

Chapter 2

Energy and Spectrum Harvesting in Sensor Networks

This chapter provides a comprehensive survey of existing literature of energy and spectrum allocation regarding ESHSNs, to understand the issues related in a better way. We first survey the EH process modeling and energy allocation which provide insights for efficient utilization of harvested energy. Then the spectrum sensing and resource allocation in SHSNs are discussed, which are of great importance to improve spectrum efficiency while guarantee PU protection. At last, we discuss the joint energy and spectrum management in ESHSNs.

2.1 Energy Harvesting

The ambient energy sources widely exist in the area of interest (AoI) of sensor networks, such as solar and wind in outdoor scenarios, vibration and heat in industrial scenarios, etc. [1]. By equipping sensors with EH module, such as solar panel and piezoelectric transducers, they can scavenge energy from the energy sources and continuously operate without battery replacement. In this section, we survey the state-of-the-art research regarding ESHSNs from the perspective of EH process modeling and energy allocation, respectively.

2.1.1 EH Process Modeling

The efficient allocation of energy in ESHSNs relies largely on the accurate model of EH process. Based on the availability of non-casual or causal knowledge of EH process at sensors, the models in the literature can be categorized into two classes, i.e., the deterministic model and stochastic models [1].

2.1.1.1 Deterministic Models

In deterministic models, sensors have the full knowledge of energy arrival instant and amount in advance, i.e., non-casual knowledge. By having the non-casual knowledge, deterministic models facilitate the design of the optimal energy allocation strategy, and assist the designers to set benchmark of performance limits of EH-powered WSNs.

The success of deterministic models heavily depends on the accurate energy profile prediction. However, the EH process can be impacted by numerous environmental factors, which makes the difficulty remains for fully understanding the behavior of ambient energy sources. The prediction error may lead to nodes failure or energy waste. When the sensors predict a sufficient energy supply in the near future, they tend to consume a large amount of energy on data sensing and transmission to improve the network performance. The prediction error leads to sensors' failure due to battery depletion. On the other hand, sensors become conservative on energy consumption if the predicted energy supply is limited. In this case, the prediction error may lead to battery overflow and wastage of energy. In [2], Wang et al. model the imperfect EH prediction by an independent random variable. In [3], Lee et al. address the prediction errors by a token-bucket-based algorithm. Summarily, the deterministic models are suitable for the applications with accurately predictable energy sources, such as solar power in large time scales.

2.1.1.2 Stochastic Models

Recently, the stochastic models have attracted abundant attention for EH process modeling. Since it does not require the non-causal knowledge of EH process, the stochastic model is adequate for the applications that cannot accurately predict the energy state information (ESI). In [4–8], the authors assume that the energy arrives according to an independent and identical distribution (i.i.d.) with fixed EH rate. Although the i.i.d. EH models capture the intermittent nature of EH process, they cannot characterize the temporal correlation of ambient energy sources, such as solar or human motion.

Numerous works exploit Markov process to model the temporal correlation of EH process [9–13]. Zordan et al. consider a two-state (“GOOD” or “BAD”) Markov chain to represent the time-correlated evolution of the energy source state in [9]. If the energy source state is bad, no energy arrives. Otherwise, the energy quantum arrives according to some mass distribution functions. In [10], Niyato et al. use a generalized Markovian model with multiple states, to describe the impact of clouds on the solar intensity. The Markov chain model is suitable for the illustration of some energy sources. For example, the weather states of solar power harvesting may change between cloudy and clear, and harvesting from vehicular engine vibration can be described by two states which represents the vehicle is either in rest or motion. Considering that the sensors may not be able to directly observe the ambient energy source state, [11–13] use hidden Markov chain to characterize the EH process, in

which sensors only have the knowledge of the amount of arrived energy, rather than the states of the ambient energy sources.

In addition to the EH process models, an appropriate choice of the underlying parameters, such as the transition probability between states and the mass distribution function, is of significance yet challenging for efficient energy allocation. In [14], Ku et al. adopt a real data-driven hidden Markov chain to capture the dynamics in the empirical solar power data. The model quantifies EH conditions to several representative states, and then sets the transition probabilities by training with historical solar power data.

2.1.2 Energy Allocation

Based on the knowledge of EH processes, sensors can allocate energy for data sensing and transmission to accomplish the operation tasks, such as event detection, source estimation or data collection, etc. Unlike battery-powered sensor networks that have stable energy supply, the energy allocation in ESHSNs needs to balance the energy consumption and energy harvesting. Depleting a sensor's battery at a rate lower or faster than the harvesting rate may lead to either energy overflow or energy outage, respectively. The energy allocation can be casted into three categories, i.e., the static, offline, and online cases, depending on the knowledge of EH process at the sensors. In static case, the sensors only have the EH rate at the current time slot without any non-casual or statistics knowledge. In offline and online cases, sensors have the non-casual or casual knowledge of EH process, respectively. In the following, we discuss the energy allocation in the static case, offline case and online case, respectively.

2.1.2.1 Static Energy Allocation

For static energy allocation, the sensors schedule energy allocation according to the current state of ambient energy sources, and reschedule when the state varies. Since only the current state of energy sources is required, static energy allocation significantly simplifies the prediction and modeling of EH process, making it suitable for applications with slowly variate sources. However, the static energy allocation may not be able to promise the long-term network performance due to the lack of non-casual and statistics knowledge of EH process.

In [15], the authors investigate the energy allocation in an EH-powered body sensor network for medical event detection. To improve the quality of service (QoS), the authors propose a QoS control scheme which schedules event detection and transmission subject to the energy neutrality constraint,¹ and drops the data with limited clinical validity. By exploiting the sensors around the source and the sink as relays,

¹The cumulative energy consumed cannot surpass the cumulative energy harvested by that time [16].

Zhang et al. propose a relay selection and power control scheme for EH-powered sensor networks to balance the residual energy in sensors [17]. In the proposed scheme, the optimal relay, which can maximize the minimum residual energy, is selected to cooperate with the source for data transmission. Zhang et al. [18] employ EH-powered spectrum sensors to detect the licensed spectrum to alleviate the spectrum scarcity problem in sensor networks. The authors optimize the detected available time of licensed spectrum while promising the sustainability of spectrum sensors.

2.1.2.2 Prediction-Based Energy Allocation

In prediction-based energy allocation, EH-powered sensor networks obtain the full (causal and non-causal) knowledge of EH processes through prediction. As we have mentioned before, the success of prediction-based energy allocation largely relies on the prediction accuracy. In [19], the authors propose an EH predictor for multiple energy sources (i.e., solar and wind) over horizons ranging from a few minutes to a few hours. The proposed predictor utilizes the correlation in EH process between consecutive time slots, and can achieve 93%–85% accuracy in solar power. In the following, we introduce the prediction-based energy allocations in the literature.

In [2], the authors propose a channel access scheme to maximize the throughput in a point-to-point communication system with the knowledge of energy arrival in K time slots. To deal with the stochasticity in the changes of channel conditions, the authors formulate a discrete-time and continuous-state Markov decision process to schedule channel access and allocate transmission power. Based on the one-step prediction on EH process, Lee et al. propose a cross-layer scheduling to jointly optimize the source rate in transport layer, network throughput in network layer, and duty cycles in media access control (MAC) layer [3].

Numerous works employ mobile sinks to collect data from EH-powered sensors [20–22]. In these scenarios, sensors can transmit data to the sink through one-hop data transmission. Therefore, their energy consumption can be significantly reduced. In [20], Mehrabi et al. maximize the throughput of a sensor network with mobile sinks, in which sensors have constant EH rate. The sink traverses among the sensors to collect data. The authors jointly schedule the speed of the sink and the time slots of data collection. Then [21] extends [20] to a scenario that sensors harvest uniformly distributed energy, and investigates the network throughput maximization problem. In [22], the sink travels in a constant speed along a straight path to collect data from sensors. The authors allocate the time slots for data collection and sensors' data transmission rate to maximize the amount of collected data.

References [23–26] optimize the network utility of large-scale WSNs in which the sensors transmit data to the sink through multi-hop relaying. In [24], Liu et al. design two algorithms to optimize the network utility by exploiting convexity of the network flow problem. The first algorithm computes the data sampling rate and routing based on dual decomposition. To deal with the fluctuations in the EH process, the other algorithm maintains the battery at a target level. In [23], Zhang et al. propose a distributed algorithm to schedule data sensing and perform routing for EHWSNs

with limited battery capacity. Furthermore, the proposed algorithm mitigates the estimation error of the EH process by adaptively scheduling the data sensing and routing in each time slot. The authors of [25] present two algorithms for balanced energy allocation of sensors, and optimal data sensing and data transmission. Deng et al. [26] formulate a convex problem to optimize the network utility, taking the coupling of energy neutrality constraints in time and space into consideration. Then, the authors decouple the problem into subproblems by means of dual decomposition and address them by distributed algorithms.

2.1.2.3 Online Energy Allocation

For online energy allocation, sensor networks require only the casual knowledge of the EH process, such as the distribution or the time-average value. In the literature, markov decision process (MDP) and Lyapunov optimization approach have been considered as effective means to design online algorithms.

Numerous works investigate the performance optimization of a point-to-point system with a single transmitter and receiver pair, using MDP-based algorithms [12, 27, 28]. In [27], the authors assume the EH process to be an ergodic stochastic process and design a MDP-based energy management scheme for a sensor with limited battery capacity and data buffer. The proposed scheme can achieve the optimal utility asymptotically while keeping the probabilities of energy outage and data buffer overflow low. In [28], the EH process evolves in an i.i.d. manner. To jointly optimize the transmission delay and energy management, the authors minimize a cost function composed of a convex function of the data buffer length and the energy used for data transmission. A MDP is formulated and addressed by Q-learning algorithm. In [12], the authors consider the imperfect knowledge of the state of charge (SoC) and design a partially observable MDP to optimize the network throughput. The optimization complexity is reduced by decoupling the optimization problem to two time scales: first, optimize the short-term performance w.r.t. the time-varying channel conditions, by enforcing constraints on average energy consumption, and neglecting the battery dynamics; then, optimize the average energy consumption while considering the dynamics in SoC.

In [6, 9, 29, 30], the authors investigate the source estimation using EHWSNs, to improve the estimation accuracy. In [6], the sensors use amplify-and-forward policy to forward the observations. The authors adopt Lyapunov optimization approach to schedule the power amplification factor in an online manner, with the objective to minimize the average mean-square error of source estimation. Knorn et al. [29] investigate a multi-sensor estimation system, in which the sensors not only harvest energy from the ambient energy sources, but also share energy with each other through wireless energy transfer. The authors schedule the data transmission and energy sharing to minimize the distortion. Zordan et al. [9] formulate a constrained MDP to minimize the distortion in data compression while promising the energy buffer level to be larger than a pre-determined threshold. The authors use Lagrangian relaxation approach to transform the problem into an equivalent unconstrained MDP,

which can be addressed by a value iteration algorithm. Tapparello et al. [30] jointly study the source coding and data transmission. The authors leverage the correlation of the source measures at closely located sensors to decrease the amount of transmitted data. To deal with the stochasticity in EH process and channel conditions, the authors use Lyapunov optimization to minimize the distortion and ensure the stability of data queues and energy buffers.

The efficient online energy allocation in multi-hop EH-powered sensor networks has also attracted attentions recently [4, 5]. Huang et al. design an online scheduling algorithm which jointly considers the data routing, admission control, and energy management. The algorithm achieves close-to-optimal utility for EHWSNs without a priori knowledge of the EH process [5]. Based on the algorithm in [5], Xu et al. investigate the utility-optimal data sensing and transmission in EHWSNs with heterogeneous energy sources, i.e., power grids and harvested energy, in [4]. Xu et al. also study the trade-off between achieved network utility and cost on energy from power grid.

2.2 Spectrum Harvesting

Although the spectrum harvesting capability alleviates the spectrum scarcity problem in sensor networks, the protection of PUs mandates spectrum sensing before data transmission, which may consume considerable amount of energy of SH sensors. Furthermore, to fully exploit the diversity gain brought by multiple licensed channels, the resource allocation, in terms of transmission channel, power and time, requires careful design to improve both energy and spectrum efficiency. In this section, we overview the related works of spectrum sensing and resource allocation in SHSNs.

2.2.1 Spectrum Sensing

Sensors are mandated to perform spectrum sensing before accessing the licensed spectrum to avoid collisions with PUs. Specially, sensors detect a certain spectrum range to identify the available channels, and then access the channels for data transmission. The popular spectrum-sensing technique includes energy detection, cyclostationary detection, and matched filter detection.

Among these techniques, energy detection has been widely considered as a promising solution for spectrum sensing in sensor networks, due to the following reasons: (i) simple implementation; (ii) relatively short sensing time; and (iii) requiring non-priori information of the PU signals. To detect the PU activities, the energy detector accumulates the samples that are overheard from the licensed channels. Then, the energy detector compares the output, i.e., the test statistic of the accumulated samples, to a predefined threshold. The PU is claimed to be active if the output

is above the threshold; otherwise, it is claimed to be inactive. In the following, we first survey the works for energy efficient, followed by the EH-powered spectrum-sensing schemes.

2.2.1.1 Energy-Efficient Spectrum Sensing

To accumulate sufficient samples on licensed channel for spectrum sensing, the sensors need to overhear the licensed channel for sample accumulation, which consumes considerable energy and exacerbate the energy scarcity problem in SHSNs [31]. On addressing this issue, a large body of research works propose energy-efficient spectrum-sensing schemes for SHSNs to conserve sensors' scarce energy resource while promising the PU protection.

The basic ideas to achieve energy-efficient spectrum sensing are to decrease the sensing duration [32, 33] and switching times [34], and select optimal detection threshold [35]. Pei et al. [32] investigate energy-efficient wideband spectrum sensing, in which the sensors can detect multiple narrowband channels and aggregate the perceived available channels for data transmission. To decrease the energy consumption in spectrum sensing, the sensing time is an optimized subject to the constraints of detection probability. In [33], the authors consider a two-PU scenario. The sensors allocate sensing time between the two PUs to maximize the aggregate detection probability and find more transmission opportunities. To account for the considerable energy consumption on the frequent on/off switching of sensors, [34] optimizes the schedule order to reduce the switch frequency. In addition to sensing duration and switching times, the energy efficiency of spectrum sensing is also subject to the detection threshold. In [35], the authors minimize the energy consumption of spectrum sensing by optimizing the detection threshold. To this end, a convex optimization problem is formulated and addressed by Lagrangian relaxation.

To exploit the spatial diversity brought by the large number of sensors, numerous researches consider the cooperative spectrum sensing in which multiple sensors simultaneously detect the activity of one PU. In cooperative sensing, the sensors report the sensing results to a fusion center which combines the results to make decision on the PU activity. The reported decisions can be either soft decision, i.e., the test statistics of the accumulated samples, or hard decision, i.e., the one-bit decision on PU activity made by each sensor.

In cooperative spectrum sensing, the possibility of energy conservation in spectrum sensing comes from the observation that some sensors may provide marginal profit in overall performance [36–38]. Deng et al. [36] studied the network lifetime extension of dedicated sensor networks for cooperative spectrum sensing. The authors schedule the on/off of sensors to prolong the network lifetime while promising the detection probability above a threshold. The scheduling of sensors is formulated to a knapsack problem, and then addressed by heuristic algorithms. Li et al. [37] investigate the cooperative spectrum-sensing schedule for a SHSN, in which sensors decide whether to join spectrum sensing for energy conservation. An evolutionary game is formulated to facilitate the decision of sensors according to their utility

history. In [38], the authors rank the sensors according to their historic detection accuracy. Then, a selection scheme is selected to find the sensors for cooperative spectrum sensing based on the ranking. Notably, the proposed scheme does not require a priori knowledge of the PU signal-to-noise ratio (SNR).

Several works study the effectiveness of the soft and hard decisions in cooperative spectrum sensing [39–41]. Mu and Tugnait [39] consider soft decision scenario in which the spectrum sensors transmit the continuous-valued sensing test statistics to the fusion center. Based on the sensing statistics, a convex optimization problem is formulated to optimize the SU's sum instantaneous throughput by jointly allocating the transmission power and spectrum access probability. In [40], the authors compare the performance of hard and soft decision-based cooperative sensing schemes with the presence of reporting channel errors. It is shown that hard decision-based sensing is more sensitive to the reporting channel errors, in comparison to the soft decision-based counterpart. Ejaz et al. [41] investigate the spectrum-sensing performance of heterogeneous spectrum harvesting networks, in which the sensors use various spectrum detection techniques for spectrum sensing, including energy detector, cyclostationary detector, etc. The authors compare the performance of these detection techniques with hard and soft decision rules through simulations.

2.2.1.2 EH-Powered Spectrum Sensing

With the emerging of EH technologies, EH-powered spectrum sensing has been gaining more and more attentions to achieve sustainable identification of spectrum opportunities [42–45]. In [42], the authors optimize the throughput of an ESH system, in which sensors cooperatively identify the PU activities. To account for the imprecise information of the PU channel state, a partially observable MDP is formulated to obtain the optimal cooperation among sensors. Zhang et al. [44] consider a scenario consisting of one PU and one sensor which both harvest energy from the same ambient energy source. By exploiting the correlation of harvested energy at the two nodes, the authors propose a two-dimensional spectrum and power-sensing scheme to improve the PU detection performance. Nobar et al. [43] analyze the performance of a RF-powered SH network which consists of a central node with EH capability and multiple sensors. The central node shares the harvested energy with the sensors through RF wireless charging. The authors analyze the throughput of sensors with fixed energy consumption on spectrum sensing. In [45], the authors consider a dual-hop SH network which incorporates multiple amplify-and-forward relays. The relays cooperatively detect the presence of PUs. According to the sensing decisions on the PU activity, the relays switch between data transmission and RF energy harvesting modes to transmit data or recharge the batteries, respectively. The authors study the system performance in terms of detection probability, average harvested energy, and outage probability.

2.2.2 *Resource Allocation in Spectrum Harvesting Sensor Networks*

Through spectrum sensing, sensors obtain the knowledge of licensed spectrum availability to facilitate data transmission. To fully benefit from the multi-channel diversity provided by SH capability, one needs to carefully allocate sensors' transmission power and access time over the available channels. Furthermore, the utilization of licensed spectrum should take the possibility of returning PU into consideration, and timely vacate the channel to avoid collisions. In the following, we overview the related works regarding protocol design and dynamic spectrum access in SHSNs.

2.2.2.1 Protocol Design

Numerous MAC protocols have been proposed for efficient spectrum access in SHSNs, based on carrier sense multiple access with collision avoidance (CSMA/CA) [46–48], and time division multiple access (TDMA) [49]. Tan and Le [46] propose a synchronized MAC, in which time is divided into fixed-size cycles consisting of three phases, i.e., the sensing phase, the synchronization phase, and the data transmission phase. The sensors detect the presence of PUs in the sensing phase and broadcast beacon signals for synchronization. In the data transmission phase, the sensors perform contention using CSMA/CA protocol to access the channels. Based on the protocol, the authors optimize the sensing period and contention window to maximize the network throughput, subject to the detection probability constraints for PUs. In [47], the authors extended the traditional RTS/CTS handshake process to PTS/RTS/CTS process. Once a sensor has data packet to transmit and detect a idle channel, it sends a Prepare-To-Sense message to neighbors and asks them to keep silence in the following duration. If the PU is detected to be present, the sensors suspend their backoff timer for a blocking time. The authors analyze the performance of the proposed protocol in terms of throughput and average packet service time. Shah and Akan [48] propose a CSMA-based cognitive adaptive MAC (CAMAC) which decrease the energy consumption on spectrum sensing. CAMAC exploits the spatial correlation of densely deployed sensors and only use a small number of sensors to sense licensed channels. The outcomes of spectrum sensing are shared with the nearby sensors for data transmission. Anamalamudi and Jin [49] design a hybrid common control channel (CCC)-based CR-MAC protocol, in which the sensors exchange control information through CCC in a TDMA manner and compete to access the available licensed channels through CSMA/CA.

In addition, [50–52] focus on the routing protocol design for multi-hop SHSNs. Ozger et al. [50] design a cluster-based routing protocol, in which sensors form clusters to deliver information through multi-hop relaying. Each cluster has at least one common channel for data transmission between the members and the head. The sensors with larger eligible node degree, more number of available channels, and more remaining energy are likely to be selected as the cluster heads. Considering the

spectrum mobility of PUs, the authors analyze the average re-clustering probability. The routing protocol proposed in [51] exploits dedicated cluster heads with infinite energy supply to organize the sensors into clusters. Spachos and Hantzinakos [52] design a reactive routing protocol, in which the destination sensor initiates the route discovery process. The sensor that is closer to the destination has higher priority to relay data packets.

References [53, 54] consider cross-layer protocols for SHSNs to improve the network performance. Ping et al. [53] propose a spectrum aggregation-based cross-layer protocol. In physical layer and MAC layer, the sensors aggregate the available channels for data transmission. In the routing layer, the authors consider three different routing selection criteria, i.e., energy efficiency, throughput maximization, and delay minimization. Shah et al. [54] propose a QoS-aware cross-layer protocol for SHSNs in smart grid applications. The authors exploit SH capability to mitigate the noisy and congested channels. The authors jointly allocate channels, schedule flow rate, and decide routings to meet the diverse QoS requirements of smart grid applications, by exploiting Lyapunov optimization approach.

2.2.2.2 Dynamics Spectrum Access

To account for highly dynamic PU activities, numerous works model the PU activity by stochastic processes and design spectrum access schemes for SHSNs [31, 55–57]. In [55] and [56], the authors model the PU activities by Markov process and take the spectrum detection errors into consideration. Urgaonkar and Neely [55] develop an opportunistic channel accessing policy to maximize the network throughput subject to the maximum collision constraint. In [56], Qin et al. optimize the delay and throughput of a multi-hop SHSN in which sensors are mounted with multiple CR transceivers. Liang et al. [31] investigate the sensing-throughput trade-off in SH systems which jointly realize spectrum sensing and access. The authors optimize the sensing duration to maximize the throughput while guaranteeing the PU protection. Sharma and Sahoo [57] model the channel occupancy as a renewal process. Sensors randomly detect the licensed channel to decrease the spectrum sensing overhead. The authors analyze the accessible time of idle channels subject to the collision probability with PUs.

There are also a large body of works that exploit game theory to design distributed spectrum access for SHSNs [58–62]. Zhang et al. [58] design a multi-channel access scheme by congestion game, in which the SUs strive to access the channel to maximize their own utility. Zheng et al. [59] consider a canonical scenario in which the users are stochastically active due to their data service requirement. The authors model interferences between users by a dynamic interference graph, based on which a graphical stochastic game is formulated to schedule the channel access and mitigate the interferences. By proving the game to be an exact potential game, the existence of the Nash equilibrium can be guaranteed. Xu et al. [60] model the PU activities by Bernoulli processes. To enable distributed channel selection, the authors formulate the channel selection problem as an exact potential game. Considering the

stochasticity in PU activities, a stochastic learning automata-based channel selection algorithm is proposed, with which sensors learn from their individual action–reward history and adjust their behaviors toward a Nash equilibrium point. Rawat et al. [61] consider a scenario in which sensors purchase licensed spectrum access opportunities from the spectrum provider (SP). The authors design a two-stage Stackelberg game with the SP as the leader and the sensors as the follower. In the first stage, the sensors maximize their payoffs while considering the constraints on transmission power and budget. In the second stage, the SPs offer competitive prices for spectrum usage to maximize their revenues subject to their system capabilities. In [62], the authors propose a two-layered game for a scenario in which the PUs share the spectrum resource with SUs to gain revenue. A two-layered game is formulated for revenue sharing between the operators of a primary network and a secondary network. The top layer forms a Nash bargaining game to determine the revenue sharing scheme, while the bottom layer forms a Stackelberg game to achieve optimal resource allocation.

2.3 Joint Energy and Spectrum Harvesting in Wireless Networks

Nowadays, the exponential growth of wireless devices leads to a continuous surge in both energy consumption and network capacity. To mitigate the caused energy and spectrum scarcity issues, it is desirable to enhance the wireless devices with ESH capabilities. In the literature, the existing works related to ESH wireless networks can be divided into two categories: energy harvested from environmental energy sources (referred to as green energy hereafter) and energy harvested from the RF signal of the PUs.

2.3.1 Green Energy-Powered SH Networks

References [63, 64] focus on the joint schedule of spectrum sensing and access powered by green energy, in which the EH process is independent of PU operation. In [63], Park et al. investigate the throughput maximization by modeling the PU activity as a discrete Markov process and the EH process as i.i.d. process. The authors formulate the stochastic optimization problem as a partially observable MDP, based on which a spectrum-sensing policy and an optimal detection threshold are jointly designed. Using the similar modeling of EH process and PU activities in [63, 64] finds that the operation of green energy-powered SH networks can be characterized in terms of a spectrum-limited regime and an energy-limited regime, depending on the detection threshold. In the former regime, the system has sufficient energy for spectrum access, while in the latter regime, the availability of energy resource

limits the number of spectrum access attempts. The authors analyze the probability to access an idle channel and an occupied channel, based on which they derive an optimal detection threshold to maximize the throughput.

References [22, 65] investigate the energy and spectrum allocation in large-scale ESHSNs. Ren et al. [22] optimize the spectrum access and energy allocation to optimize the network utility. However, [22] requires non-causal information of EH process and PU activities. In [65], the authors develop an aggregate network utility optimization framework for the design of an online energy and spectrum management based on Lyapunov optimization. The framework captures three stochastic processes, i.e., the EH process, PU activities, and channel conditions.

2.3.2 RF-Powered SH Networks

References [66–68] investigate the spectrum access and energy allocation of RF-powered SHSNs, in which the sensors harvest energy from the PU signal. Hoang et al. [66] consider a network where the sensor can perform channel access when the selected channel is idle, or harvest energy when the channel is occupied by PUs. The authors formulate an optimization formulation based on MDP to obtain channel access policy, with the objective to maximize the throughput. Furthermore, an online learning algorithm is employed to obtain the system parameter. Hoang et al. [67] extend the scenario in [66] to a cooperative multi-user network. To deal with the high-complexity brought by the MDP-based algorithm, the authors use a dual decomposition method to distributedly solve the stochastic problem. Lee et al. [68] use a stochastic-geometry model in which the sensors and PUs are randomly deployed in the AoI. Based on the stochastic-geometry model, [68] analyzes the transmission probability and the spatial throughput of sensors. In addition, the authors find the optimal transmission power and density of sensors to optimize the secondary network throughput.

2.4 Conclusion

This chapter provides a literature survey of resource allocation related to ESHSNs. First, we overview the existing works on EH process modeling and allocation in EHSNs. Then, the spectrum sensing and allocation in SHSNs are discussed. At last, we introduce the works which jointly consider energy and spectrum allocation in wireless networks with ESH capabilities. In the subsequent chapters, the EH-powered spectrum sensing and the joint allocation of energy and spectrum in ESHSNs will be studied.

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