attention has focused on stochastic energy harvesting models in which the energy renewal processes are regarded as random processes. One major advantage of this type of models is that there is no need for the non-causal knowledge of ESI, thereby being suitable for the applications when the ESI is unpredictable, while the drawback is that modeling mismatch always occurs because it is hard to fully understand the stochastic behavior of ambient energy sources. The authors in [39] present a stochastic solar radiation model to describe the impact of clouds on the intensity of solar radiation and the battery capacity recovery process. In [40]–[43], the energy generation process is described via Bernoulli models with a fixed harvesting rate under the assumption that energy harvested in each time slot is identically and independently distributed (i.i.d.). Other uncorrelated energy harvesting models applied in the literature include the uniform process [44], Poisson process [45], [46], and exponential process [47]. While these models are simple, they are inadequate to capture the temporal correlation properties of the harvested energy for most energy sources.

To this end, a correlated time process following a first-order discrete-time Markov model is adopted in [48] for modeling the energy packet arrivals. In [36], the energy arrival and amount are modeled as a Poisson counting process in time and a non-negative uniform random variable, respectively. In [49]–[53], energy from ambient sources is modeled by a two-state ("GOOD" and "BAD") Markov model to mimic the time-correlated harvesting behavior, where in BAD state, no energy arrives, and in GOOD state, the energy quantum arrival is a Bernoulli random process. In [54] and [55], the energy generation process is modeled as a two-state ("ON" and "OFF") correlated process, where the energy is harvested with a constant rate in the on state and no energy is generated in the off state.

The two-state energy harvesting model is a good approximation for the illustration of some energy sources. For example, harvesting from human motion in a body area network can be described by two states which represent the subject is either in rest or moving, and the weather states of solar power harvesting may be shaded/cloudy and clear. Some papers consider the use of generalized Markov models, where the number of scenario states is more than two, each of which is governed by a conditional probability mass function to describe the amounts of energy arrivals at each time instant [56], [57]. In general, the modeling performance can be improved when the number of Markov states increases, but the complexity is also increased.

In addition to the types of models, an appropriate choice of the underlying parameters in stochastic models such as the transition probabilities of states and the probabilities of energy arrival amounts at given states is another crucial issue. In real applications, this should be closely related to real empirical energy harvesting data measured by the energy harvester of each communication node, and the energy harvesting capability is typically node-specific. Only few attention has been paid to the construction of real data-driven energy harvesting models [8], [57]. In [57], discrete harvested energy is assumed for estimating the scenario parameters and the transition probabilities of the generalized Markov models, based on a suboptimal moving average and a Bayesian information criterion. In [8], a Gaussian mixture hidden Markov model is adopted to quantify energy harvesting conditions into several representative states and to capture the dynamics of empirical solar power data. Unlike the model in [57] which is constructed using discrete energy regardless of the underlying distribution of solar energy, this model is completely driven by real solar irradiance to determine the values of the parameters in the underlying Gaussian distributions, followed by a step to map the continuous-time model into a discrete energy harvesting model, in which the Markov chain states are described by the state transition probability and the probability of the number of harvested energy quanta at a given state. It is verified in [8] that this model works quite well for the solar power.

Some statistical information can be used to enhance the accuracy of energy arrivals. In [58], average solar power profiles as functions of time have been adopted in solar power harvesting systems, and the problem that optimally controls the sensing range of sensors in order to maximize the quality of coverage is studied with the assistance of solar power profiles. In [59], the authors analyze the correlation between large-scale solar and wind power in Sweden as well as the effect of geographic dispersion and combination of solar and wind power. These high-order statistics are likely to be used to enhance the performance of energy harvesting systems.

*3) Other Models:* Apart from the natural renewable energy sources, a new emerging solution is to collect energy from RF

TABLE II
ADVANTAGES, DISADVANTAGES, AND APPLICATIONS OF ENERGY HARVESTING MODELS

| Harvesting models | Advantages | Disadvantages | Applications |
|---|---|---|---|
| Deterministic models [35]–[38] | Serve as performance lower bounds | Need for non-causal ESI, prediction | Slowly variant sources, e.g., solar (in large time scales) |
| Time-uncorrelated stochastic models [40]–[47] | No need for non-causal ESI, simple modeling | Need for training, only for simple random sources | Time-uncorrelated sources, e.g., wind |
| Simple time-correlated stochastic models [36], [48] | No need for non-causal ESI, better modeling for dynamics | Need for training, complicated | Time-correlated sources, e.g., solar (in small time scales) |
| Multi-state Markov chain stochastic models [49]–[57] | No need for non-causal ESI, modeling for dynamics with multiple states | Need for tranining, more complicated | Time-correlated sources, e.g., human motion, solar |
| Friis free space propagation models [60] | Modeling for dedicated RF energy | Inapplicable to ambient RF energy sources | Wireless power recharging |
| Stochastic-geometry model [61] | Modeling for ambient RF energy | Inapplicable to dedicated RF energy sources | Wireless power recharging |
| Hybrid models [47], [62], [63] | Modeling for multiple sources & storages, better performance | Need for training, very complicated | Hybrid sources, e.g., solar/wind, solar/grid |

signals which are artificially generated by other external communication devices. In this model, the received RF power in free space propagation can be expressed according to the Friis equation as follows [60]:

$$P_r = P_t G_s G_r \left(\frac{\beta\lambda}{4\pi d}\right)^2, \tag{1}$$

where $\lambda$ is the wavelength, $\beta$ represents the polarization loss, $P_t$ is the transmit power, $G_t$ and $G_r$ denote the transmitting and receiving antenna gains, respectively, and $d$ is the distance between the transmitter and the receiver. The above model is commonly used for dedicated RF energy harvesting. For ambient RF sources, where the RF transmitters are not intended for energy transfer, the model becomes more complicated because the ambient RF transmitters work periodically and their transmit power varies significantly from $10^6$ W for TV towers to 0.1 W to WiFi devices. In [61], a stochastic-geometry model is investigated to characterize the average RF energy harvesting rate at sensors powered by ambient RF sources. Although the RF energy sources could be deterministic or random, the amount of the harvested energy from RF signals largely depends on two crucial factors: transmit power of dedicated or ambient transmitters and the channels (including path loss, shadowing and small-scale fading) from the transmitters to the harvesting receivers. These two factors make the RF energy sources very different from other "natural" energy sources, e.g., solar, wind, etc., and introduce a performance tradeoff between information and energy transfer in wireless networks.

Except for the ambient or RF-based energy harvesting models, there exists another special type of energy harvesting models, named hybrid models which combine the energy harvesting with the conventional power supply. This results in very different models, as compared with the ones discussed in deterministic and stochastic models, where the energy supply purely relies on energy harvesting. The authors in [47] consider a hybrid energy replenishment model for which the wireless sensor can make use of two methods to replenish the battery. One is to harvest energy from environment and store it in the battery, and the other is to replace the battery directly. In order to model this hybrid replenishment, a Markov chain model is proposed to mimic the battery energy state transition. In [62], a hybrid energy storage unit which is composed of a super capacitor and a battery is mounted on an energy harvesting transmitter. The former has good storage efficiency but limited energy capacity, while the latter is capable of infinite size but suffers from inefficient storage. In [63], not only the renewable energy sources but also the conventional energy sources such as diesel generators or power grid are considered in designing energy harvesting systems to mitigate the variability of natural energy generation. Still, there are well-established models for vibration (or motion) energy harvesting such as mass-spring models. The interested readers are referred to [17] and the references therein for details.

## III. ENERGY HARVESTING AND USAGE PROTOCOLS

Unlike the traditional battery-operated communications, the energy of ambient energy sources available to energy harvesting communication nodes is time-variant and often sporadic even though there is potentially an infinite amount of energy. The energy expenditure is inherently subject to an *energy neutrality constraint* which stipulates that at each time instant, the cumulative energy expenditure cannot surpass the cumulative energy harvested by that time, i.e., $\sum_{i=1}^{t} P_i \leq \sum_{i=1}^{k} Y_i$, where $Y_i$ and $P_i$ are the harvested and the depleted energy at the $i^{th}$ time instant, and $k$ could be $t-1$ or $t$ which hinges on whether the present harvested energy can be immediately used or not. To smooth out the randomness effect, the scavenged energy can be stored in an energy buffer, e.g., a supercapacitor or a battery, to balance the energy arrival profile and the energy consumption profile. But the capacity of the energy storage devices may be limited, and this results in the possibility of energy overflow. In addition, energy spending for data transmission should also be aware of several practical considerations such as the efficiency in storing energy, the energy leakage from the storage device, the basic processing cost at communication nodes, the sleep-and-awake mechanism, etc. Below, we first introduce three energy harvesting and usage protocols that address these considerations for natural ambient energy sources. Second, two energy harvesting protocols are presented for simultaneous wireless information and power transfer. This section serves as an important preliminary for readers to understand the fundamental performance limits and tradeoffs of the basic energy harvesting and usage schemes before we proceed with the subsequent sections in which the challenges, related

TABLE III
AMBIENT ENERGY HARVESTING AND USAGE PROTOCOLS

| Schemes | Energy buffer evolution | Available energy |
|---|---|---|
| Harvest-use (HU) | No energy storage device | $P_i \leq \lfloor Y_i - Z_i \rfloor^+$ |
| Harvest-store-use (HSU) | $B_{i+1} = \left[\left[(B_i - Z_i - P_i) - \beta_2\right]^+ + \beta_1 Y_i\right]^+$ | $P_i \leq \lfloor B_i - Z_i \rfloor^+$ |
| Harvest-use-store (HUS) | $B_{i+1} = \left[\left[B_i - \left[P_i + Z_i - Y_i\right]^+ + \beta_1 \left[Y_i - P_i - Z_i\right]^+\right]^+ - \beta_2\right]^+$ | $P_i \leq \lfloor B_i + Y_i - Z_i \rfloor^+$ |

design issues and constraints, and existing works for various energy harvesting networks are reviewed.

### A. Ambient Energy Harvesting and Usage

Three energy harvesting and usage protocols are commonly used in the literature: 1) *harvest-use* (HU), 2) *harvest-store-use* (HSU), and 3) *harvest-use-store* (HUS) [56], [64]–[68]. Let $B_i$ and $Z_i$ be the amount of energy stored in the buffer and the processing cost at the $i^{th}$ time instant, respectively. The processing cost means the power consumption spent in the data transmission circuitry, and the circuit power consumption is non-negligible in short range communications, as compared with the data transmission power. The energy buffer evolution processes of these three protocols are summarized in Table III, where $[x]^+ = \min(\max(0, x), B_{\max})$, $B_{max}$ is the maximum capacity of the energy buffer, and $\lfloor x \rfloor^+ = \max(0, x)$.

- HU [64]: The communication node is directly powered by energy harvesting systems, and there is no buffer to store the present harvested energy for future use. Data transmission occurs only when a sufficient amount of energy is acquirable to cover the processing cost, i.e., $Z_i \leq Y_i$.
- HSU [56]: There is a storage device to gather the harvested energy which can be used only after it is stored in the buffer at the next time instance. Thus, the node is active only if $Z_i \leq B_i$, and the available energy for data transmission $P_i$ is limited to $\lfloor B_i - Z_i \rfloor^+$. The energy buffer is evolved by assuming that only $\beta_1 Y_i$ harvested energy is charged in the buffer and $\beta_2$ energy in the buffer gets leaked in each time slot due to the inefficiency in storing energy, where $0 \leq \beta_1 \leq 1$ and $0 \leq \beta_2 < \infty$. For an Ni-MH rechargeable battery, $\beta_1 \approx 0.7$, and for a supercapacity, $\beta_1 \geq 0.95$. Typically, the leakage factor $\beta_2$ for a battery is very small, but that for a supercapacitor is relatively larger [62].
- HUS [65], [66]: The harvested energy that is temporarily stored in a supercapacitor can be immediately used, and the remaining energy after processing and transmission is transferred to the energy buffer for later use. This protocol requires two energy storage devices, and the maximum available energy for transmission $P_i$ is subject to $\lfloor B_i + Y_i - Z_i \rfloor^+$. As mentioned before, a supercapacitor has a faster charging efficiency than a battery, but the energy leakage for a supercapacitor is larger than that for a battery. To improve this self-discharging problem, one can alternatively adopt a battery as an energy buffer to efficiently save the remaining energy for future use.

The information-theoretic capacity of energy harvesting Gaussian channels is investigated under the ideal conditions of $\beta_2 = 0$, $\beta_1 = 1$ and $Z_i = 0$ [67], [68]. For the HSU scheme, the capacity with an unlimited energy buffer is equal to the classical additive white Gaussian noise (AWGN) channel capacity with an average power constraint equal to the average recharge rate, i.e., $C_{HSU}(B_{\max} = \infty) = \frac{1}{2}\log\left(1 + \frac{\mathbb{E}[Y_i]}{\sigma_n^2}\right)$, where $\sigma_n^2$ is the noise power, and $\mathbb{E}[\cdot]$ takes the expectation. In [68], two capacity-achieving schemes, namely save-and-transmit and best-effort-transmit, are introduced. In the former one, a portion of the total block length is used to save energy and to obtain a sufficient amount of energy for sending the remaining code symbols, while in the later one, the code symbol is sent as long as there is sufficient energy in the battery.

Furthermore, it is shown in [67] that the capacity-achieving signalling is truncated i.i.d. Gaussian with zero mean and variance $\mathbb{E}[Y_i] - \varepsilon > 0$, where $\varepsilon$ is an arbitrarily small value, and the truncation is owing to the limitation of the available energy in the battery. Besides, the capacity of the HU scheme is upper bounded by that of the HSU scheme with an unlimited energy buffer, i.e., $C_{HU} \leq C_{HSU}(B_{\max} = \infty)$. For a Bernoulli energy arrival process, a simple approximation to the capacity of the HSU scheme with a finite battery is provided in [69], and the gap between the exact and the approximate capacities is bounded within 2.58 bits. It also shows that the constant gap becomes larger for general i.i.d. energy arrival processes. While the processing cost and the energy storage inefficiency are present, the achievable rate of the HSU scheme can be extended by simply replacing $\mathbb{E}[Y_i]$ in the capacity formula with $\beta_1\mathbb{E}[Y_i] - \mathbb{E}[Z_i] - \beta_2$. With a sleep-and-awake mechanism, the achievable rate can be improved by allowing for the energy harvesting communication nodes to choose to sleep. In general, the HUS scheme has a better achievable rate than the HSU scheme, while the two schemes attain the same performance at $\beta_1 = 1$. In particular, the performances of the HSU and the HUS schemes may be worse than that of the HU scheme when $\beta_1$ is not sufficiently large. A more thorough review of the channel capacity under different sizes of the battery (e.g., finite, infinite, or zero storage) and channel conditions (e.g., AWGN or noiseless binary channels) can be found in [23].

### B. Simultaneous Wireless Information and Power Transfer

By leveraging RF signals, a new dedicated energy harvesting technology has been proposed to delivery information and power simultaneously [32], [28], [70], [26]. Nonetheless, it is impossible to realize simultaneous energy harvesting and information delivery due to practical circuit design constraints. In practice, wireless energy harvesting can be operated in a *time sharing* manner, in which the receiver uses a portion of time duration for energy harvesting and the remaining time

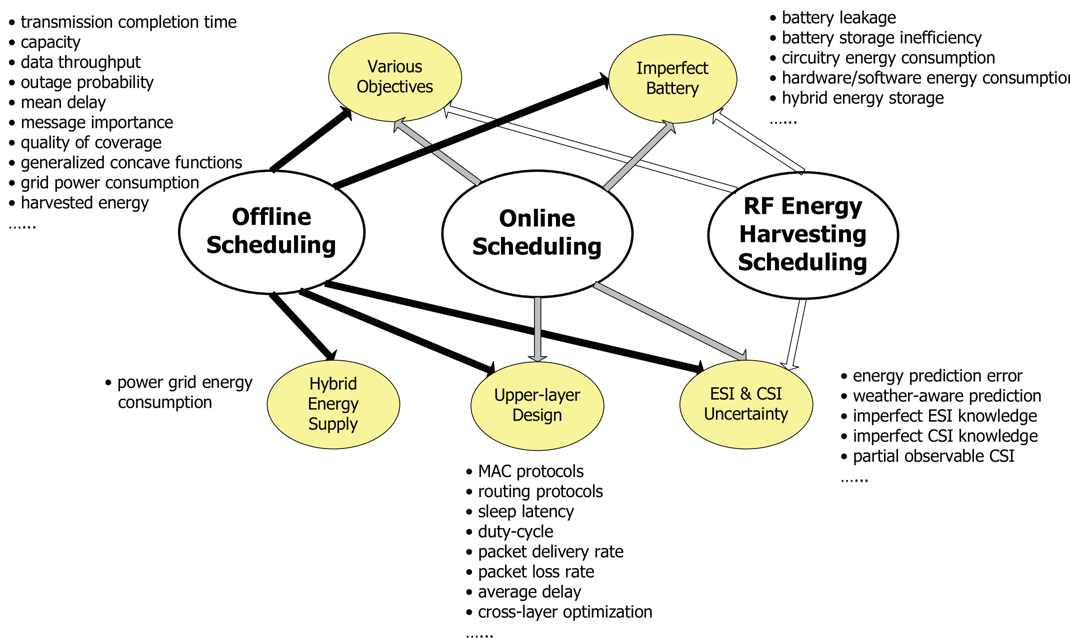


Fig. 3. Energy scheduling and related design issues.

for information processing, or a *power splitting* manner, in which the received signal power is divided into two parts for energy harvesting and information processing [71]. As compared with the power splitting scheme, the time sharing scheme is more attractive since the information receivers and energy receivers are separately operated with different power sensitivities, and the gap between them could be as large as 40 dBm, e.g., $-50$ dBm for the information receivers and $-10$ dBm for the energy receivers [72]. Note that in cellular scenarios, the term "simultaneous wireless information and power transfer (SWIPT)" is mainly used for downlink transmission, whereas the term "wireless-powered cellular networks (WPCN)" is for uplink transmission [26]. Readers can refer to Section VI.D for more detailed survey.

Some information-theoretic results regarding simultaneous wireless information and power transfer systems are reported in [73] and [74]. In [73], a fundamental tradeoff between the rates of energy transfer and information transmission is studied in several noisy channels by defining a capacity-energy function. Particularly, it is shown that in AWGN channels, the goals of maximum information rate and maximum power transfer efficiency are aligned, and the capacity-energy function is a non-increasing concave function with respect to the minimum requirement of the harvested power. The authors in [74] study the information-theoretic results for the problem of information and power transfer on a coupled-inductor circuit. The considered problem is a special case of a frequency selective fading channel, and the authors point out a non-trivial tradeoff between the information and power transfer.

## IV. Energy Scheduling and Optimization

In the previous section, we have discussed various preliminaries which are the first crucial step toward designing energy harvesting communications. In addition to the available amount of harvested energy which rests on the characteristic of energy sources and the adopted energy harvesting and usage protocols, the performance of an energy harvesting communication system is determined by how to efficiently use the harvested energy available at hands. In contrast to battery-operated systems, power management in energy harvesting systems needs to harmonize the energy consumption with the battery recharge rate since the ambient energy may arrive dynamically and sporadically. Hence, overly aggressive or conservative use of the harvested energy may either run out of the energy in a finite capacity battery (called *energy outage*) or fail to utilize the excess energy (called *energy overflow*).

An illustration of the energy scheduling schemes and the related design issues is shown in Fig. 3. In this section, we first introduce the objectives for designing energy harvesting communications in the existing works. Second, we concentrate on the design of energy scheduling policies for point-to-point communications using natural ambient energy sources. The current research approaches regarding these energy scheduling designs are two-fold: *offline* and *online*, depending on whether the knowledge of channel state information (CSI) and ESI is available non-causally or causally at the beginning of transmission. Here, the terms "offline" or "online" mean that the energy is scheduled with offline or online knowledge of energy arrivals and channel gains. A summary of offline and online energy scheduling works is provided in Table IV. Third, we turn to discuss the energy scheduling problems for RF energy harvesting in point-to-point communications.

### A. Objectives

Several objectives have been considered in the literature for designing point-to-point energy harvesting communications, including transmission completion time, data throughput, outage probability, mean delay, message importance, quality

TABLE IV
SUMMARY OF OFFLINE AND ONLINE SCHEDULING METHODS

| Paper | Types | Objectives | Description |
|---|---|---|---|
| [37] | Offline | Completion time min. | Convex optimization, relationship to energy consumption min. |
| [38] | Offline | Completion time min. | Packet scheduling, two scenarios of packet arrivals: ready before or during transmissions |
| [36] | Offline | Throughput max. by a deadline | Properties of transmit power, directional water-filling |
| [80] | Offline | Throughput max. by a deadline | Geometric explanation for power allocation via energy tunnels |
| [77] | Offline | Throughput max. | Relationship to completion time min., staircase water-filling |
| [88] | Offline | Throughput max. & mean delay min. | Stability of data queues, greedy mean-delay optimal policy |
| [75] | Offline | Completion time min. | QoS constraints, piecewise linear cumulative data departure curves |
| [84] | Offline | Outage probability min. | Non-decreasing power allocation & save-then-transmit policy |
| [85] | Offline | Weighted sum of outage prob. min. | Piecewise power allocation, divide-and-conquer algorithms |
| [83] | Offline | Throughput max. | Discrete-rate adaptation methods |
| [94] | Offline | Energy consumption min. | Packet delay constraints, discrete-rate adaptation methods |
| [89] | Offline | Generalized concave utility max. | General water-filling solutions |
| [90] | Offline | Concave non-decreasing utility max. | Constant energy spending strategies for achieving upper bounds |
| [36] | Online | Throughput max. by a deadline | Dynamic programming, event-based suboptimal policies |
| [50] | Online | Successful packets delivery max. | MDP, optimal threshold-type policies according to channel states and energy queue length |
| [77] | Online | Throughput max. | Non-decreasing optimal policies in battery states |
| [81] | Online | Throughput max. | Monotonic structures for the policy with multiple transmit power levels in battery states |
| [8] | Online | Net bit rate max. | Data-driven threshold and monotonic policies with adaptive power and modulation |
| [78] | Online | Achievable rate max. | MDP with continuous battery states, linear piecewise approximation to value functions |
| [101] | Online | Competitive ratio of offline and online | Analysis of the competitive ratio, which is equal to the total number of scheduling time slots. |
| [47] | Online | Message values max. | Optimal thresholds for threshold-based approaches |
| [53] | Online | Important values of reported data max. | Low-complexity balanced policies that adapt to energy harvesting states |
| [54] | Online | Quality of coverage max. | Energy-efficient transmission strategies for body sensor networks with energy harvesting |
| [84] | Online | Outage probability min. | Optimal and suboptimal online power allocation using dynamic programming |
| [96] | Online | Rate outage probability min. | Threshold structures for the optimal policy, saturated structures for the expected outage performance |
| [102] | Online | Total amount of transmitted data max. | Energy allocation policies for sensing and transmission using MDP |
| [103] | Online | Estimation covariance error min. | Threshold policies for binary energy allocation levels, gradient algorithms for computing thresholds |
| [51] | Online | Communication reliability max. | Modified policy iteration algorithms for energy harvesting active networked tags |
| [65] | Online | General utility max. | Dual-stage power management, outer stage for power usage, inner stge for communication parameters |
| [104] | Online | Energy efficiency max. | QoS provision, string tautening methods with mixed strategies of on, off, and first-on-then-off |
| [45] | Online | Bits in data buffer plus energy usagae | Q-learning and speedy Q-learning for real-time transmissions |
| [48] | Online | Throughput max. | Learning theoretic approaches for learning the optimal transmission policy |

of coverage, generalized concave functions, grid power consumption, harvested energy, etc. In [37], [38], [75], [76], the transmission completion time for a given data arrival profile is minimized, and this objective is often accompanied with both energy and data constraints. The data throughput is maximized according to Shannon Capacity formula in [36], [76]–[79], a concave power-rate function in [80]–[82], the number of successfully delivered bits or packets in [8], [48], [50], a discrete set of rates in [83]. The minimization of the capacity outage probability is considered in [79], [84]–[87]. The mean delay criterion is used in [88] to minimize the transmission delay in the data queue. In [47], [53], the importance of reported data is utilized for the applications of sensor networks. The quality of coverage, in terms of the average number of events that are correctly reported when they occur in the sensing region, is considered in [54]. The generalized concave functions are considered in [89] and [90] to capture the performance and the behavior of the designed transmission policies. In the presence of a hybrid power supply system, the objective of the grid power consumption minimization is discussed in [46], [91], [92]. The harvested energy is maximized in [93] for a wireless power transfer system.

### B. Offline Energy Scheduling

For offline approaches, the full (causal and non-causal) knowledge of CSI and ESI during the energy scheduling period is known to the transmitter side a priori. With the deterministic energy harvesting models, energy scheduling, or equivalently power allocation, optimization problems are commonly formulated to maximize a certain short-term utilities over a finite time horizon and solved by convex optimization techniques [36], [76], [80].

Taking point-to-point energy harvesting communications in fading channels as an example, the offline energy scheduling optimization problem is given as [36]

$$\max_{p_i \geq 0} \sum_{i=1}^{T} f_i\left(p_i\right) \tag{2}$$

subject to

$$\sum_{i=1}^{l} t_i p_i \leq \sum_{i=0}^{l-1} Y_i, \quad l = 1, \ldots, T\,; \tag{3}$$

$$\sum_{i=0}^{l} Y_i - \sum_{i=1}^{l} t_i p_i \leq B_{\max}, \quad l = 1, \ldots, T-1\,, \tag{4}$$

where the entire scheduling period is partitioned into several epoches, each of which corresponds to the occurrence of channel state change, energy arrival or both, and the $i^{th}$ epoch is denoted as $t_i$, for $i = 1, \ldots, T$. Here, the HSU protocol is adopted for illustrating energy storage and usage, and $Y_i$ represents the new arrived energy ahead of the $i^{th}$ epoch. The goal is to find the optimal power allocation $p_i$ during the $i^{th}$ epoch for maximizing the sum of the utilities $f_i\left(p_i\right)$, while being subject to the energy causality constraints in (3) and the finite battery storage constraints in (4). As the energy constraints are convex, the optimal power allocation can be found by solving Karush-Kuhn-Tucker (K.K.T.) conditions, if the utility function is concave. In general, this is true for widely used data throughput utilities, which are non-negative, strictly concave and monotonically increasing functions with respect to $p_i$. Particularly, if Shannon capacity formula, $t_i log\,(1 + h_i p_i)$, is applied, where $h_i$ is the channel gain for the $i^{th}$ epoch, the optimal power allocation behaves like the conventional water-filling. Due to the concavity of the Shannon capacity formula, it is suggested from Jensen's inequality that the water level should be as flat as possible in time in order to maximize the data throughput. However, the water level may change over time so that the imposed causality and storage constraints on the energy usage are satisfied. While the offline scheduling is unrealistic in real applications because of the need for non-causal ESI knowledge, the properties of the optimal solutions provide useful insights into designing some practical/online algorithms.

The transmission completion time minimization problem for offline scheduling has been considered in [37] and [38]. In [37], an offline completion time minimization problem that allows packet arrivals during transmission on energy harvesting fading channels is solved by establishing an equivalence to a convex energy consumption minimization problem. In [38], the optimal packet scheduling that adapts the transmission rate according to the harvested energy and the traffic load is proposed to minimize the transmission completion time in a single-user communication system. Two scenarios are considered by assuming that the packets are ready at the transmitter before the transmission starts or the packets arrive during the transmissions. The structural properties of the optimal transmission policy as well as the globally optimal scheduling algorithm are investigated, in that the basic idea is to keep the transmit power or rate as constant as possible during the entire transmission duration, while considering the causality constraints due to data and energy arrivals for the feasibility.

The data throughput maximization problem is discussed in [36], [76], [77], [80]. The work in [36] attempts to maximize the throughput by a deadline by controlling the transmit power under channel fluctuations and energy variations. From the K.K.T. conditions, it concludes that in the case of an infinite energy storage capacity, the water level is monotonically increasing, and if the energy at one epoch is spread to the next epoch, the water levels in two consecutive epochs are the same. Moreover, when the water level changes, the energy consumed up to that time instant is equal to the total harvested energy. However, the monotonicity of the water level no longer holds in the case of a finite storage capacity. A directional water-filling algorithm is proposed to find the optimal power allocation. Similarly, the problem of maximizing the data throughput under a deadline constraint is studied in [80] with finite energy storage capacity. The feasibility of the power allocation that satisfies the energy causality and the energy storage constraints is explained geometrically via a feasible energy tunnel. Assuming that the utility function is strictly concave and monotonically increasing with the power, the cumulative energy consumption profile of the optimal policy must be piece-wise linear within this tunnel as time progresses. Through the Lagrangian dual analysis, it is shown that the solutions of the completion time minimization and the throughput maximization problems are identical. The problem of energy allocation over a finite time horizon is considered in [77] so as to maximize the throughput, and the obtained structural results are analogous to [36], yielding a variation of the so-called water-filling policy that follows staircase water levels. In general, finding the optimal dynamic water-filling level is not an easy task, and recursive geometric water-filling approaches are proposed in [76] to effectively find the optimal water level for the data rate maximization and transmission completion time minimization problems.

In addition to the aforementioned two utilities, the offline approaches are investigated by considering other different objectives and constraints that can satisfy application-specific design considerations [75], [83]–[85], [88], [94]. In [88], throughput optimal and mean delay optimal energy management policies are studied for a sensor node with energy harvesting. It is assumed that the data and energy buffers are infinite, and a necessary condition for stability of the data queue under the energy neutrality constraint is proposed. The throughput optimal policy is the same as the capacity-achieving policy in [67], while a greedy policy that removes the data in the queue as much as possible is the mean delay optimal policy if the rate-power function is linear. In [75], the time instants and the amounts of energy and data arrivals are assumed to be known beforehand. Under the QoS constraints as well as the energy and data causality constraints, the optimal data transmission strategy is studied to minimize the transmission completion time for an energy harvesting node with a finite battery capacity. It is shown that the optimal cumulative data departure curve is a piecewise linear function, and the battery overflows happen only when the data buffer is empty.

The authors in [84] study the optimal power allocation to minimize the average outage probability, which is in general non-convex over the transmit power in fading channels. The optimal power profile is shown to be non-decreasing over time and has a save-then-transmit structure, and the globally optimal solution with non-causal ESI is obtained by a forward search algorithm. In [85], a weighted sum of outage probability is minimized for power scheduling under preset transmission rates over a finite time horizon. This non-convex problem is transformed into a convex one by applying high signal-to-noise power ratio (SNR) approximation. A piecewise power allocation structure is discovered for both infinite and finite battery capacities, and a divide-and-conquer algorithm is proposed to recursively find the optimal power allocation. A discrete-rate adaptation problem for optimizing the throughput is addressed in [83] for energy harvesting wireless systems with infinite-size energy buffers, while individual packet delay constraints are further included in [94] to minimize the energy consumption or to maximize the throughput in case the harvested energy is insufficient for all packets to meet the deadlines.

The optimal offline solution for a generalized concave utility function is studied in [89] and [90]. In [89], a generalized concave utility maximization problem as well as its general solution is investigated in energy harvesting wireless sensor networks. Two applications, called sum-rate maximization and distributed estimation, are demonstrated, and the solutions can be considered as the extension cases of the well-known water-filling. In [90], it is shown that if the considered utility function is a concave non-decreasing function and the energy reservoir is unlimited, the performance upper bound can be achieved by a constant energy spending strategy that equals to the average energy replenishment rate. Motivated by this insight to develop a simple energy management scheme, the performance limits of sensor nodes with finite battery and data buffers are analyzed, which shows that the optimal utility can be asymptotically achieved, while keeping battery discharge and data loss probabilities low. Finally, some useful guidelines from the literature are summarized in [25] for the design of the optimal offline policies.

### C. Online Energy Scheduling

The online approaches only account for the causal knowledge of the CSI and ESI, or some statistical knowledge of the channel and energy harvesting dynamic processes. When the transmitter only has the causal ESI, the time average of the amount of harvested energy, called energy harvesting rate, is a common figure of merit for designing the online algorithm [95]. On the other hand, with the stochastic energy harvesting models to acquire the statistical knowledge, stochastic optimization techniques, e.g., Markov decision processes (MDP), are appealing solutions to maximize the long-term utilities of relevant optimization problems [36], [50], [77], [81].

We take the design of online power control schemes in point-to-point energy harvesting communications as an example. Based on stochastic energy harvesting models, an MDP design framework can be formulated, and the main ingredients of the MDP are states $s \in \mathcal{S}$, actions $a \in \mathcal{A}$, rewards $R_a(s) \in \mathbb{R}$ and state transition probabilities $P_a\left(s' \middle| s\right)$. The state could be a composite state of quantized channel and battery conditions, and the action is referred to as the transmit power level or the amount of energy to be used. The affordable action at the states is limited to the corresponding battery condition. Furthermore, the reward is a function of the states and the actions, which could be data throughput [8], [50], outage probability [96], symbol error rate (SER) [97], etc., and the state transition probability describes the transition probability from the current state to the next state with respect to each action. The goal is to find the optimal policy $\pi(s)$ which specifies the optimal action in the state and maximizes the long-term expected discount infinite-horizon reward $V_\pi(s_0)$ starting from the initial state $s_0$ as follows:

$$V_\pi(s_0) = \mathbb{E}_\pi\left[\sum_{i=0}^{\infty} \alpha^i R_{\pi(s_i)}(s_i)\right], \; s_i \in \mathcal{S}, \; \pi(s_i) \in \mathcal{A}, \quad (5)$$

where $0 \leq \alpha < 1$ is a discount factor, and the long run average objective can be closely approximated by selecting a discount factor close to one. The optimal long-term expected reward is irrelevant to the initial state if the states of the Markov chain are recurrent. Under this circumstance, the optimal solution satisfies the Bellman's equation [98]:

$$V_{\pi^\star}(s) = \max_{a \in \mathcal{A}}\left[R_a(s) + \alpha \sum_{s' \in \mathcal{S}} P_a\left(s' \middle| s\right) V_{\pi^\star}\left(s'\right)\right]. \quad (6)$$

Standard algorithms for solving the Bellman's equation include value iteration, policy iteration and linear programming [98]. However, the main disadvantage of these algorithms is that the optimization may be computationally cumbersome as the number of states in the MDP increases even though the optimal policy can be implemented using a look-up table. Besides, constrained MDP problems can be formulated for online scheduling with a certain constraints, e.g., minimum throughput requirements in [99], [100]. To solve the constrained MDP problems, a common approach is to transform the problems into linear programming formulation and to obtain the optimal solution by applying standard optimization solvers.

The online scheduling approaches using the MDP have been extensively investigated in the literature. In [36], an optimal online policy is proposed by using dynamic programming to maximize the throughput by a deadline constraint. Due to the curse of dimensionality in the dynamic programming, several event-based suboptimal policies in response to the changes of fading levels and energy arrivals are investigated. Some structural results are explored for optimal transmission policies in [8], [50], [77] and [81]. In [50], a Markov decision problem is formulated for an energy harvesting source node with an infinite energy queue to decide whether to transmit or defer the transmission in each time slot. With a simple uncorrelated energy arrival assumption, the objective is to maximize the expected number of successfully delivered packets over a Gilbert-Elliot channel, and the optimal policy has a threshold-type policy depending on the channel state and the energy queue length. Besides, the structural properties of the maximum throughput and the corresponding optimal policy are provided in [77]. Specifically, the optimal throughput and the optimal power allocation are concave and non-decreasing, respectively, in the battery states, if the throughput-power function is concave.

The authors in [81] discuss a monotonic structure for the policy with multiple transmit power levels; that is, if a higher transmit power level is preferred to a lower one at some battery levels, then it will continue to be a preferred one at a higher battery level. While this structure may be intuitively reasonable, it does not always hold in general cases, although such cases are rare. The threshold and monotonic structures are also discussed in [8] for a solar-powered communication system with adaptive power and modulation schemes, based on a realistic energy harvesting model. With an access control mechanism and a maximum power constraint for the transmitter, an achievable rate maximization problem is cast as an MDP with continuous battery states in [78], which is different from the discrete battery-and-power assumption in the aforementioned works. The value function is approximated as a piecewise linear function to efficiently solve the problem and to obtain the continuous power allocation.

In general, the offline algorithms outperform the online algorithms due to the availability of the non-causal knowledge of energy arrivals and channels, and the author in [101] analyzes the performance of an online algorithm by evaluating its competitive ratio which is defined as the maximum ratio of the gain between the optimal offline algorithm and the online algorithm over possible sequences of energy arrivals and fading coefficients. For the general case of arbitrary sequences, the competitive ratio is equal to the total number of time slots over which the achievable rate is optimized.

The online transmission schemes are designed using other utility functions in [47], [53], [54], [84] and [96] rather than the data throughput. In [47], a threshold-based approach is investigated for single-hop transmission over a replenishable sensor network, and there exist optimal thresholds to maximize the average reward rate in terms of message values. The author in [53] attempts to maximize the long-term importance value of reported data, and a low-complexity balanced policy that solely adapts to the energy harvesting states is proposed to balance the energy consumption and energy harvesting. In [54], energy-efficient transmission strategies are developed for body sensor networks with energy harvesting to maximize the quality of coverage through an MDP design framework. In [84], optimal and suboptimal online power allocation methods are proposed to minimize the outage probability by applying dynamic programming. In [96], an MDP-based power allocation policy is proposed to minimize the rate outage performance. Therein, a threshold structure and a saturated structure are discovered for the optimal policy and the corresponding expected outage performance, respectively.

Still, some works address the design issues of online transmissions from application aspects [51], [65], [102], [103]. In addition to the transmit power, the energy allocation for sensing is considered in an energy harvesting sensor node with a finite data buffer in [102]. With the objective of maximizing the expected total amount of transmitted data in the MDP, the sensor needs to decide the amount of energy dedicated to sensing and transmission by taking into account the data buffer, battery, channel, and energy harvesting rate status. The problem of energy allocation for an energy harvesting sensor node to convey the noisy measurements to the receiver is addressed in [103], and the objective is to minimize the estimation error covariance in Kalman filtering with random packet losses over fading channels. From dynamic programming, a threshold policy is developed for binary energy allocation levels, and a suboptimal gradient algorithm is proposed for computing the threshold. In [51], a modified policy iteration algorithm is proposed for the recent application of energy-harvesting active networked tags in order to optimize the long-term communication reliability.

Considering the fact that the energy harvesting process evolves slowly compared to the channel fading, the authors in [65] propose a dual-stage power management approach, in which the outer stage schedules the power for the use in the inner stage so as to maximize the long-term average utility, while the inner stage optimizes the communication parameters to maximize the short-term utility. In [104], a string tautening method, which is comprised of three mixed policies (on, off and first-on-then-off), is developed to perform energy-efficient scheduling while providing QoS to delay-sensitive data. It demonstrates that the packet drop rate and delay time can be reduced when the energy harvesting rate and battery capacity are large enough.

Learning the underlying stochastic knowledge of the energy harvesting models must be an imperative but nontrivial step toward the implementation of the MDP-based energy management policies. This is especially difficult for some unstable energy sources or in some deployment scenarios. Some works have been conducted to address this issue. Some non-real-time and real-time approaches have been proposed by utilizing the past energy harvesting profiles to learn the randomness of the energy generated by harvesting sources [8], [45], [48]. In [8], a data-driven stochastic energy harvesting model is learned beforehand based on the historic energy harvesting records gathered by a communication node, and by applying the discounted MDP, a data-driven transmission policy is proposed to decide the optimal action at each time instant according to the past and present observations of solar irradiance.

As an alternative, Q-learning can be used to find the optimal policy for any given MDP without requiring the model of the environments. It works by learning an action-value function which ultimately gives the long-term expected reward for a given action at a given state rather than using the state transition probability to carry out the long-term expected reward statistically. In [45], two reinforcement learning algorithms, Q-learning and speedy Q-learning, are applied to derive real-time transmission policies by learning the joint randomness of data arrivals and energy arrivals generated by the sensor and the energy source, respectively. Similarly, a learning theoretic approach is proposed in [48] to learn the optimal transmission policy by tentatively performing actions and observing immediate rewards for point-to-point energy harvesting communications, and it does not require any a priori stochastic information on the data and energy harvesting Markov processes in the MDP.

### *D. Energy Scheduling in Wireless/RF Energy Harvesting*

The energy scheduling problems in dedicated RF energy harvesting are totally different from those in offline and online scheduling because the RF harvested energy is predictable and stable. Moreover, the energy scheduling for RF energy harvesting is optimized only over a single period of time without being subject to energy causality constraints. Hence, the main focus in the existing works is to optimize the time duration of information processing and energy harvesting. In [86], the authors investigate a point-to-point wireless link, in which the receiver decodes information and harvests energy from the transmitter with a fixed power supply at the same time. The optimal mode switching rule at the receiver is proposed to achieve various trade-offs between the minimum information outage probability (or the maximum ergodic throughput) and the maximum average harvested energy. Similarly, a point-to-point wireless link is considered in [105]; however, the energy harvesting receiver makes use of harvested energy to transmit information to the transmitter. Thus, the optimal time allocation between the wireless energy reception and information transmission is derived to maximize the average throughput.

Considering the two kinds of simultaneous information and energy transfer methods, power splitting and time sharing, the authors in [106] derive the average achievable rate. In [93], the receiver neither transmits data signals to the transmitter nor decodes information from the transmitter. Instead, the authors emphasize a problem that the receiver feedbacks the CSI to the transmitter for energy beamforming so as to harvest the energy as much as possible. The time duration of channel estimation at the receiver is optimized to maximize the amount of energy harvested by the receiver. In [107], a self-sustainable orthogonal frequency division multiplexing (OFDM) receiver is proposed by recycling the cyclic prefix of the received signals to extract the power. The feasibility conditions for self-sustainability are analyzed in terms of power consumption of the receiver. An OFDM two-way communication link with hostile jamming is studied in [108], wherein the receiver can decode information and harvest energy from the received source signal and jamming signal using the power splitting method. The transmit power and power splitting ratio are jointly optimized to maximize the sum throughput of the forward and backward links.

## V. Design Issues in Energy Harvesting Communications

In this section, we consider other design issues, as shown in Fig. 3, for point-to-point communications that have not been discussed in the previous section, including imperfect batteries, ESI and CSI uncertainty, upper-layer protocols, hybrid power supply, etc. These design issues are even more challenging, but practical, to the success of energy harvesting techniques. For example, the imperfection of battery storage is an unavoidable problem which will degrade the system performance. The uncertainty of ESI and CSI causes the ambiguity in scheduling the harvested energy. Some upper-layer issues have been addressed in the literature to improve the network performance by considering the different energy harvesting capabilities among nodes. While the combination of an energy harvester and a power grid can potentially improve the feasibility of energy harvesting techniques, the main challenge is how to minimize the grid power consumption and to maintain the system performance at the same time.

### A. *Imperfect Battery Storage and Other Power Consumption*

In previous works, the transmit power is the unique source of energy consumption; however, in some cases, other sources of energy consumption at the transmitter may dominate over the power radiation. For example, the circuit processing power could be larger than the transmit power for short-range communications. These design considerations, including the energy leakage and charging/discharging inefficiency of imperfect batteries, are addressed in [82], [83], [109]–[111]. In [109], throughput-optimal transmission policies that consider the non-ideal circuit power are studied for energy harvesting wireless transmitters with infinite battery storage capacity. The optimal offline policies follow a two-phase transmission structure, where in the first phase, the optimal transmission is on-off, while in the second phase, continuous transmission is optimal. Finally, an online algorithm based on the closed-form of the offline solution is proposed by using the statistical knowledge of energy arrivals to approximate the sum of causal energy profiles.

The work of [110] generalizes the power consumption model to mimic other hardware/software-dependent energy consumption sources, e.g., channel access and stream activation, in multiple parallel AWGN channels with multiple data streams. With this model, the authors study the optimal resource allocation problem to maximize the capacity via integer relaxation and dual decomposition and give a boxed water-flowing graphical representation for the asymptotically optimal solution. The result can be considered as a generalized interpretation of the directional water-filling in [36]. The influence of battery charging/discharging inefficiency on the throughput-optimal transmit power policy is studied in [111] for single-user and broadcast channel models. Interestingly, a double-threshold structure is discovered to determine when to store, retrieve, and use the harvested energy in the battery.

The effects of various energy overheads, e.g., battery leakage currents and storage inefficiencies, on discrete-rate adaptation policies of energy harvesting nodes are examined in [83]. A general framework that maximizes the transmission rate for energy harvesting communications with an imperfect battery is introduced in [82]. Different from the previous works, the cumulative energy for data transmission is bounded within minimum and maximum energy curves, which can be used to model the effects of the battery with finite size and energy leakage, respectively. In fact, the constant energy leakage can be alternatively interpreted as the constant operation (or circuit) power to keep the node awake. Hence, the optimal offline transmission strategies in [82] and [109] are similar.

An energy harvesting transmitter with hybrid energy storage which is comprised of a perfect super-capacitor and an inefficient battery is studied in [62]. The storage capacity of the super-capacitor is finite, whereas that of the battery in infinite. In contrast to the previous works, the transmitter has to manage the internal dynamics of the storage unit. The obtained solution of energy allocation generalizes the directional water-filling algorithm in [36]. Furthermore, when a linear processing cost in time is taken into account, a directional glue pouring algorithm in [112] can be applied to find the optimal solution.

### B. *ESI and CSI Uncertainty*

The successful implementation of energy harvesting communications relies on accurate estimation of energy and channel profiles or the relevant statistical information. However, accurate estimation of these profiles in real-world is typically costly and even impractical, and it inevitably causes performance degradation due to estimation error. Thus, new algorithms have been designed to accommodate these estimation errors [43], [56], [78], [113], [114]. In [78], the energy prediction error which is modeled as a discrete uniform distribution is considered in the design of MDP-based optimal power allocation. In [113], a weather-aware transmission approach is proposed based on a weather-conditioned moving average prediction algorithm to mitigate the uncertainty.

By modeling the energy harvesting process as a hidden Markov chain, the authors in [56] investigate the impact of imperfect state-of-charge knowledge, i.e., the amount of energy stored in the buffer, and design policies to cope with such uncertainty, where the state-of-charge is only known to the extent of a rough quantization. It is concluded that the knowledge of the state of the energy harvesting process is more critical than the perfect knowledge of the state-of-charge. Partially observable MDP (POMDP) can be used to find the optimal strategy when the network state information is incomplete, e.g., unknown CSI.

In [43], this work finds the outage-optimal power transmission policies with automatic repeat request, and the CSI is partially observable only through ACK/NACK feedback messages. The POMDP framework is cast to find the optimal solution, and two computationally efficient suboptimal approaches are proposed according to the belief state of the channel and the solution of the underlying MDP. In [114], a simultaneous information and power transmission system is studied under imperfect CSI at the transmitter. A robust beamforming problem is formulated to maximize the worst-case harvested energy for an energy receiver while satisfying the rate requirement for an information receiver, and the problem is efficiently solved by relaxed semidefinite programming.

### C. Upper-Layer Protocol Designs

Due to the heterogeneity of energy availability among nodes, new upper-layer algorithms are needed to adapt to the dynamic of energy harvesting and to ensure the satisfaction of network performance such as low latency, low packet loss, and high packet delivery rates. In [115], several medium access control (MAC) protocols such as time division multiple access (TDMA) and ALOHA are revisited for wireless sensor networks with energy harvesting. A performance tradeoff between a delivery probability, which measures the capability of a MAC protocol to successfully deliver data packets of any node, and a time efficiency, which measures the data collection rate at a fusion center, is analytically investigated using Markov models. For the purpose of reducing sleep latency and balancing energy consumption among nodes, two duty-cycle scheduling schemes are proposed in [116] according to the current amount of residual energy only or more aggressively based on the prospective increase in the residual energy. The proposed schemes have lower end-to-end delay and a higher packet delivery ratio than a static duty-cycle scheduling scheme.

In [55], closed-form expressions for the probabilities of event loss and average delay are derived using a Markov model which integrates the energy harvesting and event arrival processes. Based on analytical results, the sizes of the energy harvester and the capacities of the energy storage and the event queue are optimized. In [117], data collection rates and data routing structures are designed for wireless sensors under energy causality constraints. A centralized algorithm is proposed to jointly optimize the data collection rate and the flow on each link. Moreover, two distributed algorithms are proposed with or without predefined routing structures. Only few attention has been paid to cross-layer optimization in energy harvesting communications. In [118], the authors develop a cross-layer scheduling scheme among three layers: source rate control at the transport layer, flow rate and multipath routing optimization at the network layer, and duty cycling optimization at the MAC layer.

### D. Hybrid of Energy Harvesting and Power Grid

Due to the random nature of energy arrivals, it is hard to guarantee the QoS of a communication system solely powered by the harvested energy. Furthermore, the communication services may be interrupted when the energy exhaustion problem occurs. Recently, hybrid energy supply, where the energy comes from a power grid and an energy harvester, has emerged as an alternative solution to this challenge. In a hybrid energy supply system, it is essential to design energy scheduling algorithms in order to minimize the energy consumption of the power grid, while ensuring the service requirements [46], [91]–[92]. In [91], the task is to minimize the power grid energy consumption subject to harvested energy and data causality constraints in fading channels, and in particular, the considered problem is the dual problem of throughput maximization when all data packets are arrived before transmission. The structures of power allocation are also analyzed in some special cases, e.g., infinite battery capacity, grid energy only or harvested energy only, etc. In [119], a delay optimal scheduling problem is addressed for a transmitter powered by an energy harvesting battery of finite capacity together with a power grid subject to an average power constraint, and it is found that the transmitter will resort to the power grid when its data queue length exceeds a threshold and no harvested energy is available.

In [92], the design goal is to minimize the power consumption of the constant energy source for transmitting a given number of data packets within a finite number of time intervals. In [46], the average energy consumed from the power grid is analyzed for two strategies having different ways of using the harvested energy. In [87], the authors investigate transmission scheduling problems in hybrid energy supply systems under a save-then-transmit protocol, where a saving factor is used to control the ratio of harvesting time and transmission time. If the CSI is unknown, an outage probability minimization problem is formulated to find the optimal saving factor. For the case that the transmitter has the CSI, a battery energy consumption minimization problem is considered for jointly optimizing the bit allocation and the saving factor via dynamic programming, while ensuring the transmission service requirement. Moreover, stochastic dynamic programming is applied when only causal information is available.

## VI. Energy Harvesting Networking

In the past decade, the spirit of *cooperation among nodes* has fostered tremendous progress on the development of modern wireless communications. Several paradigm-shifting technologies such as cooperative communications and cognitive radios have been proposed for wireless networks in the spirit of cooperation to overwhelm the limitation of the two precious resources, power and spectrum, and the performance loss caused by wireless fading channels.

However, energy harvesting wireless networks differ from the traditional counterparts in that the nodes experience distinct energy harvesting capabilities and efficiencies and the achievable performance gain is further influenced by the availability of energy resource. Therefore, the design of energy harvesting networks must be revisited not only to account

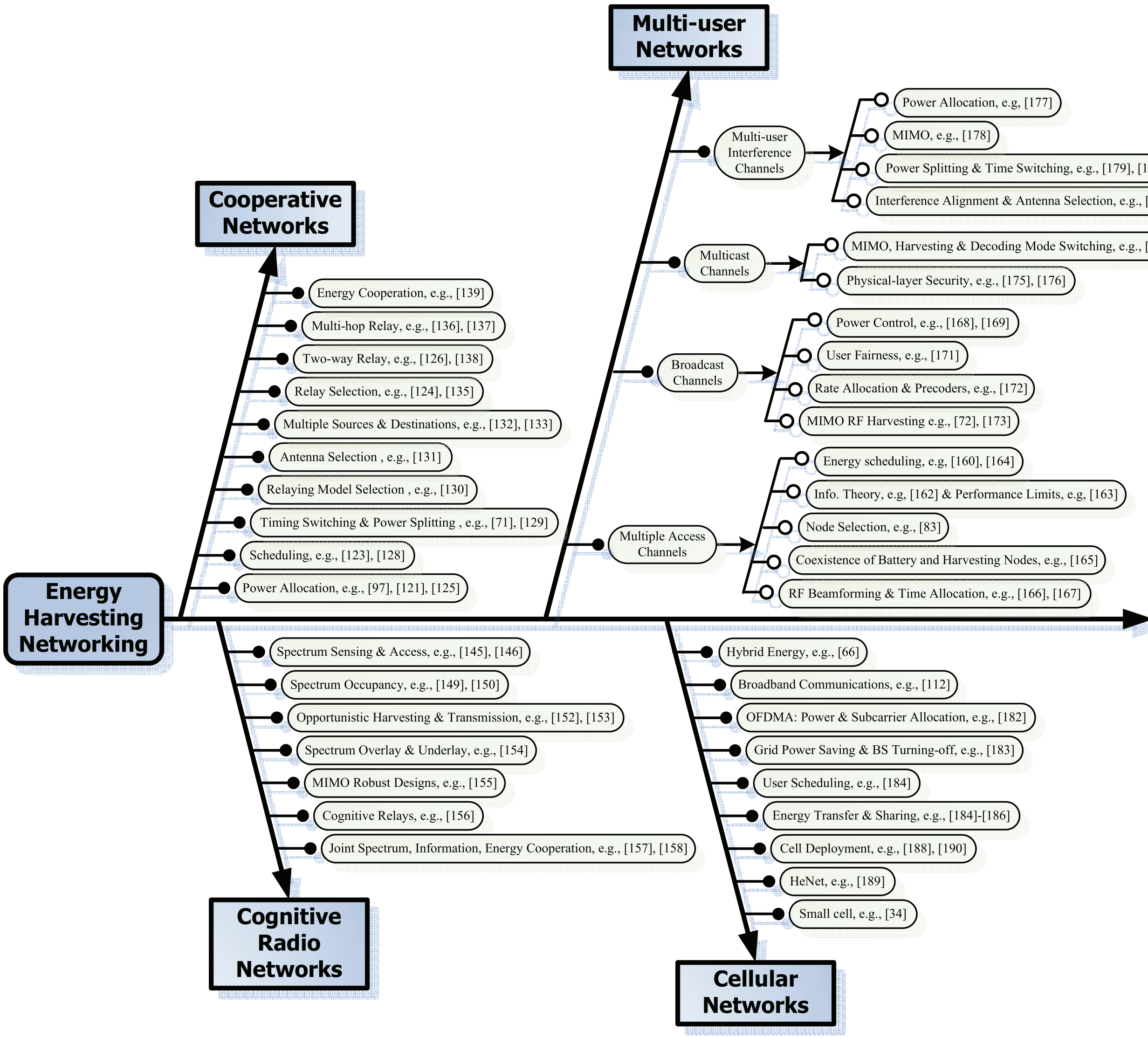

Fig. 4. A taxonomy of energy harvesting networking.

for the performance gain, probably resulted from information, spectrum or energy cooperation, but also to adapt to the temporal variation of battery recharge processes. Additionally, it necessitates to reconsider new transmission schemes for multi-user networks and cellular networks, e.g., multiple access channels, broadcast channels, and multi-user interference channels, and to study their fundamental performance limits when energy harvesting is applied. A taxonomy of energy harvesting networking is shown in Fig. 4. In this section, we will review the existing energy harvesting approaches in various basic network configurations, including cooperative networks, cognitive radio networks, multi-user networks, and cellular networks. The motivation and challenges to the inclusion of energy harvesting techniques in various types of wireless networks are discussed at the beginning of the following subsections.

### *A. Cooperative Energy Harvesting Networks*

Cooperative communication that pertains to a paradigm of information cooperation has gained much interest to mitigate the wireless channel fading and to improve the reliability of wireless links by exploiting the spatial diversity gains inherent in multi-user environments [120]. This can be achieved by allowing nodes to collaborate with each other with information transmission and thus forming virtual multi-input multi-output (MIMO) systems without the need of multiple antennas at each node.

Considering the fact that wireless cooperative nodes are often subject to space limitation to utilize a large battery with long lifetime, energy harvesting techniques have been introduced for self-sustainable cooperative relays to not only improve the throughput and reliability by harnessing the spatial diversity but also promise perpetual network lifetime without requiring periodic battery replacement. Owing to the new imposed time-varying energy constraints, several fundamental issues like relaying protocols in [121], [122], power allocation in [123], [97], relay selection in [124], [125], two-way relaying in [126], etc., have been revisited for various cooperative network configurations. In general, energy scheduling problems in cooperative communication become more complicated because the energy usage over time needs to make a tradeoff between the link performance of each hop and the battery recharge rate at each node. Below, we will review the recent advances in the topics of two-hop, two-way, and multi-hop cooperative communications and relay selection.

*1) Two-Hop Cooperative Communications:* The ambient energy harvesting for two-hop cooperative communications has been studied in the literature [97], [121]–[123], [127], [128]. The authors in [121] study power allocation for classic three-node decode-and-forward (DF) relay networks under deterministic energy harvesting models. The throughput maximization problem over a finite horizon of transmission blocks is investigated by considering the cases of delay-constrained traffic or no-delay-constrained traffic. For the latter case, a form of energy diversity is explored with delay tolerance. By deploying a half-duplex relay, a joint time scheduling and power allocation problem is addressed in [123] for a two-hop relay network with an energy harvesting source. Two design objectives are considered: short-term throughput maximization and transmission completion time minimization, where a directional water-filling algorithm found in [36] is served as a guideline for deriving the optimal solutions.

The problem of throughput maximization in a two-hop amplify-and-forward (AF) relay network is addressed in [122], where both the source and the relay nodes have the capability of harvesting energy. The offline and online power allocation schemes are designed for the two scenarios with causal or non-causal knowledge of harvested energy and channel gains, respectively. For the offline case, an alternative convex search algorithm is proposed to find the optimal power allocation at the source and the relay. For the online case, the problem is solved by an MDP framework, and a threshold property is explored under an on-off switching power control scheme.

In [97], an MDP-based relay transmission policy is found to minimize the long-term SER of a DF cooperative system. The asymptotic SER and its performance bound are analyzed to quantify the diversity gain and the energy harvesting gain, which reveals that full diversity is guaranteed if the probability of harvesting zero energy quantum is zero. In [127], stability analysis is conducted for a non-cooperative protocol and an orthogonal DF cooperative scheme in an energy harvesting network with three nodes. The optimal transmission power is found to maximize the stable data throughput. The authors prove that the cooperative transmission scheme is a better solution in the case of poor energy arrival rates, whereas the direct transmission scheme is suitable for high energy arrival rates. In [128], optimal relay scheduling is investigated to decide whether the energy harvesting relay helps the energy harvesting source to forward information or transmits its own information. The problem is formulated as the MDP and the POMDP by considering the long-term link coverage quality as the utility.

Dedicated energy harvesting from RF signals is naturally applicable to cooperative networks as it facilitates information relaying [29]. The main design concern in this direction is to determine an appropriate time sharing or power splitting ratio that enables the best tradeoff between signal relaying and energy harvesting. In [71], two relaying protocols of time sharing and power splitting are considered for two-hop relay networks, where the relay harvests energy and decodes information from the RF signal of the source. The analytical expressions for the outage probability and the ergodic capacity are derived to quantify the effect of various parameters such as energy harvesting time, power splitting ratio, source-to-relay distance, etc. Moreover, the study in [29] shows the superiority of a new unidirectional receiver, where the energy at the relays either enters or leaves the energy storage without being split in time or power. The work of [129] studies a three-node cooperative network, where the relay node is operated in two modes: harvesting energy from the RF signal of the source node or relaying the source's data to the destination. A greedy switching policy, where the second mode is executed only when the relay has sufficient energy to ensure decoding at the destination, is investigated by using Markov chain to characterize the outage performance. A two-user cooperative network, which includes two source nodes and one destination node, is considered in [130], and the source nodes rely on the RF energy harvesting from the destination node and may cooperate by using either DF or network coding methods. The system outage probability is minimized by optimizing the time allocation. Also the design of RF energy harvesting is extended to relay channels with multiple antenna configurations to reap the benefit of spatial processing in the current literature.

In [131], a joint antenna selection and power splitting scheme is proposed to determine the optimal power splitting ratio and the optimized antenna set which is engaged in signal relaying. The relay networks in the presence of multiple source-destination pairs are studied in some existing works. In [132], relay transmission strategies are proposed for one-way relay networks, wherein multiple source nodes communicate with their respective destination nodes via a RF energy harvesting relay. The outage probabilities are analyzed for two centralized power allocation schemes, equal power and sequential water filling, and a distributed auction-based power allocation scheme. A cooperative network with multiple source-destination pairs and an energy harvesting relay in considered in [133], where the relay exploits the DF protocol and harvests energy from the RF signals of the sources. The outage probability is analyzed by considering the spatial randomness of user locations. Furthermore, the cooperation is modeled as a canonical coalitional game, and a grand coalition, which means forming a larger cooperative group is better than acting alone, is preferred in high SNR regimes. The authors in [134] use non-cooperative games to derive power splitting ratios for all relays, each of which is dedicated to one source-destination pair. Each link is regraded as a strategic player who aims at maximizing its own data rate. The existence and uniqueness of the game are analyzed, and a distributed algorithm is proposed to achieve the Nash equilibriums.

*2) Relay Selection:* Relay selection is a pragmatic technique to reduce the complexity for multiple relay-assisted networks. Unlike the conventional relay selection schemes where the source node selects the relay which provides the best equivalent SNR among all relays, relay selection in energy harvesting communications needs to further take the energy harvesting condition at each relay into account. This is because if a relay is often selected, its battery may drain out quickly due to a slow recharge rate. Some existing works have focused on the cooperative systems with multiple relays, which allows the relay nodes to leverage the energy harvesting opportunity. The works in [95], [124], [125] address relay selection problems with ambient energy harvesting. In [124], voluntary AF relays are applied to assist in forwarding signals from a source node to a destination node. The SER of the system is analyzed under energy constrained and energy unconstrained cases, and asymptotic analysis is conducted for the cases when the SNR or the number of relays is large. In [125], a survival probability of energy harvesting relays, i.e., a probability that the remaining energy is greater than zero during one data transmission frame, is introduced in order to jointly optimize the resource block allocation, power control and relay selection for orthogonal frequency division multiple access (OFDMA) systems. In [95], joint relay selection and power allocation schemes are proposed to maximize the throughput of a cooperative network, wherein an energy harvesting source communicates with a destination via multiple energy harvesting relay nodes exploiting an AF protocol. An offline optimization problem is formulated as a non-convex mixed integer nonlinear program and solved by Bender's decomposition. Two online but suboptimal schemes, namely the energy harvesting rate-assisted scheme and the naive scheme, are proposed with low complexity. The relay selection problem with dedicated energy harvesting is studied in [135]. Therein, the authors consider a two-hop relay network with multiple relay nodes which can harvest RF energy opportunistically from the source or other relays, and they propose the optimal time allocation for the source and the relays by solving a linear program.

*3) Two-Way and Multi-Hop Cooperative Communications:* Relevant design issues are also extended to two-way and multi-hop relay networks with ambient energy harvesting in [52], [126], [136], [137] and dedicated energy harvesting in [138]. In [126], the authors investigate the optimal transmission policy for energy harvesting two-way relay networks. Through an MDP framework, a long-term outage probability is minimized by adapting the relay transmission power to the wireless channel states, battery energy amount and causal solar energy states. An interesting saturated structure for the outage probability is revealed in high SNR, and a saturation-free condition that guarantees a zero outage probability is proposed. Furthermore, when only partial state information about the relay is available at the source node, the transmission scheduling problem is cast as a POMDP in [52]. In [136], a cooperative automatic repeat request (ARQ) transmission protocol for multiple energy harvesting sensor nodes is investigated to maximize the throughput, and it is shown that the proposed scheme improves the system throughput by balancing the sensor nodes' energy consumption to match their own battery recharge rates. In [137], power allocation, routing, and scheduling decision are investigated for a multi-hop network powered by finite-capacity energy storage devices using quadratic Lyapunov and weight perturbation optimization techniques. A non-regenerative two-way relay network which includes two source nodes, a relay node equipped with multiple antennas, and a RF energy harvester is considered in [138]. The objective is to maximize the sum rate of the two-way relay network by designing relay beamforming under a transmit power constraint at the relay and an energy harvesting constraint at the RF energy harvester. An iterative algorithm based on semi-definite programming and rank-one decomposition is proposed to find the optimal solution.

Due to the heterogeneity and the variability of energy harvesting conditions, recent advances in energy harvesting communications also stimulate the interest of researchers in another dimension of cooperation, termed energy cooperation, which relies on dedicated energy harvesting for sharing energy among nodes. In [139], energy cooperation is studied for several basic network structures, including relay channels, two-way channels, etc. In this context, nodes can cooperate with each other to transfer energy from one of the nodes to the other over wireless physical channels despite the possible energy transfer loss. In [79], joint power allocation for cooperation communications with or without one-way energy sharing from the source to the relay is studied under the assumption of non-causal CSI and ESI, and in general, the energy sharing could improve the end-to-end throughput. In [140], a sum distortion minimization problem over a finite-time horizon is studied for multi-sensor estimation systems, in which sensors can not only harvest ambient energy but also share energy with their neighoring nodes. The optimal policy for energy allocation and sharing is proposed, and it is found that the average distortion decreases when the battery capacity and the energy transfer efficiency increase. The authors in [27] consider three relay placement scenarios for two-hop energy transfer (close to the RF source, the destination, and midpoint of the two nodes), and the experimental results show that the destination node can obtain more energy when the relay is closer to the destination.

**Concluding remark:** In this subsection, two-hop energy harvesting cooperative networks have been reviewed, where offline and online energy scheduling are studied for source and relay nodes which strike a balance between energy harvesting, energy expenditure and information relaying. Relay selection is shown to significantly improve the performance by leveraging the energy harvesting opportunity. More complicated cooperative networks, e.g., two-way and multi-hop, together with a new concept of energy cooperation, have been also introduced.

### *B. Cognitive Energy Harvesting Networks*

Cognitive radio has been deemed as a key enabling technology to resolve the problem of spectrum scarcity due to the ever increasing demand for wireless services and applications [141], [142]. In cognitive radios, secondary users are allowed to share the spectrum owned by primary users with one-way cooperation or full cooperation according to the design criteria of spectrum overlay or spectrum underlay, which enables us to use the spectrum resource in a more flexible and efficient fashion. Recently, incorporation of the concept of cooperative relaying into cognitive radio networks has opened up a new research direction which aims at the cooperation of information transmission and spectrum sharing among nodes [143]. In this new paradigm, the secondary user acts as a relay for improving the primary user's throughput, and in return, the primary user provides the secondary user with more spectrum usage opportunities [144].

Energy harvesting has been also applicable to cognitive radios, creating a fascinating new research line on green cognitive radio networks. In this context, the secondary users are capable of harnessing green energy to support the subsequent dynamic spectrum access of the licensed bands owned by the primary users. Since the available energy is random and intermittent, many research issues that have been well developed in the conventional cognitive radio networks, e.g., spectrum sensing, spectrum management and handoff, spectrum allocation and sharing, are required to be reconsidered to enhance the network reliability. The choice of parameters in cognitive radios, like mode selection, sensing duration and detection threshold, becomes even more crucial [30]. In such a network, several conflicting objectives need to be considered due to sporadic and unstable energy sources and limited spectrum resource: (1) obtaining the knowledge of spectrum activity; (2) protecting primary users from interference or collision ; (3) maximizing the transmission opportunity of secondary users, and (4) harvesting, spending or conserving energy. Hence, a common question arises as to how the secondary user efficiently uses the harvested energy over time to achieve these objectives. Below, we will first review the recent advances in the topics of spectrum sensing and channel access, followed by the study of cognitive relay and cooperation.

*1) Spectrum Sensing and Channel Access:* The design of spectrum sensing and channel access policies has been addressed in the recent works [145]–[151] which apply ambient energy harvesting. In [145], optimal cognitive sensing and access policies are investigated to maximize the data throughput for a secondary user with an energy queue. By formulating the problem as an MDP, the secondary user can either remain idle or execute spectrum sensing based on the belief of primary activity and the amount of energy in the battery. A similar scenario is considered in [146] by taking the constraints of energy causality and collision into account, and a theoretical upper bound on the maximum achievable throughput of the secondary user is derived as a function of the energy arrival rate, the temporal correlation of primary activity, and the detection threshold of spectrum sensing. With a multi-slot spectrum sensing paradigm, joint optimization for save-ratio (a fraction of time spent on harvesting, sensing and throughput), sensing duration and sensing threshold is studied in [147] to maximize the secondary user's expected achievable throughput while keeping primary users protected. It is shown that both the data-fusion and decision-fusion spectrum sensing strategies finally converge to a single-slot spectrum sensing when the maximum achievable throughput is attained. In [148], collaborative sensing scheduling is designed for multiple nodes with energy harvesting so that the time average utility, which is a concave function of the number of active sensing nodes, is maximized at a fusion center under individual energy causality constraints, and the optimal offline scheduling has a property that the nodes should be selected as fair as possible for performing sensing actions.

By treating the spectrum occupancy state as incomplete information, POMDP design frameworks are formulated to find the optimal transmission policies in some works [149], [150]. In [149], a secondary user with energy harvesting capability can opportunistically access the channels licensed by the primary users. A channel selection criterion is proposed to maximize the average spectral efficiency of the secondary user by exploiting not only the knowledge of channel occupancy and channel gains but also the dependency of the actions of sensing and accessing channels on the energy harvesting probability. Based on this criterion, a POMDP framework is developed to find the optimal and myopic policies for determining which channels to be sensed. In [150], the joint optimization of spectrum sensing policies and detection thresholds is solved by a constrained POMDP for maximizing the expected total throughput of an energy harvesting secondary user subject to the constraints of energy causality and collision. To reduce the complexity, the problem is then converted into an unconstrained POMDP by identifying the feasible set of detection thresholds that satisfy the collision requirement. As an extension, the work in [151] jointly optimizes the sensing duration and the sensing threshold to maximize the average throughput of the secondary network.

Different from the cognitive networks that use natural renewable energy sources, a secondary user with ambient RF energy harvesting can utilize not only an idle channel to transmit data packets but also a busy channel to recharge its battery. Several works have been devoted to taking advantage of waiting time of secondary users in order to obtain more energy and transmission opportunities. The authors in [152] propose a cognitive radio network architecture that enables a secondary transmitter to harvest RF energy from its neighboring primary transmitters and to reuse the spectrum of the primary network. By introducing interference guard zones and energy harvesting zones, transmission probability and the corresponding spatial throughput of the secondary users are derived based on a stochastic-geometry model of user locations. Finally, the throughput is maximized by jointly optimizing transmission power and density.

In [153], the authors consider a cognitive radio network in which the secondary user can transmit packets or harvest RF energy when the selected channel is idle or occupied by primary users, respectively. A channel access policy is proposed to maximize the data throughput of the secondary user via the MDP, and based on a policy gradient method, an online learning algorithm which does not require model parameters is proposed to adapt the channel access actions by observing the environments. In [154], depending upon the sensing results of the primary channel, the secondary user can operate in overlay or underlay transmission modes, remain in sleep mode to conserve energy, or harvest energy from the primary users. An energy threshold is applied to determine the transmission mode, and a POMDP framework is used to select the action of sensing the channel or staying idle according to the battery state and the belief about the activity of the primary user.

Dedicated RF energy harvesting is applied for cognitive radio in [155], and a robust transceiver design is investigated for wireless information and power transmission in underlay multiple-input multiple-output (MIMO) cognitive radio networks with channel uncertainty. An alternative optimization approach between the transmit covariance matrix at the secondary transmitter and the preprocessing matrix at the secondary information-decoding receiver is proposed to maximize the sum harvested power at energy harvesting receivers, while guaranteeing the interference constraints at the primary receivers and the required mean square error performance at the secondary information-decoding receiver.

*2) Cognitive Relays and Cooperation:* The idea of cooperative communication is also integrated into cognitive radio in the recent literature, which enables the secondary user to obtain more transmission opportunities by serving as a relay for the primary transmission. Consequently, there exist tradeoffs between the time durations of energy harvesting, data transmission and cooperative transmission for the secondary user. The authors in [156] consider a cognitive radio system in which an ambient energy harvesting secondary user with an unlimited energy buffer can obtain more transmission opportunities by optionally cooperating with a primary user. The optimal actions, in terms of energy harvesting time and relaying power, are analyzed for cooperative and non-cooperative modes to maximize the achievable throughput of the secondary user. Accordingly, an optimal cooperation protocol which involves a two-level test is proposed to make the optimal decision.

In [157], joint information, energy and spectrum cooperation between the primary system and the secondary system is investigated in cognitive radio networks to achieve better spectrum utilization, in which the secondary transmitter can use the energy transferred from the primary transmitter to help relay signals to the primary receiver as well as serve its own receiver through spectrum sharing. In [158], a secondary user maintains a relaying queue to store unsuccessfully delivered primary packets, and a queuing delay constraint is imposed for a primary user to stimulate cooperation with the secondary user which employs Alamouti space-time coding schemes. A throughput maximization problem for the secondary user is then solved under the constraints of the stability of all data queues and the primary end-to-end queuing delay.

**Concluding remark:** In this subsection, recent works regarding the tradeoff between energy harvesting, spectrum sensing and channel access in cognitive radio networks have been reviewed. The POMDP design methodology is effective to solve the problem when spectrum occupancy states of primary users are incomplete. The idea of the combination of cognitive radios and cooperative communications as well as the related works have been introduced, which provides a new paradigm of spectrum and energy exchange between primary and secondary users.

### C. Multi-User Energy Harvesting Networks

Multi-user wireless networks have been widely studied in the literature. In contrast to the single-user paradigm, reviewed in Section IV and Section V, one of the most distinctive features in the multi-user paradigm is the mutual interference created from multiple users to one another. To guarantee the QoS among users, it becomes very important to deal with the interference by carefully utilizing the harvested energy, which is in general very limited, in multi-user energy harvesting networks. Typically, there are four types of multi-user paradigms: multiple access channels, broadcast channels, multicast channels, and multi-user interference channels, and a review of the state-of-the-art research in this field is provided in the following.

*1) Multiple Access Channels:* Two-user multiple access systems are investigated in [159]–[161]. In [159], each user is able to harvest energy from nature and have a fixed amount of data to be transmitted to the receiver. A generalized iterative backward water-filling algorithm is proposed to characterize the maximum data departure regions of the transmitters, and based on the obtained region, a decomposed transmission completion time problem is solved by finding the power and rate policies via convex optimization. In [160], resource allocation is investigated for multiple access channels with wired connections to share harvested energy and transmitter side information between the two users. The achievable throughput region is characterized by maximizing the weighted sum throughput over a finite horizon of time slots, subject to energy harvesting constraints. In [161], a stability region is carried out for a pair of busty users randomly accessing a common receiver, and the impact of the energy availability and the battery capacity on the stability region is quantified.

Some works have focused on the scenario with multiple users [83], [162]–[165]. In [162], a multi-user system in multiple access channels is studied from the information-theoretic viewpoint, and it is shown that coordination among distributed nodes is needed in order to satisfy energy transfer constraints. The performance limits of a multiple access network with energy harvesting nodes are studied in [163]. By applying a compound Poisson dam model to capture the dynamics of the battery, an upper bound on the sum rate is derived, and the necessary conditions for the optimal power policies and the associated algorithms are proposed to maximize the achievable sum rate for both finite and infinite capacity of batteries.

With the goal of maximizing the sum rate, offline energy scheduling over a finite number of time slots is investigated in [164] for $K$-user multiple access channels with ambient energy harvesting. The energy scheduler is bounded by the constraints of the battery capacity and the maximum energy consumption of transmitters, and an iterative dynamic water-filling algorithm is developed to obtain the optimal solution. In [165], the authors investigate a multiple access wireless sensor network with two kinds of sensors, energy harvesting nodes and conventional nodes. Two performance criteria, namely $k$-outage duration and $n$-transmission duration, along with their the performance bounds, are proposed and analyzed to evaluate this hybrid network. Furthermore, cost-effective hybrid deployments for sensor nodes are studied to optimize these two criteria. In [83], a system with multiple rate-adaptive energy harvesting nodes in which one is selected for opportunistic transmission is investigated, and a throughput-optimal joint selection and rate adaptation rule is proposed.

Some works consider an issue that multiple access users are replenished by the downlink RF signals from transmitters [166], [167]. In [166], an access point first transmits the signal to multiple users for energy harvesting, and then the users exploit the harvest energy to transmit information to the access point using the TDMA scheme. The sum throughput of the network is maximized by optimizing the time allocation of the access point and all users under the constraints of average harvested energy values. In [167], the authors consider a wireless powered communication network in which a power station first replenishes multiple users via beamforming and each user transmits information to a common sink node by applying the TDMA scheme. A joint design of beamforming and user's time allocation is proposed to maximize the sum throughput.

*2) Broadcast Channels:* In [168], the authors study a transmission completion time minimization problem for an ambient energy harvesting transmitter which has a preset number of data packets to be delivered to each user. The structural property of the optimal total transmit policy is analyzed and a cut-off power policy is revealed for splitting the total power among users. Based on this, an iterative algorithm is proposed to find the globally optimal policy. An extension of [168] with a finite capacity battery is later investigated in [169]. In this case, the total transmit power sequence can be found by the directional water-filling algorithm, and there exist cut-off power levels to determine the power allocation among users by iteratively executing the directional water-filling. The work [170] considers the problem of transmission error and energy deficiency for a downlink broadcast network with energy harvesting sensor nodes. By designing the transmission period, three broadcast policies, called reliability-first, throughput-first and eclectic, are proposed to make a tradeoff between the reliability and the throughput.

The fairness issue among users is considered in [171], and the goal is to optimize the proportionally fair throughput by allocating time slots, power, and rate to multiple receivers. The joint design is decomposed into two subproblem problems in terms of power allocation and time allocation and solved by biconvex optimization techniques. In [172], the authors discuss the problem of rate allocation and precoder design for a multi-user MIMO broadcast system. Each user is equipped with an energy harvesting device, and the power consumption at the RF front-end and decoding stages is included in the design of the optimal transmission policies with or without perfect CSI and battery knowledge.

Broadcast channels with dedicated RF energy harvesting are studied in [72], [173]. In [72], the authors study a three-node MIMO broadcast system, where one receiver harvests energy and another receiver decodes information from the signals sent by a transmitter. When the receivers are separated, a rate-energy region is characterized for the optimal transmission strategy to achieve different trade-offs. When the receivers are co-located, the rate-energy regions are characterized for time sharing and power splitting schemes. The authors in [173] extend the work [72] to the scenario with multiple information receivers. A cooperative beam selection scheme is proposed to select a maximum number of active beams for data transmission while satisfying the energy harvesting requirement, and the performance tradeoff between the average harvested energy and the sum rate is analyzed.

*3) Multicast Channels:* Multi-cast energy harvesting networks, where a transmitter sends common information to multiple receivers simultaneously, are studied in [174]–[176]. In these existing works, it is assumed that the receivers can either decode information or harvest RF energy. By following the time switching protocol, a novel mode switching method is proposed based on random beamforming techniques, and it can achieve better power and information transfer performance, as compared with a periodic receiver mode switching method. An MIMO multicast system, consisting of one source node and two subsets of destination nodes referred to as information decoders and energy harvesters, is studied in [174]. The source precoder and the information decoders are jointly designed according to two criteria. One is to minimize the worst mean square error under source transmit power and harvested energy constraints. The other is to maximize the total harvested energy at the energy harvesters under source transmit power and worst mean square error constraints.

The work [175] extends the design to the case when there exists an eavesdropper. With channel uncertainties, a robust secure transmission scheme is proposed to maximize the worst-case secrecy rate under transmit power and harvested energy constraints. In [176], two problems are investigated to address a physical-layer security issue that information sent to the information receivers can be eavesdropped by the energy receivers. In the first problem, the secrecy rate for the information receiver is maximized subject to individual harvested energy constraints at energy receivers, while in the second problem, the weighted sum of harvested energy is maximized subject to a secrecy rate constraint at the information receivers.

*4) Multi-User Interference Channels:* The works [177] and [178] attempt to design energy harvesting transmission schemes in two-user interference channels. In [177], a short-term sum-throughput maximization problem is investigated with two transmitters which harvest energy from ambient energy sources. The optimal power allocation is found by iteratively executing modified versions of single-user directional water-filling algorithm. Examples of interference channels with known sum capacities such as asymmetric interference channels and very strong interference channels are examined. In [178], considering an MIMO interference channel, each receiver can either decode information or harvest RF energy. According to the receiving modes, the optimal transmission strategies and the performance, in terms of maximum achievable rate and energy or rate-energy tradeoff, are studied for four scenarios. Some works extend the design to $K$-user interference channels. The aim of [179] is to minimize the total transmit power by jointly optimizing user beamforming and power splitting under both SINR and energy harvesting constraints, and a decentralized algorithm is proposed based on second-order cone programming relaxation.

In addition to the existing power splitting, the authors in [180] propose several time splitting schemes such as time-division mode switching to maximize the system throughput of multi-antenna interference channels subject to power and energy harvesting constraints. In [181] and [31], interference is recycled to replenish the battery. To achieve this goal, the idea of interference alignment and receive antenna selection is exploited in [181] to divide the received signals into two orthogonal subspaces of signal and interference which are used to decode information and harvest energy, respectively. Also the rate-energy region is characterized for a random selection scheme in this work. Wireless energy harvesting in multi-user interference alignment networks is studied in [31], where a power-to-rate ratio-based user selection scheme is designed to schedule the energy harvesting priority among users. Moreover, a joint transmit power allocation and receiver power splitting scheme is proposed to further enhance the achievable rate-energy region.

**Concluding remark:** In this subsection, various energy harvesting design issues are reviewed for multi-user interference networks, including multiple access channels, broadcast channels, multicast channels, and multi-user interference channels. For multiple access channels, energy scheduling and data transmission problems for $K$ communication nodes which could be energy harvesting nodes or conventional nodes are introduced. Moreover, a scenario that uplink transmission is supplied by downlink energy transfer is discussed. For broadcast channels, directional water-filling is extended to $K$ downlink users, and the design issues of fairness, precoders, rate allocation, and dedicated RF energy harvesting are addressed. Both beamforming and security issues are reviewed for multicast channels. Energy scheduling for two-user interference channels is reviewed, and an idea of recycling interference is introduced by applying interference alignment techniques.

### D. Energy Harvesting Cellular Networks

The explosive growth of wireless multimedia services is anticipated to tremendously increase energy consumption in cellular networks. In response to the trend of reducing the carbon footprint and the operation cost of cellular networks, clean and sustainable energy sources have been deemed to be an alternative source, other than the conventional power grid, to power cellular systems. In particular, to meet future traffic demands, a very dense deployment of small cells which have smaller cell coverage and require less transmit power makes it realistic to enable self-powered base stations. In conventional cellular networks, e.g., macrocell, the energy consumption from power grid can be effectively reduced by equipping base stations with energy harvesting modules. To gain these benefits, it is essential to develop intelligent mechanisms, e.g., resource allocation, user scheduling, cell planning, etc., which can adapt to energy harvesting capabilities at base stations. Besides, there is a doubly near-far problem for energy harvesting cellular users at the cell edge who can harvest less energy in downlink but require higher transmit power in uplink [32]. This phenomenon makes the fairness among users challenging. We will discuss the relevant issues, including resource allocation, user scheduling and cell planning, for designing energy harvesting cellular networks in this subsection.

*1) Resource Allocation and User Scheduling:* The authors in [66] investigate resource allocation strategies, in which the transmitter can access a hybrid energy supply system consisting of an energy harvester and a conventional power grid. They seek to minimize the total energy cost at the transmitter, instead of energy consumption, subject to an outage constraint, and the problem is cast as mixed integer programming. The authors in [112] investigate energy harvesting broadband communications with multiple flat-faded subcarriers by considering both transmission and processing energy. Convex optimization problems as well as the properties of the corresponding optimal solutions are formulated with three different objectives, including maximization of data throughput by a deadline, maximization of residual energy in the battery by a deadline, and minimization of transmission completion time for a given amount of data.

In [182], power and subcarrier allocation algorithms are designed for an OFDMA downlink network with a hybrid energy harvesting base station. By taking into account circuit energy consumption, a finite energy storage capacity, and a minimum required data rate, an offline problem is formulated to maximize the weighted energy efficiency of the network and solved by using Dinkelbach method. A suboptimal event-driven algorithm which is triggered by the changes of channel fading and energy arrival is proposed by utilizing the statistical average of the time duration of each event. With the knowledge of data traffic and energy harvesting profiles, a grid power minimization problem for a downlink cellular network is considered in [183] by turning off some base stations and assigning resource block. A blocking probability is derived and served as the QoS constraint for the problem, and a two-stage dynamic programming which in turn determines the on-off state and the resource allocation of the base stations is proposed to reduce the computational complexity.

The authors in [184] consider delay-optimal transmission control and user scheduling for downlink coordinated MIMO systems with energy harvesting capability. The transmission control is operated with a longer timescale, while the user scheduling is adaptive with a shorter timescale. The considered problem is modeled as a POMDP framework, and a distributed method is proposed to reduce the implementation complexity by exploiting approximate dynamic programming and distributed stochastic learning. RF energy harvesting is also applied in cellular networks to sustain the data transmission of mobile users. The authors in [185] study a multiple access system in which a base station broadcasts RF energy to recharge the batteries of multiple uplink energy harvesting users. The information and energy transmission can be implemented either in time division duplex or frequency division duplex, and online rate and power allocation strategies are proposed to maximize the achievable rates.

The idea of energy cooperation has also been applied for cellular networks in [63], in which energy transfer is allowed between two base stations to help compensate for the energy deficiency problem one another due to either lower generation of renewable energy or higher traffic demand of users. A paradigm of joint energy and information cooperation is found in [186], and base stations in coordinated multi-point systems can share their energy powered by hybrid power supplies to cooperatively transmit data signals to mobile terminals.

*2) Cell Planning:* A cellular network planning problem is discussed in [187] by considering the use of renewable energy sources and the concept of energy balancing. The design framework aims at maximizing the total cost of installation, connection, and consumed power from electric grid, subject to the constraints of a minimum QoS requirement and a power outage probability. The authors propose a heuristic two-phase planning approach, namely, QoS-aware base station deployment and energy balancing connection, for this NP-hard problem. In [33], the authors elaborate on how to deploy renewable energy harvesters for a group of base stations by jointly considering the dynamics of harvested energy and power consumption. Based on the predicted availability of harvested energy, data traffic service is shaped to maximize the operation periods of base stations, while the degradation of users' quality-of-experience is minimized. The problems of cell deployment and power allocation are jointly studied in [188] to improve the energy sustainability and efficiency for two-tier green cellular networks which are composed of small cells and macrocells.

The authors in [189] consider heterogeneous cellular networks in which base stations, solely powered by self-sustained energy harvesting modules, across tiers are associated with different energy harvesting rates, energy storage capacity and deployment densities. The availability, which is defined as the fraction of time that a base station is turned on, is theoretically analyzed using random walk theory and stochastic geometry. In [190], an uplink cellular network is overlaid with randomly deployed power stations for wirelessly recharging mobile users via microwave radiation, and based on a stochastic geometry model, the network deployment is investigated under an outage constraint of data links. The study in [34] pinpoints that the combination of solar and wind, which complement to each other in time, is a good hybrid energy source to power small cell networks. The cell deployment guideline is provided by considering the tradeoffs between the outage probability, grid power consumption and base station density.

**Concluding remark:** In this subsection, various resource allocation issues, including power allocation, subcarrier allocation and user scheduling, are reviewed for energy harvesting cellular systems, e.g., OFDMA. With ambient energy sources, grid power minimization and energy cooperation problems for base stations are studied. Moreover, cell planning and power station deployment issues are addressed to maintain the network performance, while reducing the dependence on the grid power.

## VII. Application Systems

*1) Internet of Things:* Driven by the vision of smart cities and homes, IoT is an emerging technology to add ubiquitous internet capability to every objective which not only collects data from the surrounding environments and interacts with the physical world but also provides services to exchange data with other objectives for autonomous reasoning and decision making. Things in the IoT can refer to a wide variety of heterogeneous objectives such as home appliances, sensors, machines, portable devices, etc. There are many applications of IoT, which can be divided into the following domains: transportation and logistics, healthcare, smart environments, and personal and social applications [191]. For example, by using IoT, goods in supermarkets can automatically contact its provider for logistics management.

As another example, the deployment of sensors can monitor the environmental pollution or emergency events and improve the automation by taking an immediate action according to real-time data aggregation in the IoT. One can thus expect that a plethora of objectives will be connected together to form a huge intelligent network in an IoT system.

In addition to the problems of transmitting, storing, and processing mass information, how to power these IoT nodes is another challenging problem that needs to be addressed. In many applications, nodes are placed in hard-to-reach, hazardous or toxic areas, and thus, they cannot be connected to grid power. Even if these nodes can be powered by batteries, battery replacement may be difficult and expensive. Energy harvesting techniques should be good alternatives to prolong the lifetime of IoT systems. In fact, if the node's energy requirement is low enough [192], it is possible for IoT nodes to exclusively rely on power harvested from ambient energy sources like solar, indoor light, wind, vibration, motion, RF signals, etc. for perpetual operation. Referring to [193], energy harvesting can increase the lifetime of low-power sensor nodes by $\sim$110 and $\sim$510 percent in uniformly distributed ring topology and randomly distributed multi-hop topology, respectively.

*2) Green Cellular Infrastructures and Systems:* With the maturing of standardization and the on-going deployment for the fourth-generation wireless networks, research communities in both academic and industry are now on the tracks of envisioning and developing the fifth-generation (5G) wireless technologies. One of the typical and commonly accepted concepts in 5G systems is "*Green*". Green means not only to improve the network energy efficiency but also to decrease the dependency on electric grid. Energy harvesting techniques can be applied to 5G cellular networks with several potential advantages.

First, in conventional cellular networks, eighty percent of energy is consumed at the base stations, and network operators can reduce the grid power and ramp up more clean and renewable energy sources like solar and wind. The use of green sites can also lower the carbon footprint and electricity bill of running cellular networks. Second, solar and wind-powered base stations can speed up the revolution of mobile communications in developing counties like Africa and India, especially in some rural areas which lack power grid infrastructures for base stations to connect. The new base stations can use solar panels to generate and store solar power during the daytime, with the support of battery or backup wind turbine at night. It is estimated that twelve solar panels are enough to run an off-grid base station and even occasionally transfer redundant power to the electric grid [194]. By 2014, the percentage of these off-grid base stations in developing countries is around 8% and a growing demand for non-diesel-based mobile communications infrastructures is foreseen in the near future [194].

Pike Research stated that more than 390,000 green base stations will be deployed from 2012 to 2020 worldwide [195]. Many network operators and providers have engaged in studying and deploying green base stations over the past few years. Sony Ericsson and Motorola have considered the use of solar energy for rural base stations several years ago [196]. In Africa, more than a quarter of Vodacom's base stations in Lesotho are now powered through a combination of solar and wind energy [197]. Telekom has started operations of the first wind turbine-powered base station in Eibesthal in Lower Austria [198]. After the great Japan earthquake, NTT DOCOMO has started field testing for disaster-proof, environmentally friendly base stations which are equipped with solar panels, high-capacity rechargeable batteries and green power controllers [199]. In particular, these base stations can still be run with renewable energy if the commercial power gird is destroyed during a disaster.

## VIII. Future Research Directions

Many research efforts have been devoted to the development of energy harvesting communications and networks. In the previous sections, we have given a comprehensive overview on the energy harvesting problems and the pertinent cutting-edge approaches proposed by various researchers. In this section, we discuss the future research directions which require research community to pay attention to in order to design more advanced and reliable energy harvesting communication systems.

*1) Fundamental Limits of Energy Harvesting Channel Capacity:* Currently, channel capacity with energy harvesting transmitters is known for AWGN channels with unlimited-size battery and binary channels with a unit-sized battery. The energy harvesting channel capacity in general noisy channels for any finite-size battery remains an open research problem. Besides, the channel capacities with various ESI side information about the transmitter at the receiver side and the effect of energy harvesting receivers on the capacities are still open [23]. Further research is necessary for characterizing the fundamental performance limits of energy harvesting communications and networks from the information-theoretic aspect.

*2) Energy Harvesting at Receiver Side:* So far in the literature, most of the energy scheduling problems are studied for energy harvesting transmitters, and signal processing at the receivers is assumed to be powered by constant batteries or cost-free. To realize fully self-sustained communication systems, new design frameworks are needed to further embrace energy consumption at the receiver sides which apply energy harvesting for signal reception and decoding. One work along this line is [200], which investigates threshold policies to minimize the outage probability for energy harvesting transmitters and receivers. Packet sampling and decoding policies are studied in [201] for energy harvesting receivers. Moreover, communications between any two nodes are two-way, rather than one-way, in most wireless applications. In such a scenario, each node can act as either a transmitter or a receiver, depending on the allocated resource, in order to exchange messages with each other over the same physical medium. To alleviate the energy outage problems, energy usage for the two nodes should be balanced, for example, by transferring energy from one node to the other or appropriately scheduling the transmission and sleeping periods. It is interesting to study the receiver-side energy harvesting and its impact on the network performance.

*3) Energy Harvesting Models and Combination of Heterogeneous Energy Sources:* Energy harvesting models are essential to the implementation of energy scheduling for communication nodes. While a wide variety of models have been adopted in the existing works, there is a need to investigate models which are carefully verified through experiments and specific to each kind of energy sources, since distinct energy sources may posses very different energy arrival characteristics. Besides, the recharge process can deviate from an i.i.d. assumption and its average recharge rate is time-varying for a long time duration. A practical model that integrates several heterogeneous energy sources is another worthwhile research direction because energy harvesting-based communication nodes may rely on multiple energy sources for simultaneously recharging the battery, e.g., solar and vibrational sources for wearable devices.

*4) Robust Designs with Imperfect Knowledge:* In most of existing works, the knowledge of ESI and CSI, which could be presented in terms of data profiles in deterministic models or parameters in stochastic models, is assumed to be perfectly known to energy harvesting-based communication systems. However, in practice, the ESI knowledge is time-varying, and it is difficult to predict and estimate because of the dynamic activities of energy sources or the mobility of nodes. Although the CSI can be acquired by performing channel estimation, frequent estimation is not allowed due to the limited energy resource. Other knowledge in the networks includes primary user's activity in cognitive radio, battery storage conditions among nodes, etc. Undoubtedly, imperfect knowledge at nodes will degrade the achievable performance, and the degradation should be seriously taken care of in the design of energy scheduling, particularly when the time duration is long [203], [204]. Hence, robust designs are needed to deal with the possible imperfection in energy harvesting networks.

*5) Multiple Antennas Techniques:* In many applications, the transmit power level of wireless energy harvesting nodes is low due to the limited amount of harvested energy, and it necessitates energy-efficient transmission schemes which can effectively compensate for path loss and channel fading in wireless environments. Multiple antenna technologies like beamforming, space-time coding, distributed antennas, massive MIMO, can be exploited to save energy consumption at nodes. Furthermore, in RF energy harvesting, multiple antennas can be utilized to improve the transfer efficiency and distance in capturing RF energy when the energy is transferred from one node to another, and high-resolution beams can also be used to achieve information security [202]. More recently, multiple antennas have been advocated to relieve the loop-interference problem in full-duplex techniques, anticipating significant performance improvement for simultaneous information and power transfer [205]. A massive distributed antenna system has been shown as a promising network architecture to overcome the doubly near-far problem because the distance from antenna units to user equipments is geographically averaged [206]. The inclusion of multiple antennas in energy harvesting networks provides new research dimensions and opportunities in energy optimization problems.

*6) Security in RF Energy Harvesting:* In RF energy harvesting networks, the operating power sensitivity of energy receivers is typically much larger than that of information receivers. Hence, only the receivers which are in close proximity to the transmitter are scheduled for RF energy harvesting, and there may be situations that energy receivers act as eavesdroppers to overhear the messages sent to information receivers. This near-far problem gives rise to a challenging physical-layer security issue, and further research is needed to reach a compromise among the performance metrics of energy harvesting requirement, transmission secrecy and QoS [207], [208]. In addition, the existing transmission protocols such as time switching and power splitting are primarily designed for the tradeoff of information extraction and energy harvesting, we need more investigation on new transmission protocols to properly incorporate the security concern, for example, by introducing artificial noise in the transmitted signals or sending extra jamming signals.

*7) Energy Harvesting Networks with Multiple Nodes:* Although extensive studies have been carried out on energy harvesting communications, there are still some challenges when attempting to optimize the performance of an entire network consisting of multiple energy harvesting nodes. Research issues that are needed to be further explored in this direction include (a) routing, (b) multi-hop relaying, (c) relay selection, (d) cooperative spectrum sensing and sharing, (e) energy, spectrum and information cooperation from game-theoretic perspective, (f) multi-user interference mitigation and management, (g) distributed energy scheduling, (h) device-to-device communications, (i) machine-to-machine communications, (j) cross-layer optimization, (k) deployment of green small cells, etc.

*8) Energy Harvesting for Activity Recognition:* Recently, some researchers have opened a new research direction in energy harvesting computing and communication, where the non-uniform property of energy harvesting power signals can be used as the source for activity recognition, further reducing the energy demand of computing in devices [209]. For example, in human activity recognition, different activities (e.g., walking and running) generate kinetic power signals with different signatures (e.g., maximum values and auto-correlation values), and these observations can be turned into a positive use for classifying human activities, instead of using accelerometers. This is particularly attractive when the power consumption of the recognition devices becomes a bottleneck due to a small amount of power that can be harvested from the environment.

## IX. Conclusions

Nowadays, the demand for power by wireless communications is continually rising due to the widespread applications of wireless data services. Energy harvesting techniques have been proposed as a revolutionary solution toward green communications. In addition to being environmentally-friendly, energy harvesting capabilities facilitate the implementation of truly untethered mobile and ubiquitous communication systems. In this survey, we presented a comprehensive overview of energy harvesting communications and networks. To this end, characteristics of different energy sources, fundamental concepts about energy scheduling approaches, various research challenges and topics on energy harvesting communications were discussed. Next, we provided detailed discussions about the state-of-the-art research contributions in various network architectures which exploit the concept of cooperation among information, spectrum and energy domains, including cooperative, cognitive radio, multi-user, and cellular networks. Finally, possible application systems and several directions for future research were pinpointed. The comprehensive overview provided in this survey hopefully can serve as guidelines for further development of more realistic energy harvesting networks.

## References

[1] C. Han, *et al.*, "Green radio: Radio techniques to enable energy-efficient networks," *IEEE Commun. Mag.*, vol. 49, no. 6, pp. 46–54, Jun. 2011.

[2] J. A. Paradiso and T. Starner, "Energy scavenging for mobile and wireless electronics," *IEEE Pervasive Comput.*, vol. 4, no. 1, pp. 18–27, 2005.

[3] S. Sudevalayam and P. Kulkarni, "Energy harvesting sensor nodes: Survey and implications," *IEEE Commun. Surv. Tuts.*, vol. 13, no. 3, pp. 443–461, Third Quart. 2011.

[4] H. Zervos, P. Harrop, and R. Das, "Energy harvesting and storage 2014-2024: Forecasts, technologies, players," IDTechEx Rep., Oct. 2014.

[5] A. Paidimarri, N. Ickes, and A. P. Chandrakasan, "A +10 dBm 2.4 GHz transmitter with sub-400pW leakage and 43.7% system efficiency," in *Proc. IEEE Int. Solid-State Circuits Conf.*, 2015, pp. 1–3.

[6] R. J. M. Vullers, R. V. Schaijk, H. J. Visser, J. Penders, and C. V. Hoof, "Energy harvesting for autonomous wireless sensor networks," *IEEE Solid State Circuits Mag.*, vol. 2, no. 2, pp. 29–38, Spring 2010.

[7] R. V. Prasad, S. Devasenapathy, V. S. Rao, and J. Vazifehdan, "Reincarnation in the ambiance: Devices and networks with energy harvesting," *IEEE Commun. Surv. Tuts.*, vol. 16, no. 1, pp. 195–213, First Quart. 2014.

[8] M. L. Ku, Y. Chen, and K. J. R. Liu, "Data-driven stochastic models and policies for energy harvesting sensor communications," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 8, pp. 1505–1520, Aug. 2015.

[9] Y. K. Tan and S. K. Panda, "Energy harvesting from hybrid indoor ambient light and thermal energy sources for enhanced performance of wireless sensor nodes," *IEEE Trans. Ind. Electron.*, vol. 58, no. 9, pp. 4424–4435, Sep. 2011.

[10] W. S. Wang, T. O'Donnell, N. Wang, M. Hayes, B. O'Flynn, and C. O'Mathuna, "Design considerations of sub-mW indoor light energy harvesting for wireless sensor systems," *ACM J. Emerg. Technol. Comput. Syst.*, vol. 6, no. 2, pp. 1–18, Jun. 2010.

[11] V. Leonov, "Thermoelectric energy harvesting of human body heat for wearable sensors," *IEEE Sens. J.*, vol. 13, no. 6, pp. 2284–2291, Jun. 2013.

[12] P. Cuffe, P. Smith, and A. Keane, "Transmission system impact of wind energy harvesting networks," *IEEE Trans. Sustain. Energy*, vol. 3, no. 4, pp. 643–651, Oct. 2012.

[13] J. A. R. Azevedo and F. E. S. Santos, "Energy harvesting from wind and water for autonomous wireless sensor nodes," *IET Circuits Devices Syst.*, vol. 6, no. 6, pp. 413–420, Jun. 2012.

[14] L. Xie and M. Cai, "Human motion: Sustainable power for wearable electronics," *IEEE Pervasive Comput.*, vol. 13, no. 4, pp. 42–49, Oct. 2014.

[15] D. Ramasur and G. P. Hancke, "A wind energy harvester for low power wireless sensor networks," in *Proc. IEEE Int. Instrum. Meas. Tech. Conf.*, 2012, pp. 2623–2627.

[16] R. K. Sathiendran, R. R. Sekaran, B. Chandar, and B. S. A. G. Prasad, "Wind energy harvesting system powered wireless sensor networks for structural health monitoring," in *Proc. IEEE Int. Conf. Circuit Power Compt. Technol.*, 2014, pp. 523–526.

[17] P. D. Mitcheson, E. M. Yeatman, G. K. Rao, A. S. Holmes, and T. C. Green, "Energy harvesting from human and machine motion for wireless electronic devices," *Proc. IEEE*, vol. 96, no. 9, pp. 1457–1486, Sep. 2008.

[18] H. J. Visser and R. J. M. Vullers, "RF energy harvesting and transport for wireless sensor network applications: Principles and requirements," *Proc. IEEE*, vol. 101, no. 6, pp. 1410–1423, Jun. 2013.

[19] X. Lu, P. Wang, D. Niyato, D. I. Kim, and Z. Han, "Wireless networks with RF energy harvesting: A contemporary survey," *IEEE Commun. Surv. Tuts.*, vol. 17, no. 2, pp. 757–789, Second Quart. 2015.

[20] S. Kim, *et al.*, "Ambient RF energy-harvesting technologies for self-sustainable standalone wireless sensor platforms," *Proc. IEEE*, vol. 102, no. 11, pp. 1649–1666, Nov. 2014.

[21] I. Krikidis, S. Timotheou, S. Nikolaou, Z. Gan, D. W. K. Ng, and R. Schober, "Simultaneous wireless information and power transfer in modern communication systems," *IEEE Commun. Mag.*, vol. 52, no. 11, pp. 104–110, Nov. 2014.

[22] C. R. Valenta and G. D. Durgin, "Harvesting wireless power: Survey of energy-harvester conversion efficiency in far-field, wireless power transfer systems," *IEEE Microw. Mag.*, vol. 15, no. 4, pp. 108–120, Jun. 2014.

[23] O. Ozel, K. Tutuncuoglu, S. Ulukus, and A. Yener, "Fundamental limits of energy harvesting communications," *IEEE Commun. Mag.*, vol. 53, no. 4, pp. 126–132, Jun. 2015.

[24] S. Ulukus, *et al.*, "Energy harvesting wireless communications: A review of recent advances," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 3, pp. 360–381, Mar. 2015.

[25] Y. He, X. Cheng, W. Peng, and G. L. Stuber, "A survey of energy harvesting communications: Models and offline optimal policies," *IEEE Commun. Mag.*, vol. 53, no. 6, pp. 79–85, Jun. 2015.

[26] S. Bi, C. Ho, and R. Zhang, "Wireless powered communication: Opportunities and challenges," *IEEE Commun. Mag.*, vol. 53, no. 4, pp. 117–125, Apr. 2015.

[27] D. Mishra, S. De, S. Jana, S. Basagni, K. Chowdhury, and W. Heinzelman, "Smart RF energy harvesting communications: Challenges and opportunities," *IEEE Commun. Mag.*, vol. 53, no. 4, pp. 70–78, Apr. 2015.

[28] K. Huang and X. Zhou, "Cutting the last wires for mobile communications by microwave power transfer," *IEEE Commun. Mag.*, vol. 53, no. 6, pp. 86–93, Jun. 2015.

[29] K. Liu and P. Lin, "Toward self-sustainable cooperative relays: State of the art and the future," *IEEE Commun. Mag.*, vol. 53, no. 6, pp. 56–62, Apr. 2015.

[30] L. Mohjazi, M. Dianati, G. K. Karagiannidis, S. Muhaidat, and M. Al-Qutayri, "RF-powered cognitive radio networks: Technical challenges and limitations," *IEEE Commun. Mag.*, vol. 53, no. 4, pp. 94–100, Apr. 2015.

[31] N. Zhao, F. R. Yu, and V. C. M. Leung, "Wireless energy harvesting in interference alignment networks," *IEEE Commun. Mag.*, vol. 53, no. 6, pp. 72–78, Jun. 2015.

[32] H. Tabassum, E. Hossain, A. Ogundipe, and D. I. Kim, "Wireless-powered cellular networks: Key challenges and solution techniques," *IEEE Commun. Mag.*, vol. 53, no. 6, pp. 63–71, Jun. 2015.

[33] A. Kwasinski and A. Kwasinski, "Increasing sustainability and resiliency of cellular network infrastructure by harvesting renewable energy," *IEEE Commun. Mag.*, vol. 53, no. 4, pp. 110–116, Apr. 2015.

[34] Y. Mao, Y. Luo, J. Zhang, and K. B. Letaief, "Energy harvesting small cell networks: Feasibility, deployment, and operation," *IEEE Commun. Mag.*, vol. 53, no. 6, pp. 94–101, Jun. 2015.

[35] S. Reddy and C. R. Murthy, "Profile-based load scheduling in wireless energy harvesting sensors for data rate maximization," in *Proc. IEEE Int. Conf. Commun.*, 2010, pp. 1–5.

[36] O. Ozel, K. Tutuncuoglu, J. Yang, S. Ulukus, and A. Yener, "Transmission with energy harvesting nodes in fading wireless channels: Optimal policies," *IEEE J. Sel. Areas Commun.*, vol. 29, no. 8, pp. 1732–1743, Sep. 2011.

[37] F. M. Ozcelik, G. Uctu, and E. Uysal-Biyikoglu, "Minimization of transmission duration of data packets over an energy harvesting fading channel," *IEEE Commun. Lett.*, vol. 16, no. 12, pp. 1968–1971, Dec. 2012.

[38] J. Yang and S. Ulukus, "Optimal packet scheduling in an energy harvesting communication system," *IEEE Trans. Commun.*, vol. 60, no. 1, pp. 220–230, Jan. 2012.

[39] D. Niyato, E. Hossain, and A. Fallahi, "Sleep and wakeup strategies in solar-powered wireless sensor/mesh networks: Performance analysis and optimization," *IEEE Trans. Mobile Comput.*, vol. 6, no. 2, pp. 221–236, Feb. 2007.

[40] B. Medepally, N. B. Mehta, and C. R. Murthy, "Implications of energy profile and storage on energy harvesting sensor link performance," in *Proc. IEEE Global Commun. Conf.*, 2009, pp. 1–6.

[41] N. Michelusi, K. Stamatiou, and M. Zorzi, "On optimal transmission policies for energy harvesting devices," in *Proc. IEEE Inf. Theory Appl. Workshop*, 2012, pp. 249–254.

[42] N. Michelusi and M. Zorzi, "Optimal random multiaccess in energy harvesting wireless sensor networks," in *Proc. IEEE Int. Conf. Commun.*, 2013, pp. 463–468.

[43] A. Aprem, C. R. Murthy, and N. B. Mehta, "Transmit power control policies for energy harvesting sensors with retransmissions," *IEEE J. Sel. Topics Signal Process.*, vol. 7, no. 5, pp. 895–906, Oct. 2013.

[44] A. Kansal, J. Hsu, S. Zahedi, and M. B. Srivastava, "Power management in energy harvesting sensor networks," *ACM Trans. Embedded Comput. Syst.*, vol. 6, no. 4, pp. 32/1–32/38, Sep. 2007.

[45] K. J. Prabuchandran, S. K. Meena, and S. Bhatnagar, "Q-learning based energy management policies for a single sensor node with finite buffer," *IEEE Wireless Commun. Lett.*, vol. 2, no. 1, pp. 82–85, Feb. 2013.

[46] Y. Mao, G. Yu, and C. Zhong, "Energy consumption analysis of energy harvesting systems with power grid," *IEEE Wireless Commun. Lett.*, vol. 2, no. 6, pp. 611–614, Dec. 2013.

[47] J. Lei, R. Yates, and L. Greenstein, "A generic model for optimizing single-hop transmission policy of replenishable sensors," *IEEE Trans. Wireless Commun.*, vol. 8, no. 2, pp. 547–551, Feb. 2009.

[48] P. Blasco, D. Gunduz, and M. Dohler, "A learning theoretic approach to energy harvesting communication system optimization," *IEEE Trans. Wireless Commun.*, vol. 12, no. 4, pp. 1872–1882, Apr. 2013.

[49] S. Mao, M. H. Cheung, and V. W. S. Wong, "An optimal energy allocation algorithm for energy harvesting wireless sensor networks," in *Proc. IEEE Int. Conf. Commun.*, 2012, pp. 265–270.

[50] M. Kashef and A. Ephremides, "Optimal packet scheduling for energy harvesting sources on time varying wireless channels," *J. Commun. Netw.*, vol. 14, no. 2, pp. 121–129, Apr. 2012.

[51] Z. Wang, A. Tajer, and X. Wang, "Communication of energy harvesting tags," *IEEE Trans. Commun.*, vol. 60, no. 4, pp. 1159–1166, Apr. 2012.

[52] H. Li, N. Jaggi, and B. Sikdar, "Cooperative relay scheduling under partial state information in energy harvesting sensor networks," in *Proc. IEEE Global Commun. Conf.*, 2010, pp. 1–5.

[53] N. Michelusi, K. Stamatiou, and M. Zorzi, "Transmission policies for energy harvesting sensors with time-correlated energy supply," *IEEE Trans. Commun.*, vol. 61, no. 7, pp. 2988–3001, Jul. 2013.

[54] A. Seyedi and B. Sikdar, "Energy efficient transmission strategies for body sensor networks with energy harvesting," *IEEE Trans. Commun.*, vol. 58, no. 7, pp. 2116–2126, Jul. 2010.

[55] S. Zhang, A. Seyedi, and B. Sikdar, "An analytical approach to the design of energy harvesting wireless sensor nodes," *IEEE Trans. Wireless Commun.*, vol. 12, no. 8, pp. 4010–4024, Aug. 2013.

[56] N. Michelusi, L. Badia, and M. Zorzi, "Optimal transmission policies for energy harvesting devices with limited state-of-charge knowledge," *IEEE Trans. Commun.*, vol. 62, no. 11, pp. 3969–3982, Nov. 2014.

[57] C. K. Ho, P. D. Khoa, and P. C. Ming, "Markovian models for harvested energy in wireless communications," in *Proc. IEEE Int. Conf. Commun. Syst.*, 2010, pp. 311–315.

[58] B. Gaudette, V. Hanumaiah, S. Vrudhula, and M. Krunz, "Optimal range assignment in solar powered active wireless sensor networks," in *Proc. IEEE INFOCOM*, 2012, pp. 2354–2362.

[59] J. Widen, "Correlations between large-scale solar and wind power in a future scenario for Sweden," *IEEE Trans. Sustain. Energy*, vol. 2, no. 2, pp. 177–184, Apr. 2011.

[60] S. He, J. Chen, F. Jiang, D. K. Y. Yau, G. Xing, and Y. Sun, "Energy provisioning in wireless rechargeable sensor networks," *IEEE Trans. Mobile Comput.*, vol. 12, no. 10, pp. 1931–1942, Oct. 2013.

[61] I. Flint, X. Lu, N. Privault, D. Niyato, and P. Wang, "Performance analysis of ambient RF energy harvesting: A stochastic geometry approach," in *Proc. IEEE Glob. Commun. Conf.*, 2014, pp. 1448–1453.

[62] O. Ozel, K. Shahzad, and S. Ulukus, "Optimal energy allocation for energy harvesting transmitters with hybrid energy storage and processing cost," *IEEE Trans. Signal Process.*, vol. 62, no. 12, pp. 3232–3245, Jun. 2014.

[63] Y. K. Chia, S. Sun, and R. Zhang, "Energy cooperation in cellular networks with renewable powered base stations," *IEEE Trans. Wireless Commun.*, vol. 13, no. 12, pp. 6996–7010, Dec. 2014.

[64] I. Krikidis, G. Zheng, and B. Ottersten, "Harvest-use cooperative networks with half/full-duplex relaying," in *Proc. Wireless Commun. Net. Conf.*, 2013, pp. 4256–4260.

[65] S. Reddy and C. R. Murthy, "Dual-stage power management algorithms for energy harvesting sensors," *IEEE Trans. Wireless Commun.*, vol. 11, no. 4, pp. 1434–1445, Apr. 2012.

[66] X. Kang, Y. K. Chia, C. K. Ho, and S. Sun, "Cost minimization for fading channels with energy harvesting and conventional energy," *IEEE Trans. Wireless Commun.*, vol. 13, no. 8, pp. 4586–4598, Aug. 2014.

[67] R. Rajesh, V. Sharma, and P. Viswanath, "Capacity of Gaussian channels with energy harvesting and processing cost," *IEEE Trans. Inf. Theory*, vol. 60, no. 5, pp. 2563–2575, May 2014.

[68] O. Ozel and S. Ulukus, "Achieving AWGN capacity under stochastic energy harvesting," *IEEE Trans. Inf. Theory*, vol. 58, no. 10, pp. 6471–6483, Oct. 2012.

[69] Y. Dong, F. Farnia, and A. Ozgur, "Near optimal energy control and approximate capacity of energy harvesting communication," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 3, pp. 540–557, Mar. 2015.

[70] W. Lumpkins, "Nikola Tesla's dream realized: Wireless power energy harvesting," *IEEE Consum. Electron. Mag.*, vol. 3, no. 1, pp. 39–42, Jan. 2014.

[71] A. A. Nasir, X. Zhou, S. Durrani, and R. A. Kennedy, "Relaying protocols for wireless energy harvesting and information processing," *IEEE Trans. Wireless Commun.*, vol. 12, no. 7, pp. 3622–3636, Jul. 2013.

[72] R. Zhang and C. K. Ho, "MIMO broadcasting for simultaneous wireless information and power transfer," *IEEE Trans. Wireless Commun.*, vol. 12, no. 5, pp. 1989–2001, May 2013.

[73] L. R. Varshney, "Transporting information and energy simultaneously," in *Proc. IEEE Int. Symp. Inf. Theory*, 2008, pp. 1612–1616.

[74] P. Grover and A. Sahai, "Shannon meets Tesla: Wireless information and power transfer," in *Proc. IEEE Int. Symp. Inf. Theory*, 2010, pp. 2363–2367.

[75] M. Gregori and M. Payaro, "Energy-efficient transmission for wireless energy harvesting nodes," *IEEE Trans. Wireless Commun.*, vol. 12, no. 3, pp. 1244–1254, Mar. 2013.

[76] P. He, L. Zhao, S. Zhou, and Z. Niu, "Recursive waterfilling for wireless links with energy harvesting transmitters," *IEEE Trans. Veh. Tech.*, vol. 63, no. 3, pp. 1232–1241, Mar. 2014.

[77] C. K. Ho and R. Zhang, "Optimal energy allocation for wireless communications with energy harvesting constraints," *IEEE Trans. Signal Process.*, vol. 60, no. 9, pp. 4808–4818, Sep. 2012.

[78] Z. Wang, V. Aggarwal, and X. Wang, "Power allocation for energy harvesting transmitter with causal information," *IEEE Trans. Commun.*, vol. 62, no. 11, pp. 4080–4093, Nov. 2014.

[79] H. Li, J. Xu, R. Zhang, and S. Cui, "A general utility optimization framework for energy-harvesting-based wireless communications," *IEEE Commun. Mag.*, vol. 53, no. 4, pp. 79–85, Apr. 2015.

[80] K. Tutuncuoglu and A. Yener, "Optimum transmission policies for battery limited energy harvesting nodes," *IEEE Trans. Wireless Commun.*, vol. 11, no. 3, pp. 1180–1189, Mar. 2012.

[81] B. T. Bacinoglu and E. Uysal-Biyikoglu, "Finite-horizon online transmission scheduling on an energy harvesting communication link with a discrete set of rates," *J. Commun. Netw.*, vol. 16, no. 3, pp. 1–8, Jun. 2014.

[82] B. Devillers and D. Gunduz, "A general framework for the optimization of energy harvesting communication systems with battery imperfections," *J. Commun. Netw.*, vol. 14, no. 2, pp. 130–139, Apr. 2012.

[83] P. S. Khairnar and N. B. Mehta, "Discrete-rate adaptation and selection in energy harvesting wireless systems," *IEEE Trans. Wireless Commun.*, vol. 14, no. 1, pp. 219–229, Jan. 2015.

[84] C. Huang, R. Zhang, and S. Cui, "Optimal power allocation for outage probability minimization in fading channels with energy harvesting constraints," *IEEE Trans. Wireless Commun.*, vol. 13, no. 2, pp. 1074–1087, Feb. 2014.

[85] S. Wei, W. Guan, and K. J. R. Liu, "Power scheduling for energy harvesting wireless communications with battery capacity constraint," *IEEE Trans. Wireless Commun.*, vol. 14, no. 8, pp. 4640–4653, Aug. 2015.

[86] L. Liu, R. Zhang, and K. C. Chua, "Wireless information transfer with opportunistic energy harvesting," *IEEE Trans. Wireless Commun.*, vol. 12, no. 1, pp. 288–300, Jan. 2013.

[87] Y. Mao, G. Yu, and Z. Zhang, "On the optimal transmission policy in hybrid energy supply wireless communication systems," *IEEE Trans. Wireless Commun.*, vol. 13, no. 11, pp. 6422–6430, Nov. 2014.

[88] V. Sharma, U. Mukherji, V. Joseph, and S. Gupta, "Optimal energy management policies for energy harvesting sensor nodes," *IEEE Trans. Wireless Commun.*, vol. 9, no. 4, pp. 1326–1336, Apr. 2010.

[89] N. Roseveare and B. Natarajan, "An alternative perspective on utility maximization in energy-harvesting wireless sensor networks," *IEEE Trans. Veh. Technol.*, vol. 63, no. 1, pp. 344–356, Jan. 2014.

[90] R. Srivastava and C. E. Koksal, "Basic performance limits and tradeoffs in energy-harvesting sensor nodes with finite data and energy storage," *IEEE/ACM Trans. Netw.*, vol. 21, no. 4, pp. 1049–1062, Aug. 2013.

[91] J. Gong, S. Zhou, and Z. Niu, "Optimal power allocation for energy harvesting and power grid coexisting wireless communication systems," *IEEE Trans. Commun.*, vol. 61, no. 7, pp. 3040–3049, Jul. 2013.

[92] I. Ahmed, A. Ikhlef, D. W. K. Ng, and R. Schober, "Power allocation for an energy harvesting transmitter with hybrid energy sources," *IEEE Trans. Wireless Commun.*, vol. 12, no. 12, pp. 6255–6267, Dec. 2013.

[93] G. Yang, C. K. Ho, and Y. L. Guan, "Dynamic resource allocation for multiple-antenna wireless power transfer," *IEEE Trans. Signal Process.*, vol. 62, no. 14, pp. 3565–3577, Jul. 2014.

[94] F. Shan, J. Luo, W. Wu, M. Li, and X. Shen, "Discrete rate scheduling for packets with individual deadlines in energy harvesting systems," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 3, pp. 438–451, Mar. 2015.

[95] I. Ahmed, A. Ikhlef, R. Schober, and R. K. Mallik, "Joint power allocation and relay selection in energy harvesting AF relay systems," *IEEE Wireless Commun. Lett.*, vol. 2, no. 2, pp. 239–242, Apr. 2013.

[96] W. Li, M. L. Ku, Y. Chen, and K. J. R. Liu, "On outage probability for stochastic energy harvesting communications in fading channels," *IEEE Trans. Signal Process. Lett.*, vol. 22, no. 11, pp. 1893–1897, Nov. 2015.

[97] M. L. Ku, W. Li, Y. Chen, and K. J. R. Liu, "On energy harvesting gain and diversity analysis in cooperative communications," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 12, pp. 2641–2657, Dec. 2015, to be published.

[98] M. L. Puterman, *Markov Decision Processes—Discrete Stochastic Dynamic Programming*. Hoboken, NJ, USA: Wiley, 1994.

[99] M. A. Murtaza and M. Tahir, "Optimal data transmission and battery charging policies for solar powered sensor networks using Markov decision process," in *Proc. Wireless Commun. Netw. Conf.*, 2013, pp. 992–997.

[100] D. Niyato and P. Wang, "Delay-limited communications of mobile node with wireless energy harvesting: Performance analysis and optimization," *IEEE Trans. Veh. Technol.*, vol. 63, no. 4, pp. 1870–1885, May 2014.

[101] R. Vaze, R. Garg, and N. Pathak, "Dynamic power allocation for maximizing throughput in energy-harvesting communication system," *IEEE/ACM Trans. Netw.*, vol. 22, no. 5, pp. 1621–1630, Oct. 2014.

[102] S. Mao, M. H. Cheung, and V. W. S. Wong, "Joint energy allocation for sensing and transmission in rechargeable wireless sensor networks," *IEEE Trans. Veh. Technol.*, vol. 63, no. 6, pp. 2862–2875, Jul. 2014.

[103] M. Nourian, A. S. Leong, and S. Dey, "Optimal energy allocation for Kalman filtering over packet dropping links with imperfect acknowledgments and energy harvesting constraints," *IEEE Trans. Autom. Contr.*, vol. 59, no. 8, pp. 2128–2143, Jan. 2014.

[104] X. Chen, W. Ni, X. Wang, and Y. Sun, "Provisioning quality-of-service to energy harvesting wireless communications," *IEEE Commun. Mag.*, vol. 53, no. 4, pp. 102–109, Apr. 2015.

[105] X. Chen, C. Yuen, and Z. Zhang, "Wireless energy and information transfer tradeoff for limited-feedback multiantenna systems with energy beamforming," *IEEE Trans. Veh. Tech.*, vol. 63, no. 1, pp. 407–412, Jan. 2014.

[106] C.-F. Liu and C.-H. Lee, "MISO information and power transfer with finite-rate feedback under fading channel," in *Proc. IEEE Int. Conf. Commun.*, 2014, pp. 3794–3799.

[107] M. Maso, S. Lakshminarayana, T. Q. S. Quek, and H. V. Poor, "A composite approach to self-sustainable transmissions: Rethinking OFDM," *IEEE Trans. Commun.*, vol. 62, no. 11, pp. 3904–3917, Nov. 2014.

[108] Z. Fang, T. Song, and T. Li, "Energy harvesting for two-way OFDM communications under hostile jamming," *IEEE Signal Process. Lett.*, vol. 22, no. 4, pp. 413–416, Apr. 2015.

[109] J. Xu and R. Zhang, "Throughput optimal policies for energy harvesting wireless transmitters with non-ideal circuit power," *IEEE J. Sel. Areas Commun.*, vol. 32, no. 2, pp. 322–332, Feb. 2014.

[110] M. Gregori and M. Payaro, "On the optimal resource allocation for a wireless energy harvesting node considering the circuitry power consumption," *IEEE Trans. Wireless Commun.*, vol. 13, no. 11, pp. 5968–5984, Nov. 2014.

[111] K. Tutuncuoglu, A. Yener, and S. Ulukus, "Optimum policies for an energy harvesting transmitter under energy storage losses," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 3, pp. 467–481, Mar. 2015.

[112] O. Orhan, D. Gunduz, and E. Erkip, "Energy harvesting broadband communication systems with processing energy cost," *IEEE Trans. Wireless Commun.*, vol. 13, no. 11, pp. 6095–6107, Nov. 2014.

[113] Y. Li, Z. Jia, and S. Xie, "Energy-prediction scheduler for reconfigurable systems in energy-harvesting environment," *IET Wireless Sens. Syst.*, vol. 4, no. 2, pp. 80–85, Jun. 2014.

[114] Z. Xiang and M. Tao, "Robust beamforming for wireless information and power transmission," *IEEE Wireless Commun. Lett.*, vol. 1, no. 4, pp. 372–375, Aug. 2012.

[115] F. Iannello, O. Simeone, and U. Spagnolini, "Medium access control protocols for wireless sensor networks with energy harvesting," *IEEE Trans. Commun.*, vol. 60, no. 5, pp. 1381–1389, May 2012.

[116] H. Yoo, M. Shim, and D. Kim, "Dynamic duty-cycle scheduling schemes for energy-harvesting wireless sensor networks," *IEEE Commun. Lett.*, vol. 16, no. 2, pp. 202–204, Feb. 2012.

[117] R. S. Liu, K. W. Fan, Z. Zheng, and P. Sinha, "Perpetual and fair data collection for environmental energy harvesting sensor networks," *IEEE/ACM Trans. Netw.*, vol. 19, no. 4, pp. 947–960, Aug. 2011.

[118] S. Lee, B. Kwon, S. Lee, and A. C. Bovik, "BUCKET: Scheduling of solar-powered sensor networks via cross-layer optimization," *IEEE Sens. J.*, vol. 15, no. 3, pp. 1489–1503, Mar. 2015.

[119] J. Liu, H. Dai, and W. Chen, "Delay optimal scheduling for energy harvesting based communications," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 3, pp. 452–466, Mar. 2015.

[120] K. J. R. Liu, A. K. Sadek, W. Su, and A. Kwasinski, *Cooperative Communications and Networking*. Cambridge, U.K.: Cambridge Univ. Press, 2008.

[121] C. Huang, R. Zhang, and S. Cui, "Throughput maximization for the Gaussian relay channel with energy harvesting constraints," *IEEE J. Sel. Areas Commun.*, vol. 31, no. 8, pp. 1469–1479, Aug. 2013.

[122] A. Minasian, S. Shahbazpanahi, and R. S. Adve, "Energy harvesting cooperative communication systems," *IEEE Trans. Wireless Commun.*, vol. 13, no. 11, pp. 6118–6131, Nov. 2014.

[123] Y. Luo, J. Zhang, and K. B. Letaief, "Optimal scheduling and power allocation for two-hop energy harvesting communication systems," *IEEE Trans. Wireless Commun.*, vol. 12, no. 9, pp. 4729–4741, Sep. 2013.

[124] B. Medepally and N. B. Mehta, "Voluntary energy harvesting relays and selection in cooperative wireless networks," *IEEE Trans. Wireless Commun.*, vol. 9, no. 11, pp. 3543–3553, Nov. 2010.

[125] S. Jangsher, H. Zhou, V. O. K. Li, and K.-C. Leung, "Joint allocation of resource blocks, power, and energy-harvesting relays in cellular networks," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 3, pp. 482–495, Mar. 2015.

[126] W. Li, M. L. Ku, Y. Chen, and K. J. R. Liu, "On outage probability for two-way relay networks with stochastic energy harvesting," *IEEE Trans. Commun.*, 2015, to be published.

[127] I. Krikidis, T. Charalambous, and J. S. Thompson, "Stability analysis and power optimization for energy harvesting cooperative networks," *IEEE Signal Process. Lett.*, vol. 19, no. 1, pp. 20–23, Jan. 2012.

[128] H. Li, N. Jaggi, and B. Sikdar, "Relay scheduling for cooperative communications in sensor networks with energy harvesting," *IEEE Trans. Wireless Commun.*, vol. 10, no. 9, pp. 2918–2928, Sep. 2011.

[129] I. Krikidis, S. Timotheou, and S. Sasaki, "RF energy transfer for cooperative networks: Data relaying or energy harvesting?," *IEEE Commun. Lett.*, vol. 16, no. 11, pp. 1772–1775, Nov. 2012.

[130] G. L. Moritz, J. L. Rebelatto, R. Demo Souza, B. F. Uchoa-Filho, and Y. Li, "Time-switching uplink network-coded cooperative communication with downlink energy transfer," *IEEE Trans. Signal Process.*, vol. 62, no. 19, pp. 5009–5019, Oct. 2014.

[131] Z. Zhou, M. Peng, Z. Zhao, and Y. Li, "Joint power splitting and antenna selection in energy harvesting relay channels," *IEEE Signal Process. Lett.*, vol. 22, no. 7, pp. 823–827, Jul. 2015.

[132] Z. Ding, S. M. Perlaza, I. Esnaola, and H. V. Poor, "Power allocation strategies in energy harvesting wireless cooperative networks," *IEEE Trans. Wireless Commun.*, vol. 13, no. 2, pp. 846–860, Feb. 2014.

[133] Z. Ding and H. V. Poor, "Cooperative energy harvesting networks with spatially random users," *IEEE Signal Process. Lett.*, vol. 20, no. 12, pp. 1211–1214, Dec. 2013.

[134] H. Chen, Y. Li, Y. Jiang, Y. Ma, and B. Vucetic, "Distributed power splitting for SWIPT in relay interference channels using game theory," *IEEE Trans. Wireless Commun.*, vol. 14, no. 1, pp. 410–420, Jan. 2015.

[135] L. Tang, X. Zhang, and X. Wang, "Joint data and energy transmission in a two-hop network with multiple relays," *IEEE Commun. Lett.*, vol. 18, no. 11, pp. 2015–2018, Nov. 2014.

[136] M. Tacca, P. Monti, and A. Fumagalli, "Cooperative and reliable ARQ protocols for energy harvesting wireless sensor nodes," *IEEE Trans. Wireless Commun.*, vol. 6, no. 7, pp. 2519–2529, Jul. 2007.

[137] L. Huang and M. J. Neely, "Utility optimal scheduling in energy-harvesting networks," *IEEE/ACM Trans. Netw.*, vol. 21, no. 4, pp. 1117–1130, Aug. 2013.

[138] Q. Li, Q. Zhang, and J. Qin, "Beamforming in non-regenerative two-way multi-antenna relay networks for simultaneous wireless information and power transfer," *IEEE Trans. Wireless Commun.*, vol. 13, no. 10, pp. 5509–5520, Oct. 2014.

[139] B. Gurakan, O. Ozel, J. Yang, and S. Ulukus, "Energy cooperation in energy harvesting communications," *IEEE Trans. Commun.*, vol. 61, no. 12, pp. 4884–4898, Dec. 2013.

[140] S. Knorn, S. Dey, A. Ahlen, and D. E. Quevedo, "Distortion minimization in multi-sensor estimation using energy harvesting and energy sharing," *IEEE Trans. Signal Process.*, vol. 63, no. 11, pp. 2848–2863, Jun. 2015.

[141] B. Wang and K. J. R. Liu, "Advances in cognitive radio networks: A survey," *IEEE J. Sel. Topics Signal Process.*, vol. 5, no. 1, pp. 5–23, Feb. 2011.

[142] K. J. R. Liu and B. Wang, *Cognitive Radio Networking and Security: A Game Theoretical View.* Cambridge, U.K.: Cambridge Univ. Press, 2010.

[143] K. Letaief and W. Zhang, "Cooperative communications for cognitive radio networks," *Proc. IEEE*, vol. 97, no. 5, pp. 878–893, May 2009.

[144] M. Naeem, A. Anpalagan, M. Jaseemuddin, and D. C. Lee, "Resource allocation techniques in cooperative cognitive radio networks," *IEEE Commun. Surv. Tuts.*, vol. 16, no. 2, pp. 729–744, Jun. 2014.

[145] A. Sultan, "Sensing and transmit energy optimization for an energy harvesting cognitive radio," *IEEE Wireless Commun. Lett.*, vol. 1, no. 5, pp. 500–503, Oct. 2012.

[146] S. Park and D. Hong, "Achievable throughput of energy harvesting cognitive radio networks," *IEEE Trans. Wireless Commun.*, vol. 13, no. 2, pp. 1010–1022, Feb. 2014.

[147] S. Yin, Z. Qu, and S. Li, "Achievable throughput optimization in energy harvesting cognitive radio systems," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 3, pp. 407–422, Mar. 2015.

[148] J. Yang, X. Wu, and J. Wu, "Optimal scheduling of collaborative sensing in energy harvesting sensor networks," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 3, pp. 512–523, Mar. 2015.

[149] J. J. Pradha, S. S. Kalamkar, and A. Banerjee, "Energy harvesting cognitive radio with channel-aware sensing strategy," *IEEE Commun. Lett.*, vol. 18, no. 7, pp. 1171–1174, Jul. 2014.

[150] S. Park and D. Hong, "Optimal spectrum access for energy harvesting cognitive radio networks," *IEEE Trans. Wireless Commun.*, vol. 12, no. 12, pp. 6166–6179, Dec. 2013.

[151] W. Chung, S. Park, S. Lim, and D. Hong, "Spectrum sensing optimization for energy-harvesting cognitive radio systems," *IEEE Trans. Wireless Commun.*, vol. 13, no. 5, pp. 2601–2613, May 2014.

[152] S. Lee, R. Zhang, and K. Huang, "Opportunistic wireless energy harvesting in cognitive radio networks," *IEEE Trans. Wireless Commun.*, vol. 12, no. 9, pp. 4788–4799, Sep. 2013.

[153] D. T. Hoang, D. Niyato, P. Wang, and D. I. Kim, "Opportunistic channel access and RF energy harvesting in cognitive radio networks," *IEEE J. Sel. Areas Commun.*, vol. 32, no. 11, pp. 2039–2052, Nov. 2014.

[154] M. Usman and I. Koo, "Access strategy for hybrid underlay-overlay cognitive radios with energy harvesting," *IEEE Sens. J.*, vol. 14, no. 9, pp. 3164–3173, Sep. 2014.

[155] C. Xu, Q. Zhang, Q. Li, Y. Tan, and J. Qin, "Robust transceiver design for wireless information and power transmission in underlay MIMO cognitive radio networks," *IEEE Commun. Lett.*, vol. 18, no. 9, pp. 1665–1668, Sep. 2014.

[156] S. Yin, E. Zhang, Z. Qu, L. Yin, and S. Li, "Optimal cooperation strategy in cognitive radio systems with energy harvesting," *IEEE Trans. Wireless Commun.*, vol. 13, no. 9, pp. 4693–4707, Sep. 2014.

[157] G. Zheng, Z. Ho, E. A. Jorswieck, and B. Ottersten, "Information and energy cooperation in cognitive radio networks," *IEEE Trans. Signal Process.*, vol. 62, no. 9, pp. 2290–2303, Sep. 2014.

[158] A. El Shafie, "Space-time coding for an energy harvesting cooperative secondary terminal," *IEEE Commun. Lett.*, vol. 18, no. 9, pp. 1571–1574, Sep. 2014.

[159] J. Yang and S. Ulukus, "Optimal packet scheduling in a multiple access channel with energy harvesting transmitters," *J. Commun. Netw.*, vol. 14, no. 2, pp. 140–150, Apr. 2012.

[160] D. Zhao, C. Huang, Y. Chen, F. Alsaadi, and S. Cui, "Resource allocation for multiple access channel with conferencing links and shared renewable energy sources," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 3, pp. 423–437, Mar. 2015.

[161] J. Jeon and A. Ephremides, "On the stability of random multiple access with stochastic energy harvesting," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 3, pp. 571–584, Mar. 2015.

[162] A. M. Fouladgar and O. Simeone, "On the transfer of information and energy in multi-user systems," *IEEE Commun. Lett.*, vol. 16, no. 11, pp. 1733–1736, Nov. 2012.

[163] M. B. Khuzani and P. Mitran, "On online energy harvesting in multiple access communication systems," *IEEE Trans. Inf. Theory*, vol. 60, no. 3, pp. 1883–1898, Mar. 2014.

[164] Z. Wang, V. Aggarwal, and X. Wang, "Iterative dynamic water-filling for fading multiple-access channels with energy harvesting," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 3, pp. 382–395, Mar. 2015.

[165] S. Rao and N. B. Mehta, "Hybrid energy harvesting wireless systems: Performance evaluation and benchmarking," *IEEE Trans. Wireless Commun.*, vol. 13, no. 9, pp. 4782–4793, Sep. 2014.

[166] H. Ju and R. Zhang, "Throughput maximization in wireless powered communication networks," *IEEE Trans. Wireless Commun.*, vol. 13, no. 1, pp. 418–428, Jan. 2014.

[167] Q. Sun, G. Zhu, C. Shen, X. Li, and Z. Zhong, "Joint beamforming design and time allocation for wireless powered communication networks," *IEEE Commun. Lett.*, vol. 18, no. 10, pp. 1783–1786, Oct. 2014.

[168] J. Yang, O. Ozel, and S. Ulukus, "Broadcasting with an energy harvesting rechargeable transmitter," *IEEE Trans. Wireless Commun.*, vol. 11, no. 2, pp. 571–583, Feb. 2012.

[169] O. Ozel, J. Yang, and U. Sennur, "Optimal broadcast scheduling for an energy harvesting rechargeable transmitter with a finite capacity battery," *IEEE Trans. Wireless Commun.*, vol. 11, no. 6, pp. 2193–2203, Jun. 2012.

[170] C. C. Kuan, G. Y. Lin, H. Y. Wei, and R. Vannithamby, "Reliable multicast and broadcast mechanisms for energy-harvesting devices," *IEEE Trans. Veh. Technol.*, vol. 63, no. 4, pp. 1813–1826, Apr. 2014.

[171] N. Tekbiyik, T. Girici, E. Uysal-Biyikoglu, and K. Leblebicioglu, "Proportional fair resource allocation on an energy harvesting downlink," *IEEE Trans. Wireless Commun.*, vol. 12, no. 4, pp. 1699–1711, Apr. 2013.

[172] J. Rubio and A. Pascual-Iserte, "Energy-aware broadcast multiuser-MIMO precoder design with imperfect channel and battery knowledge," *IEEE Trans. Wireless Commun.*, vol. 13, no. 6, pp. 3137–3152, Jun. 2014.

[173] T. Wu and H. C. Yang, "RF energy harvesting with cooperative beam selection for wireless sensors," *IEEE Wireless Commun. Lett.*, vol. 3, no. 6, pp. 585–588, Dec. 2014.

[174] A. Ikhlef, "Optimal MIMO multicast transceiver design for simultaneous information and power transfer," *IEEE Commun. Lett.*, vol. 18, no. 12, pp. 2153–2156, Dec. 2014.

[175] R. Feng, Q. Li, Q. Zhang, and J. Qin, "Robust secure transmission in MISO simultaneous wireless information and power transfer system," *IEEE Trans. Veh. Technol.*, vol. 64, no. 1, pp. 400–405, Jan. 2015.

[176] L. Liu, R. Zhang, and K. C. Chua, "Secrecy wireless information and power transfer with MISO beamforming," *IEEE Trans. Signal Process.*, vol. 62, no. 7, pp. 1850–1863, Apr. 2014.

[177] K. Tutuncuoglu and A. Yener, "Sum-rate optimal power policies for energy harvesting transmitters in an interference channel," *J. Commun. Netw.*, vol. 14, no. 2, pp. 151–161, Apr. 2012.

[178] J. Park and B. Clerckx, "Joint wireless information and energy transfer in a two-user MIMO interference channel," *IEEE Trans. Wireless Commun.*, vol. 12, no. 8, pp. 4210–4221, Aug. 2013.

[179] Q. Shi, L. Liu, W. Xu, and R. Zhang, "Joint transmit beamforming and receive power splitting for MISO SWIPT systems," *IEEE Trans. Wireless Commun.*, vol. 13, no. 6, pp. 3269–3280, Jun. 2014.

[180] C. Shen, W. C. Li, and T. H. Chang, "Wireless information and energy transfer in multi-antenna interference channel," *IEEE Trans. Signal Process.*, vol. 62, no. 23, pp. 6249–6264, Dec. 2014.

[181] B. Koo and D. Park, "Interference alignment and wireless energy transfer via antenna selection," *IEEE Commun. Lett.*, vol. 18, no. 4, pp. 548–551, Apr. 2014.

[182] D. W. K. Ng, E. S. Lo, and R. Schober, "Energy-efficient resource allocation in OFDMA systems with hybrid energy harvesting base station," *IEEE Trans. Wireless Commun.*, vol. 12, no. 7, pp. 3412–3427, Jul. 2013.

[183] J. Gong, J. S. Thompson, S. Zhou, and Z. Niu, "Base station sleeping and resource allocation in renewable energy powered cellular networks," *IEEE Trans. Commun.*, vol. 62, no. 11, pp. 3801–3813, Nov. 2014.

[184] Y. Cui, V. K. N. Lau, and Y. Wu, "Delay-aware BS discontinuous transmission control and user scheduling for energy harvesting downlink coordinated MIMO systems," *IEEE Trans. Signal Process.*, vol. 60, no. 7, pp. 3786–3795, Jul. 2012.

[185] Z. Hadzi-Velkov, N. Zlatanov, and R. Schober, "Multiple-access fading channel with wireless power transfer and energy harvesting," *IEEE Commun. Lett.*, vol. 18, no. 10, pp. 1863–1866, Oct. 2014.

[186] J. Xu, Y. H. Guo, and R. Zhang, "CoMP meets energy harvesting: a new communication and energy cooperation paradigm," in *Proc. IEEE Global Commun. Conf.*, 2013, pp. 2508–2513.

[187] M. Zheng, P. Pawelczak, S. Stanczak, and H. Yu, "Planning of cellular networks enhanced by energy harvesting," *IEEE Trans. Commun. Lett.*, vol. 17, no. 6, pp. 1092–1095, Jun. 2013.

[188] Z. Zheng, X. Zhang, L. X. Cai, R. Zhang, and X. Shen, "Sustainable communication and networking in two-tier green cellular networks," *IEEE Wireless Commun.*, vol. 21, no. 4, pp. 47–53, Aug. 2014.

[189] H. S. Dhillon, Y. Li, P. Nuggehalli, Z. Pi, and J. G. Andrews, "Fundamentals of heterogeneous cellular networks with energy harvesting," *IEEE Trans. Wireless Commun.*, vol. 13, no. 5, pp. 2782–2797, May 2014.

[190] K. Huang and V. K. N. Lau, "Enabling wireless power transfer in cellular networks: Architecture, modeling and deployment," *IEEE Trans. Wireless Commun.*, vol. 13, no. 2, pp. 902–912, Feb. 2014.

[191] A. Luigi, I. Antonio, and M. Giacomo, "The internet of things: A survey," *Comput. Netw.*, vol. 54, no. 15, pp. 2787–2805, Oct. 2010.

[192] Y. Chen, *et al.*, "Time-reversal wireless paradigm for green internet of things: An overview," *IEEE Internet Things J.*, vol. 1, no. 1, pp. 81–98, Feb. 2014.

[193] P. Kamalinejad, C. Mahapatra, Z. Sheng, S. Mirabbasi, V. C. M. Leung, and Y. L. Guan, "Wireless energy harvesting for the internet of things," *IEEE Commun. Mag.*, vol. 53, no. 6, pp. 102–108, Jun. 2015.

[194] J. Heimbuch. (2010). *T-Mobile USA Builds its First Cell Tower Powered by Solar Energy* [Online]. Available: http://www.treehugger.com/solar-technology/t-mobile-usa-builds-its-first-cell-tower-powered-by-solar-energy.html

[195] K. A. Adamson, and C. Wheelock, "Off-grid power for mobile base stations," Navigant Research, Rep., Jan. 2013.

[196] M. McDermott. (2009). *100+ Solar-Powered Ericsson Cell Phone Base Stations Coming to Africa* [Online]. Available: http://www.treehugger.com/clean-technology/100-solar-powered-ericsson-cell-phone-base-stations-coming-to-africa.html

[197] Cellular News. (2012). *Quarter of Vodacom Lesotho Network Powered by Green Base Stations* [Online]. Available: http://www.cellular-news.com/story/55038.php

[198] Cellular News. (2009). *Telekom Austria's First Wind Turbine-Powered Mobile Phone Base Station* [Online]. Available: http://www.cellular-news.com/story/Operators/36190.php

[199] NTTDOCOMO. (2013). *DOCOMO to Field Test Solar-Powered Green Base Stations* [Online]. Available: http://www.nttdocomo.co.jp/english/info/media_center/pr/2013/0322_01.html

[200] S. Zhou, T. Chen, W. Chen, and Z. Niu, "Outage minimization for a fading wireless link with energy harvesting transmitter and receiver," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 3, pp. 496–511, Mar. 2015.

[201] R. D. Yates and H. Mahdavi-Doost, "Energy harvesting receivers: packet sampling and decoding policies," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 3, pp. 558–570, Mar. 2015.

[202] X. Chen, Z. Zhang, H.-H. Chen, and H. Zhang, "Enhancing wireless information and power transfer by exploiting multi-antenna techniques," *IEEE Commun. Mag.*, vol. 53, no. 4, pp. 133–141, Apr. 2015.

[203] J. Rubio and A. Pascual-Iserte, "Energy-aware broadcast multiuser-MIMO precoder design with imperfect channel and battery knowledge," *IEEE Trans. Wireless Commun.*, vol. 13, no. 6, pp. 3137–3152, Jun. 2014.

[204] I. Ahmed, A. Ikhlef, D. W. K. Ng, and R. Schober, "Power allocation for a hybrid energy harvesting relay system with imperfect channel and energy state information," in *Proc. IEEE Wireless Commun. Netw. Conf.*, 2014, pp. 990–995.

[205] Z. Ding, *et al.*, "Application of smart antenna technologies in simultaneous wireless information and power transfer," *IEEE Commun. Mag.*, vol. 53, no. 4, pp. 86–93, Apr. 2015.

[206] F. Yuan, S. Jin, Y. Huang, K. Wongm, Q. T. Zhang, and H. Zhu, "Joint wireless information and energy transfer in massive distributed antenna systems," *IEEE Commun. Mag.*, vol. 53, no. 6, pp. 109–116, Jun. 2015.

[207] D. W. K. Ng, E. S. Lo, and R. Schober, "Robust beamforming for secure communication in systems with wireless information and power transfer," *IEEE Trans. Wireless Commun.*, vol. 13, no. 8, pp. 4599–4615, Aug. 2014.

[208] M. R. A. Khandaker and K.-K. Wong, "Robust secrecy beamforming with energy-harvesting eavesdroppers," *IEEE Wireless Commun. Lett.*, vol. 4, no. 1, pp. 10–13, Feb. 2015.

[209] S. Khalifa, M. Hassan, and A. Seneviratne, "Pervasive self-powered human activity recognition without the accelerometer," *Proc. IEEE Int. Conf. Pervasive Comput. Commun.*, 2015, pp. 79–86.


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