RF Energy Harvesting and Transfer in Cognitive Radio Sensor Networks: Opportunities and Challenges

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The authors investigate RF energy harvesting and transfer in CRSNs. They introduce the architecture and advantages of RF-powered CRSN, typical applications, as well as the key challenges arising from applying RF energy harvesting and transfer into CRSNs. They then propose a resource allocation framework to demonstrate how to jointly control the dynamic channel access and energy management to optimize network utility while guaranteeing network stability and sustainability.

Abstract

By enabling sensor nodes to opportunistically access licensed channels, CRSN can provide a spectrum-efficient networking solution in the era of the Internet of Things. On the other hand, it also consumes extra energy for spectrum sensing and switching. This is a double-edged sword posing a dilemma between spectrum efficiency and energy efficiency. Recent advances in RF energy harvesting and transfer promote RF-powered CRSN in providing a promising way to address this challenge. In RF-powered CRSNs, sensor nodes can dynamically access the vacant licensed channels for interference-free data transmission and can also utilize the strong signals over the occupied licensed channels for energy harvesting. In this article, we investigate RF energy harvesting and transfer in CRSNs. We first introduce the architecture and advantages of RF-powered CRSN, typical applications, as well as the key challenges arising from applying RF energy harvesting and transfer into CRSN. We then propose a resource allocation framework to demonstrate how to jointly control the dynamic channel access and energy management to optimize network utility while guaranteeing network stability and sustainability. Some future directions are finally envisioned for further research.

Introduction

Wireless sensor networking (WSN) has been a promising networking solution for data gathering and event monitoring in the coming era of the Internet of Things (IoT). However, due to the explosion of wireless devices and services making the unlicensed spectrum increasingly crowded, traditional WSNs operating over industrial, scientific, and medical (ISM) bands suffer from severe and uncontrollable interference [1]. According to the report of Gartner Inc., connected things will reach 25 billion by 2020, which may lead to significant internetwork interference for overlapping IoT applications [2]. By applying cognitive radio technology into WSN, cognitive radio sensor networking (CRSN) has the potential to address the interference problem caused by spectrum scarcity [3]. Sensor nodes in CRSNs are equipped with cognitive radio modules, which can enable them to sense the availability of licensed channels and opportunistically access the vacant channels. In such a way, CRSN can provide a spectrum-efficient networking solution for data collection. However, since sensor nodes are generally battery-powered, the development and spread of CRSNs are impeded by the highly constrained network lifetime. Moreover, CRSN has to consume extra energy to support CR functionalities, such as spectrum sensing and switching, which further deteriorates the network lifetime.

To provision sustainable network operations, energy harvesting technologies, such as micro solar and wind generators, have been widely employed in sensor nodes during the past few years. Recently, increasing attention has been paid to harvesting energy from RF signals, which can provide power to sensor nodes day and night, indoor and outdoor, regardless of whether they are stationary or mobile. This technology enables sensor nodes to actively and passively harvest energy from dedicated RF power sources and ambient RF signals (e.g., WiFi signals, TV, and microwave radio), respectively, and transfer energy among different sensor nodes. Although the conversion efficiency of RF energy transfer is low, especially over a long transmission distance, it is still enough for low-powered and duty-cycled sensor nodes. Furthermore, the technique of RF energy harvesting is still evolving and expected to be more applicable in the near future.

Applying the RF energy harvesting and transfer technology in CRSNs can provide a spectrum-efficient, energy-efficient, and long-lived wireless networking solution. In traditional CRSNs, sensor nodes have to stay idle or transmit data over the unlicensed channel when primary user (PU) signals over licensed channels are sensed to be strong. This situation changes in RF-powered CRSNs, since the strong PU signals can also be harvested for battery charging by sensor nodes. Meanwhile, from the energy harvesting perspective, sensor nodes in CRSNs can harvest energy from the signals of active PUs to recharge their batteries. These advantages have drawn some emerging CRSN applications, such as smart buildings and e-healthcare systems, to utilize RF energy harvesting for sustainable operations. However, due to the characteristics of CRSNs (e.g., power- and capability-constrained sensor nodes, many-to-one and multihop network topology), some new

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research issues and challenges are arising when integrating RF energy harvesting into CRSNs. In addition, RF-powered sensor nodes can transfer energy among each other by simply transmitting and receiving RF signals, which has great potential to address the classic energy hole problem caused by unbalanced energy consumption in multihop CRSNs.

In this article, we first introduce the architecture, advantages, and typical applications of RF-powered CRSN, as well as some associated challenges when applying RF energy harvesting and transfer into CRSNs. Additionally, we present a simple resource allocation framework to address the network utility maximization problem in a single-hop RF-powered CRSN, where the channel access and energy management of sensor nodes are jointly optimized to achieve near-optimal network utility, stability, and sustainability. Finally, we outline some future research directions and conclude this article.

Architecture and Applications of RF-Powered Cognitive Radio Sensor Networks

RF Energy Harvesting and Transfer

Through wireless energy transfer, RF energy transfer can provide a relatively far-field energy provisioning solution compared to non-radiative technologies, such as inductive coupling and magnetic resonant coupling. The recent advances in RF energy harvesting endow this technology with increasing capability to power small wireless devices, such as sensor nodes. Different from the traditional forms of energy harvesting (e.g., solar and wind), RF energy harvesting does not depend on the time-varying energy resources and require additional harvesting devices (e.g., solar panels and wind turbines). These advantages make RF energy harvesting perfectly suitable for the size-limited and embedded sensor nodes [4]. Body sensor nodes in body area networks (BANs) are typical representatives of utilizing this technology. The efficiency of RF energy harvesting highly depends on a number of factors, including the wavelength of the harvested RF signals, the transmission power of energy sources, the distance between the energy source and harvesting device, as well as the underlying channel condition [5]. In the following, we briefly introduce three categories of RF energy harvesting and transfer techniques according to different RF energy sources.

RF Energy Harvesting from Dedicated RF Sources: Harvesting devices can harvest energy from some dedicated RF sources that are deployed to emit strong RF signals. Dedicated RF sources can provide stable and relatively predictable energy for harvesting devices. A representative application is the Powercaster transmitter, which is a commercial product that can transmit RF energy with 1 W or 3 W power over 915 MHz band. According to the experimental results, the energy harvesting rate of a harvesting device is 189 μW at 5 m, but decreases to 1 μW at 11 m [6].

RF Energy Harvesting from Ambient RF Sources: Energy can also be harvested from the RF signals radiated by ambient RF sources, such as surrounding mobile devices, and TV and radio towers. An existing experimental study shows that the energy harvesting rate is 60 μW from the broadcasting signals of the KING-TV tower, which is 4.1 km away and uses 960 kW transmission power over 674–680 MHz [7]. Since the ambient RF energy is not intended for harvesting devices, it can provide sustaining power supply without any deployment cost. However, due to the dynamics of the RF sources (e.g., mobility, time-varying transmit power, and intermittent transmission), the harvested energy from ambient RF sources is generally stochastic and unpredictable in most scenarios.

RF Energy Transfer Among Mobile Devices: Wireless communication devices can act as RF sources to power their neighboring devices, causing the power to be stably transferred among nearby devices. Recently, some RF energy transmitters/receivers have been designed to transmit/receive information and power simultaneously, based on time switching or power splitting. It offers a low-cost option for sustainable operations of wireless systems without hardware modification on the transmitter side, and allows the information receiver and RF energy harvester to share the same antenna or antenna array. This technology can be exploited well to transfer energy associated with information for the relay nodes to avoid unbalanced energy consumption.

RF-Powered Cognitive Radio Sensor Networks

An RF-powered CRSN generally comprises a number of distributed cognitive sensor nodes, equipped with RF energy harvesting modules, to sense a specific area and send the sensed data to an access point (or sink node). The CRSN coexists with a primary network, where PUs communicate with base stations over a set of licensed channels. Compared to traditional WSNs, cognitive sensor nodes in CRSNs can opportunistically access licensed channels without interfering with PUs. Moreover, empowered by RF energy harvesting capability, cognitive sensor nodes have an additional option to utilize the strong PU signals over occupied licensed channels for energy harvesting. The hardware architecture of a cognitive sensor node with RF energy harvesting capability is shown in Fig. 1. The RF front-end and controller can support dedicated RF charging antennas and data transceivers to achieve simultaneous RF energy harvesting and data transmission/reception over different channels. Moreover, time-switching or power-splitting techniques can also be utilized to achieve simultaneous wireless information and power transfer (SWIPT) over the same channel by a simple modification on the RF front-end. With such a hardware architecture, sensor nodes can dynamically coordinate their channel access for opportunistic data transmission and energy replenishment.

Empowered by the capability of opportunistic channel access and RF energy harvesting/transfer, RF-powered CRSNs have many advantages compared to traditional energy harvesting WSNs in terms of network deployment, real-time traffic support, energy efficiency, and so on. Table 1 outlines the comparison to show the advantages of RF-powered CRSN.

Due to the potential benefits mentioned above, RF-powered CRSN can be applied to a wide range of fields, such as smart building, E-healthcare systems, and real-time surveillance systems, to provide a spectrum-efficient and sustainable networking solution.

Through wireless energy transfer, RF energy transfer can provide a relatively far-field energy provisioning solution compared to non-radiative technologies, such as inductive coupling and magnetic resonant coupling. The recent advances in RF energy harvesting endow this technology with increasing capability to power small wireless devices, such as sensor nodes.

RF energy harvesting and transfer provide great opportunities for CRSNs to improve the network performance and prolong the network lifetime. However, as challenges always come with opportunities, some research challenges are also arisen from applying the technique into CRSNs.

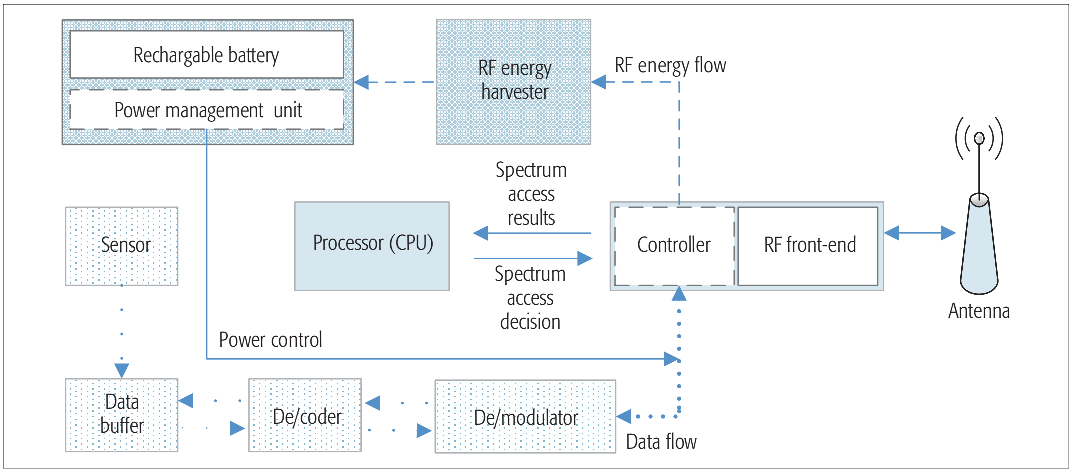

Figure 1. The hardware architecture of a RF-powered cognitive radio sensor node.

Key Research Issues in RF-Powered CRSNs

RF energy harvesting and transfer provide great opportunities for CRSNs to improve the network performance and prolong the network lifetime. However, as challenges always come with opportunities, some research challenges have also arisen from applying the technique in CRSNs. In this section, we briefly introduce some key research issues in efficient spectrum management for RF energy harvesting and transfer.

Energy-Efficient Spectrum Sensing for Data Transmission and Energy Harvesting

Enabled by the capability of RF energy harvesting, sensor nodes in CRSNs can take advantage of a licensed channel, no matter whether the licensed channel is detected to be idle or busy. In other words, if a sensor node detects a strong PU signal over a licensed channel, it can harvest energy from the strong RF signal. Reversely, it can access this channel for data transmission when the PU signal is detected to be weak. However, different from mobile devices in cognitive radio networks (CRNs), sensor nodes have to consume considerable energy to support CR functionalities [8], such as spectrum sensing and switching. In particular, if a CRSN is deployed in a poor radio environment, sensor nodes have to spend a long sensing duration to detect the availability of licensed channels (i.e., PU signals), which would consequently increase the energy consumption in spectrum sensing. Therefore, it is crucial to carefully design an energy-efficient spectrum sensing scheme for data transmission and RF energy harvesting in RF-powered CRSNs. In [1], Ren *et al.* investigated the spectrum sensing and accessing problem for energy-efficient data gathering in clustered CRSNs. With the consideration of the energy consumption in channel sensing and switching, they determine the condition when sensor nodes should sense and access a licensed channel for improving the energy efficiency according to the packet loss rate of the unlicensed channel. This analytical idea can also be applied to control spectrum sensing for RF-powered CRSNs. However, it is more challenging to design a spectrum sensing scheme to optimize the energy efficiency or the quality of service (QoS) performance of RF-powered CRSNs. This is because sensor nodes in RF-powered CRSNs need to be charged frequently by RF energy harvesting over the licensed channels, and thus channel sensing should also be devised for energy conversion. Not only the stochastic availability of licensed channels but also the stochastic RF energy harvesting rates over the occupied channels can have significant impact on network performance.

Joint Dynamic Channel Access and Energy Management in CRSNs

Dynamic channel access is one of the most important features and also one of the most critical challenges in RF-powered CRSNs. But different from traditional CRN, RF-powered CRSN has to schedule the dynamic channel access with full consideration of energy management. This is because the amount of harvested energy is highly dependent on the RF signal strength over the accessed channel. Since some important system variables, including PU activities as well as the harvested RF energy and data transmission over the accessed channel, vary stochastically over time, network performance optimization by jointly controlling channel access and energy management can be formulated as a complex stochastic optimization problem in RF-powered CRSNs. In [9], Zhang *et al.* propose a Lyapunov-based stochastic resource management algorithm to optimize the network utility of a single-hop energy-harvesting CRSN. By jointly controlling dynamic channel access, sampling rates, and power allocation of sensor nodes, the proposed scheme can achieve near-optimal network utility while guaranteeing network stability and sustainability, and controlled interference to PUs. Moreover, for some large-scale CRSN applications, sensor nodes have to relay the data traffic from the far-away nodes to the sink and form a multihop network topology according to a specific routing scheme [10]. It further increases the difficulty of the joint dynamic channel access and energy management problem in RF-powered CRSNs, because co-channel interference should be avoided by controlling the opportunistic channel access for sensor nodes. Particularly, when dynamic routing schemes are applied in RF-powered CRSNs, a more complex cross-layer resource management algorithm should be

Comparison metrics	Traditional energy harvesting WSN	RF-powered CRSN
Network deployment	Faces significant internetwork interferences when deployed nearby the spectrum-overlapped wireless networks/applications	Dynamic spectrum management can support efficient coexistence of spatially overlapping wireless networks/applications in terms of communication performance and resource utilization.
Real-time traffic support	The transmission delay of real-time traffic highly depends on the co-channel interference from other sensor nodes and nearby wireless applications	Opportunistic licensed channel access can provide spectrum-efficient and interference-free wireless communications for realtime data traffic.
Energy efficiency	Data packet losses caused by interference lead to significant energy consumption for data retransmission	Cognitive radio enables sensor nodes to transmit data over different channel according to the varying channel conditions, and hence to reduce the power consumption for data retransmission and reception.
Energy replenishment	Passive energy harvesting from renewable energy sources, such as solar, wind, etc.	Active and passive energy harvesting from dedicated RF energy sources and ambient RF signals, respectively
Network lifetime	Network lifetime and performance are limited by the unbalanced energy consumption of spatially varied sensor nodes, even with renewable energy supply.	RF energy transfer among sensor nodes can alleviate and fundamentally address the inherent unbalanced energy consumption problem to improve the network lifetime.

Table 1. Comparison between traditional EH-WSN and RF-powered CRSN.

developed to coordinate the channel access of sensor nodes adapting to the changing network topology.

Simultaneous Wireless Information and Power Transfer for Balancing Energy Consumption

In RF-powered CRSNs, sensor nodes can act as RF transmitters and receivers to transfer energy among different sensor nodes. With recent advances in RF energy transfer, SWIPT has been developed to jointly transmit energy with information using the same waveform. Applying SWIPT into CRSNs has the potential to efficiently address the well-known challenge in multihop sensor networks, that is, the energy hole problem caused by unbalanced energy consumption. Due to the many-to-one traffic pattern in multihop sensor networks, sensor nodes located close to the sink node may face a huge amount of energy consumption for forwarding the data traffic from other sensor nodes. The unbalanced energy consumption leads to an energy bottleneck area, which has worse impact than the throughput bottleneck in sensor networks [11]. Existing solutions to address the energy hole problem (in most cases, to mitigate the problem), such as adaptive duty cycling [12] and energy-aware dynamic routing [11], have significant synchronization and maintenance cost. If SWIPT is utilized in multihop CRSNs, the energy consumption of sensor nodes can be well balanced by simultaneously transmitting energy to the forwarding node with the data traffic. Two challenges arise in exploiting SWIPT in CRSNs. First, in the RF context, both information and power transmission suffer from channel fading and path loss, which make them sensitive to channel quality and transmission distance. It consequently motivates us to design SWIPT schemes considering the stochastic channel quality and different distances between sensor nodes. The second is that some QoS indicators (e.g., data utility and network throughput) are inconsistent, sometimes contradictory, performance metrics with energy conservation. This dilemma is magnified in SWIPT-enabled CRSNs, since data transmission and power transfer have to compete for the same limited RF resources. Therefore, a trade-off should be achieved between the QoS and network sustainability by carefully designing SWIPT schemes.

Charge or Transmit? A Resource Allocation Framework in RF-Powered CRSNs

In this section, we present a resource allocation framework to jointly control the dynamic channel access and RF energy harvesting for network utility optimization in a time-switching-based RF-powered CRSN.

Modeling of Stochastic Processes and Network Utility

As mentioned above, the stochasticity in PU activities and channel conditions, as well as the coupling between RF energy harvesting and channel access, pose significant challenges for efficient resource allocation in RF-powered CRSNs. To address this challenge, we model the availability of data and energy by the data queues and energy queues, respectively. The input and output processes of the queues are characterized as multiple stochastic processes.

We consider an RF-powered CRSN consisting of one sink with enough energy and multiple cognitive sensor nodes denoted by a set $\mathcal{N} = (1, \cdots, n, \cdots, N)$, operating over unit-sized slots $\mathcal{T} = (1, \cdots, t, \cdots)$. The sensor nodes harvest energy from the RF signals of PUs, and transmit the data to the sink through K orthogonal channels forming the set $\mathcal{K} = (1, \cdots, k, \cdots, K)$. The sensor nodes operate based on a time switching mode, which can either harvest energy or transmit data in one time slot. At the beginning of each slot, the sink obtains the information regarding the idleness of channels from a spectrum database, such as the Google spectrum database. Hence, we do not consider the cost of channel sensing. Compared to the energy consumption of data transmission, the energy consumed in information sharing among sensor nodes is marginal, and thus is omitted in the modeling.

First, we model the data queue to quantify the amount of data saved in the data buffer. The data

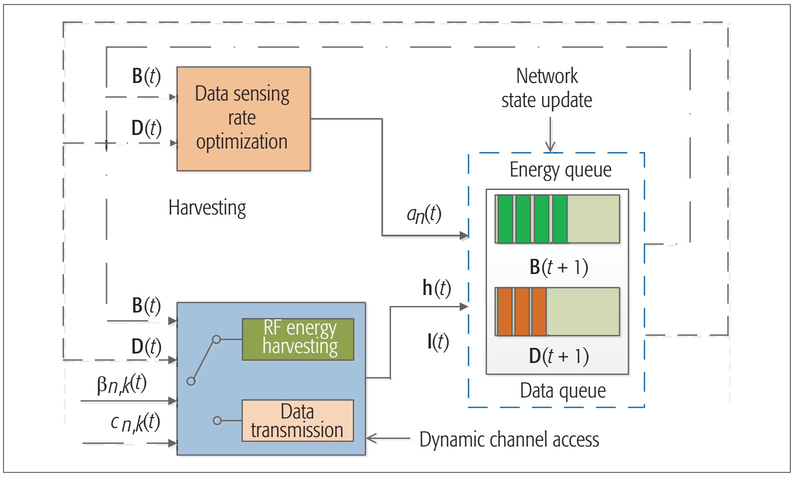

Figure 2. An illustration of the network utility optimization framework.

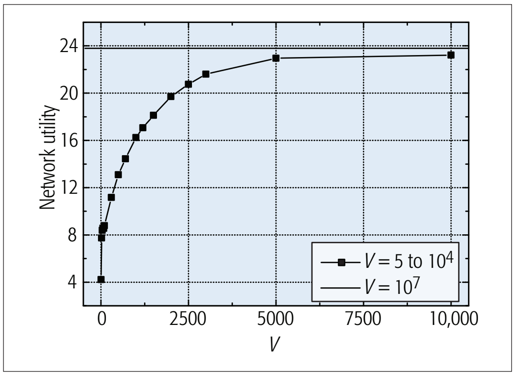

Figure 3. Network utility vs. V.

queue takes the sensed data $a_n(t)$ as the input and the transmitted data $c_{n,k}(t)$ as the output, which evolves as follows:

$$D_n(t+1) = \left[D_n(t) - \sum_{k \in \mathcal{K}} I_{n,k}(t) c_{n,k}(t) \right]^+ + a_n(t), \quad (1)$$

where $I_{n,k}(t) \in \{0, 1\}$ denotes the channel allocation indicator, which indicates whether channel k is allocated to sensor node n. Notably, given that the data queue is stable, that is, the time-average input is less than the time-average output, all the sensed data can be transmitted to the sink eventually.

Then we describe the dynamics of the energy queues, which quantifies the available energy of sensor nodes. The sensor nodes can select a channel with active PU to harvest energy or with inactive PU to transmit data. The energy queue evolves across the time slots as follows:

$$B_n(t+1) = \left[B_n(t) + \sum_{k \in \mathcal{K}} H_{n,k}(t) \beta_{n,k}(t) - P_n(t) \right]_0^{\Omega}, \quad (2)$$

where $\beta_{n,k}(t)$ denotes the harvested energy over channel k and $P_n(t)$ denotes the energy consumed by both data sensing and transmission, and Ω is the battery capacity of a sensor node. Furthermore, $H_{n,k}(t) \in \{0, 1\}$ represents the decision on from which channel to harvest energy. Since the sensor nodes operate in a time-switching mode, we have $H_{n,k}(t) + I_{n,k}(t) \le 1$.

The network utility at slot t is given by $U(t) = \Sigma_{n=1}^{N} \log(1 + a_n(t))$, which is a concave function with respect to the amount of sensed data. At each slot, the sink schedules the data sensing rate $a_n(t)$, the channel allocation indicator $I_{n,k}(t)$, and the RF harvesting indicator $H_{n,k}(t)$ to maximize the time-average network utility while guaranteeing the data queue and energy queue to be stable over a long run.

Resource Allocation Framework

The decision of the sensing, channel allocation, and RF harvesting variables across time slots jointly impact the queue lengths and the long-term network utility, which makes the long-term utility optimization of the RF-powered CRSN challenging. In this subsection, we propose the network utility optimization framework, which separately optimizes the data sensing rate, and schedules the RF charging and data transmission at each slot to achieve close-to-optimal network utility. To this end, we first decompose the time-coupled problem to subproblems at each slot by a Lyapunov optimization approach. We define a Lyapunov function as

$$L(t) = \frac{1}{2} \sum_{n=1}^{N} \left[D_n(t)^2 + \left(\hat{B}_n(t) \right)^2 \right],$$

where $\hat{B}_n(t) = \Omega - B_n(t)$ denotes the spare capacity in node n's battery. Since the objective is to maximize the time-average network utility, we can further define the Lyapunov drift-minus-utility function as

$$\Delta_V(t) = L(t + 1) - L(t) - VU(t), \quad (3)$$

where V is the non-negative weight to express how much we emphasize utility maximization.

Based on that, we can focus on how to minimize $\Delta_V(t)$ at each time slot instead of solving the original problem. Since $\Delta_V(t)$ is a quadratic function for which it is difficult to find an optimal solution, we can alternatively minimize its upper bound with a linear structure. The details of leveraging Lyapunov optimization to transform minimizing $\Delta_V(t)$ to minimizing its upper bound can be refereed to [13].

The proposed framework consists of two separate subproblems, with the objective to optimize the data sensing rate, RF charging, and data transmission decisions. Figure 2 shows the framework structure and the data flow among the subproblems, in which the variables are determined by solving the data sensing rate optimization, and RF charge or transmit scheduling subproblems, respectively. According to the decisions, the framework updates the network state, which is then fed back to the RF-powered CRSN to facilitate resource allocation in the next time slot. Notably, the framework only requires the information of PU activities and channel conditions at the current slot, which is useful for the RF-powered CRSN that lacks prior knowledge of the stochastic processes.

Performance Evaluation

We consider a single-hop RF-powered CRSN[1] that consists of 10 sensors in a circle with radius 20 m. The sink resides in the core of the circle and is equipped with four CR transceivers. The sensors transmit data through the licensed spectrum, which is divided into $K = 4$ orthogonal channels.

The PUs on each channel remains inactive, with probability 0.6 at each slot. The channel capacity of sensor n on channel k at slot t is determined by

$$c_{n,k} = \log\left(1 + \frac{\left|\eta_{n,k}(t)\right|^2 P_t}{d_n^3 N_0}\right),$$

where $|\eta_{n,k}(t)|^2$ denotes the channel fading, d_n is the distance between sensor n and the sink, and $N_0 = 10^{-5}$ denotes the noise power. To express the stochastic nature of wireless channel fading, we assume that $|\eta_{n,k}(t)|^2$ is uniformly distributed between [0.9, 1.1]. The RF energy harvested from PU signals ranges uniformly distributed between [0, 2].

Figure 3 shows the network utility with respect to V. The value of V represents the weight for maximizing network utility against queue stability; higher utility can be achieved by increasing V, as shown in Fig. 3. Once V increases to a saturation point ($V = 5 \times 10^3$ in our setting), larger V can no longer increase utility, which implies that the available energy and licensed channels are fully utilized by the RF-powered CRSN. We adopt an extremely large V ($V = 10^7$) to calculate the optimal utility. It can be seen from the figure that our proposed solution can achieve close-to-optimal network utility.

Figures 4 and 5 show the dynamics of energy queue and data queue across slots, respectively. As shown in Fig. 4, the sensors accumulate energy in the startup phase. After the sensors store sufficient energy, the energy queue length converges and fluctuates around a time-average value that increases with V. To support the operation of the RF-powered CRSN, the sensor needs to equip a battery with capacity larger than the time-average value. Consistent with Fig. 4, the data queue length increases with V in Fig. 5, implying that a larger data buffer is required to achieve higher network utility.

Future Research Directions

RF energy harvesting and transfer have shown potential and advantages for powering CRSNs. However, as this technology is still in its infancy, the low energy harvesting efficiency, as well as its high dependence on channel quality and distance, are impeding the development of related applications. In this section, we present some future research directions with great potential to improve the performance of RF-powered CRSN.

MU-MIMO and Distributed Energy Beamforming

One of the most urgent future research areas should focus on improving the power of RF signals and RF energy harvesting efficiency. Since single-antenna transmitters with omnidirectional radiation suffer from significant path loss with increasing transmission distance, multi-antenna transmission is an effective solution for achieving spatial multiplexing as in multiple-input multiple-output (MIMO) systems, by employing beamforming techniques to improve the RF energy harvesting efficiency. In [14], Reynolds *et al.* validate the effectiveness of MIMO by their indoor experiments, where the incident RF signal power is increased by over 8 dB, nearly an order of magnitude, using an 8 × 8 element MIMO setup. However, since sensor nodes are generally small and cannot handle multiple antennas, distributed energy beamforming, which leverages multiple sensor nodes as spatially distributed transmission resources to form a multi-user MIMO (MU-MIMO) system (with a large virtual antenna), may be a better solution for improving RF energy harvesting efficiency in CRSNs. However, the underlying challenges in applying these advanced techniques, such as accurate channel state information feedback, and frequency and time synchronization, should be well studied in the future to improve the performance of RF-powered CRSNs.

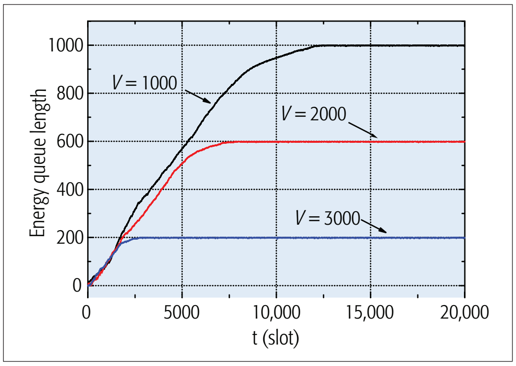

Figure 4. Impacts of V on battery capacity.

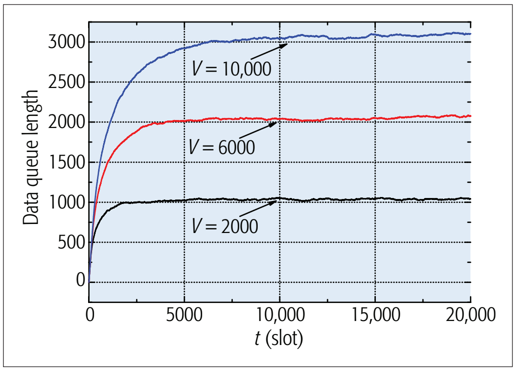

Figure 5. Impacts of V on data buffer size.

Dedicated MAC and Routing Protocols for SWIPT in CRSNs

Besides exploiting physical layer techniques to enhance the RF energy harvesting and transfer performance, future efforts can also be made in designing dedicated medium access control (MAC) and routing protocols for SWIPT in CRSNs. A well designed MAC protocol for SWIPT should be able to adaptively allocate the media resources and RF signals to improve network performance according to the dynamically accessed channels, the channel quality (physical layer performance), and so on. For example, some related design issues could be how to control the access and transmission duration of neighboring nodes, as well as how to split RF signals for information decoding and energy harvesting. Meanwhile, dynamic channel access and channel quality, and different splitting rates of RF signals for decoding and harvesting lead to a dynamic end-to-end performance of the network layer, including end-to-end delay and network throughput. However, current routing protocols for existing networks may face significant performance degradation under these unique challenges, leaving some open issues and challenges for future study.

RF energy harvesting and transfer have shown its potentials and advantages to power CRSNs. However, as this technology is still in its infancy, the low energy harvesting efficiency, as well as its high dependence on channel quality and distance, are impeding the development of related applications.

[1] The single-hop scenario is typical in sensor networks with applications ranging from e-health systems to intra-cluster data collection.

The ever-evolving RF energy harvesting has shown the potential to power billions of connected devices in the coming Internet-of-Things era. We believe that CRSNs, as one of the most promising networking solutions for the coming era, will significantly benefit from this technology to achieve perpetual, self-maintained and autonomous network operations.

RF Energy Harvesting and Transfer in Battery-less Sensor Networks

It is predicted that the era of a trillion sensors is coming, where sensors equipped with temporary storage units (e.g., capacitors) will make up a significant portion [15]. Ambient RF signals or dedicated RF power beacons can act as energy sources for battery-less sensor nodes to build a pollution-free communication system in the evolution of IoT. Due to the intermittent ambient RF signals and unstable wireless channels, battery-less sensor nodes may face unpredictable outage, posing great challenges for guaranteeing sustainable operations. Thus, how to deploy the dedicated RF power beacons and schedule sensor nodes to harvest ambient RF energy over different channels are critical but challenging issues to reduce the outage probability in battery-less sensor networks. Moreover, mobile RF energy sources, such as unmanned aerial vehicles, can also act as sink nodes to provide periodic energy replenishment and data collection for battery-less sensor networks. In such cases, how to design a flexible moving path along with the RF charging and data collection mechanisms become interesting and potential research issues.

Conclusion

In this article, we have introduced the architecture of RF-powered CRSN, typical RF-powered CRSN applications, and some research challenges arising from enabling RF energy harvesting and transfer in CRSNs. A framework of dynamic channel access in RF-powered CRSN has also been developed to show that the opportunistic channel access could be jointly controlled with energy management of sensor nodes to achieve near-optimal network utility while guaranteeing the network stability and sustainability. Finally, some future research directions have been envisioned to nurture continuous improvements in this field of study. The ever evolving RF energy harvesting has shown the potential to power billions of connected devices in the coming Internet of Things era. We believe that CRSNs, as one of the most promising networking solutions for the coming era, will significantly benefit from this technology to achieve perpetual, self-maintained, and autonomous network operations.

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