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A Survey of Energy and Spectrum Harvesting Technologies and Protocols for Next Generation Wireless Networks

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ABSTRACT Energy harvesting (EH) and spectrum harvesting (SH) are two promising and useful green communication and networking mechanisms for the next-generation wireless networks. While the former techniques exploit ambient energy sources to scavenge energy, the latter exploit the unused or moderately used electromagnetic spectrum. With the advent of cyber-physical systems and the Internet-of-Things (IoT), the presence of tens of billions of low power sensor devices would soon be a reality. These small sensing devices would be present in many systems around us, such as home appliances, telecommunication devices, medical electronics, transport systems, etc. These miniaturized, low-power consuming devices may exploit EH and SH techniques for energy storage and communication. These EH-SH-enabled sensors or low-power nodes need to consume very little energy for sensing and communicating opportunistically. However, several theoretical problems and practical challenges exist in EH-SH communications. In this comprehensive survey paper, we first present the historical background of EH, and SH techniques, and their development over several decades. Specifically, we focus on EH-SH communication technologies and protocols for a wide range of systems and networks. We present a detailed survey of the various harvesting techniques and protocols from recent literature. Finally, we describe exciting open, intra-disciplinary, and inter-disciplinary challenges for further research on EH-SH communication technologies.

INDEX TERMS Cognitive radio, cooperative sensing, energy harvesting, Internet of Things, next generation wireless networks, spectrum harvesting.

I. INTRODUCTION

Energy efficiency [1]–[3] and spectrum efficiency [4], [5] are the two most important parameters for next-generation beyond-5G communication networks which have primary focus on green communications. These two parameters are also linked to the capacity and the power requirements of the communication network [6]. In conventional wireless networks, the energy and spectral efficiency issues have been mostly dealt with separately; there is a need to provide an integrated approach to the same. Further, with the advent of a multitude of services on wireless devices and the greater proliferation of these devices, there is an urgent need to have energy as well as spectral efficient solutions. The diverse energy requirements for various physical objects such as sensors are proliferating due to the advent of technologies like the Internet of things (IoT) and its variants, such as the Internet of medical things. These nodes need sufficient bandwidth and energy to communicate reliably and efficiently. There are various sensors, devices, and physical objects that are powered by batteries. However, in several remote applications, the frequent replacement of batteries is not a feasible option. Therefore, energy harvesting from ambient energy resources [7] is an excellent alternative to enhance node lifetime, and hence, the network lifetime.

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In recent years, the Internet has proliferated, connecting humans and systems worldwide so that uniquely recognizable devices can interact wirelessly with each other, supporting various kinds of applications and people on a wide scale. Thus, the conventional Internet has evolved into another intelligent network infrastructure called the IoT [8], [9]. A recent survey by Cisco [10], projected a 2.4-fold increase in machine-to-machine (M2M) connections from 6.1 billion in 2018 to 14.7 billion by 2023, and 5.3 billion users, which is 66% of the global population, will be connected to the Internet by 2023. IoT's highlights include hard and fast observation, dependable transmission, and smart functioning; ''hard and fast observation'' alludes to gathering and obtaining data anywhere and anytime by utilizing the recognition and estimation strategy, ''dependable transmission'' implies to have devices connected through a data network, such that accurate information is interchanged and transmitted by combining communication networks, and ''smart functioning'' corresponds to investigating the broad set of information and data from various industry sectors and businesses through different smart technology applications, such as big data, machine learning, etc., to improve visibility into the practical world and economic and social activities to realize smart decision-making and measures.

As IoT continues to grow rapidly, it is becoming a massive network that links almost every element of our activities [11]. IoT devices are usually powered using batteries. This results in high maintenance costs, with the replacement of batteries being difficult and expensive. Additionally, in certain environments such as industrial sensor nodes, sensors are installed in areas that are challenging to access or unreachable. Therefore, energy efficiency is critical in these applications. Further, for IoT devices, optimal energy storage and management frameworks [12], [13] are designed to realize the long and routine functioning of devices. The advent of cognitive radio (CR) technology has been perceived as a productive strategy to tackle spectrum shortages and low utilization scenarios using optimum sensing techniques. Security is also an important aspect to be considered in IoT [14].

Energy sources are of two types: non-renewable and renewable [15]. Examples of the former are nuclear, oil, coal, and natural gas, which are limited and would eventually be exhausted. On the other hand, the latter type of resources is readily available or replaceable within a short time, such as solar, wind, and biomass. Note that these renewable energy sources, though environment friendly, are not very efficient, and their performance depends on several factors. However, green research communities believe that green or renewable energy resources are useful for several next-generation green communication systems and networks. Techniques that use these renewable energy resources to harvest energy are called energy harvesting techniques [16], [17]. As discussed earlier, energy harvesting provides an opportunity with unique features for IoT and next generation wireless communications that conventional battery operated devices cannot provide. According to [18], the energy harvesting market amounts up to USD 440.39 million in 2019, which will increase to USD 817.2 million in 2025. Further, according to [19], the cognitive radio market is expected to reach USD 8.31 billion by 2024. In the electromagnetic spectrum, the useful frequencies suitable for communications are limited and licensed, such as 5G radio-frequency (RF) spectrum, TV frequency bands, and RF bands. However, most of the electromagnetic spectrum is underutilized. Therefore, for efficient utilization of the precious EM spectrum, the cognitive devices or radios need to be smart enough to sense and acquire the unused spectrum accurately. Spectrum harvesting (SH) [20] involves techniques that make the scarce spectrum resources available for various applications.

The motivation behind using EH and SH in next-generation communication networks, in general, can be summarized as follows:

- ***Achieving energy efficiency***: In next-generation communication networks, one of the main concerns is to increase the battery life, which powers the wireless devices. Cognitive radio (CR) [21]–[24] assisted energy harvesting techniques are discussed in the literature, which can be combined with different energy harvesting techniques to provide energy-efficient solutions. The energy harvesting can be done from natural sources like wind and solar energy or radio frequency sources, also called RF energy harvesting. The important consideration is optimizing device operations, which may lead to extending the life of the devices on battery.
- ***Achieving spectrum access***: Spectrum access in next-generation communication networks can be classified as priority-based, i.e., based on the reliability and latency considerations, or as tier-based, i.e., based on the location of wireless devices in the different tiers of the heterogeneous network [25]. The switching of wireless devices between different spectrum resources based on the device usage requirements is an important parameter.
- ***Achieving interference management***: Next-generation heterogeneous networks are highly dense, and interference needs to be taken into account for reliable communication to take place. The inter-cell and the intra-cell interference are in the next generation networks like the device-to-device (D2D) communication networks [26], [27] make power management an important consideration along with interference management. Energy harvesting solutions using cognitive radio have been reported in literature and are helpful in reducing the interference.
- ***Achieving high data rate and low latency***: The use cases envisioned for the next-generation communication networks are based on higher data rates and low latency, which are the typical characteristics of these communication networks. Efficient spectrum utilization is possible by using EH cognitive radio, which, along with the capability of energy harvesting providing higher energy, will help in achieving high data rates and low latency.

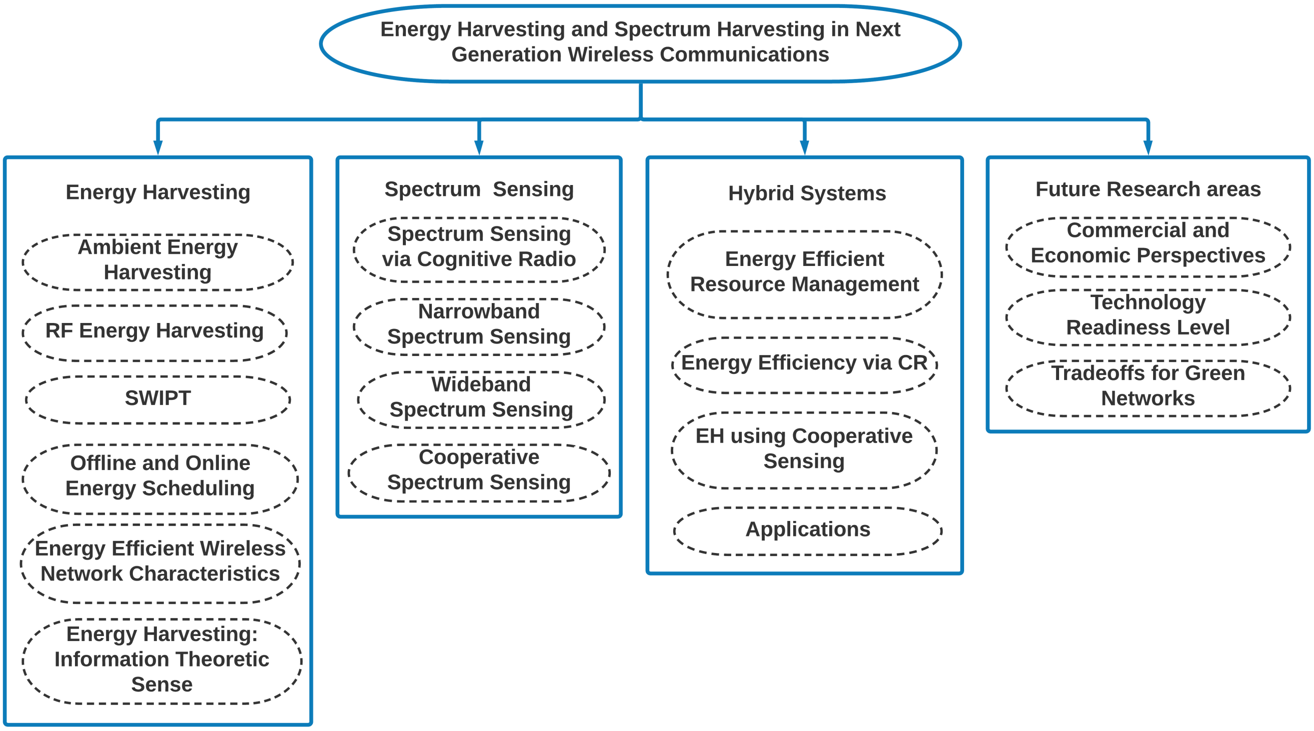

FIGURE 1. EH and SH in next generation wireless networks: A schematic flow showing the flow/ salient sections covered in the survey.

This paper presents a comprehensive review of the energy and spectrum harvesting technologies and protocols for next-generation wireless networks. The major contributions of this paper are summarized as follows:

- We present a detailed overview and comparison of the different EH techniques in next-generation wireless networks and discuss various EH techniques like the RF, ambient energy harvesting techniques.
- We provide an overview of SH techniques in next-generation wireless networks including CR based and cooperative sensing techniques and provide a detailed summary of the various narrowband and broadband sensing techniques.
- We give the future research areas and challenges for the EH and SH techniques along with the technology readiness level (TRL) description.

The remainder of the paper is organized as follows. Section II gives a review of the EH in next-generation wireless networks. Section III provides a review of the SH in next-generation wireless networks. Section IV discusses the hybrid systems and applications of EH and SH in these networks. Section V gives an overview of the future research areas, and finally, Section VI concludes the paper. Fig. 1 describes the brief outline of the paper.

EH has several appealing benefits and distinctive characteristics for next-generation wireless communications that are not offered by traditional battery or grid-power dependent communication systems. These include self-sustainable capacity, lower carbon footprint, and no requirement of battery replacement in wireless sensor nodes, with simple implementation in most of the complex scenarios. Thus, EH in wireless networks [28]–[33] is being studied extensively by the research community and being implemented in wide range of applications. Energy efficiency [34]–[36] and EH [37] are two ways to attain green communications [38], [39]. Different energy sources can be utilized, which can supply us with ambient renewable energy sources such as wind, solar [40], [41], motion, electromagnetic (EM) waves, water [42], [43]. In the past few years, there has been a lot of research on ambient EH [44]–[48]. The limitations of batteries such as leakages, limited storage capacity, charging, and discharging along with harvesting and management frameworks to optimize transmission are discussed in [49]–[52]. Designing the dimensions of photovoltaic (PV) panel and capacity of batteries for energy storage for solar-powered systems is discussed in [53]–[56]. Some studies have focused on radio frequency (RF) energy harvesting, which is capable of carrying both energy and information in wireless communication. A detailed study of RF energy harvesting using the ambient backscatter communication (AmBSC) system for passive IoT is done in [57]–[61]. Simultaneous wireless information and power transfer (SWIPT) is used to recover both information and energy from RF signals as detailed in [62]–[65]. Two architectures: *power splitting* [66]–[68] and *time switching* [69]–[71], are proposed which help to overcome the difficulties arising from practical circuit design constraints.

Scheduling of energy is also a primary method to manage the harvested energy to maintain *energy neutrality constraint* EH in wireless sensor networks; various *offline* [72]–[77] and *online* [78]–[80] methods have been discussed in the literature.

In [81], the authors presented information-theoretic limits and scheduling policies, and medium access control (MAC) protocols are presented in [82], [83]. In addition to it, the authors discuss simultaneous information and power transfer. Further, the authors state that the challenges lie in various layers as well as in the integration with the development of circuits and systems that harvest energy and transfer information. In [84], the authors focus on RF-EH and summarize advances in EH wireless communications and networks. The authors cover a wide range of topics viz., physical layer information-theoretic limits, and MAC protocols. The authors emphasize the development of efficient protocols for EH networks with energy and information transfer capabilities. Another survey paper on EH in IoTs [85] gives a classification of approaches to optimize harvested energy, their comparisons, analysis along with the proposed solutions. Furthermore, it also presents standards for interoperability.

Sharing of spectrum in the context of cognitive radio (CR) is discussed in [86], [87], and spectrum assignment in cognitive radio based IoT is studied in [88]. Routing mechanisms for cognitive sensor networks are proposed in [89]. A collaborative spectrum sensing mechanism with energy shortfalls is proposed in [90]. Spectrum sensing in CR is discussed in [91]–[93] where the radio senses the spectrum and transmits information simultaneously in the whole time slot. Opportunistic spectrum access with modelling using Markov chains is presented in [94]. A collaborative CR to schedule for energy efficiency and increased throughput for secondary users is framed in [95]. A MAC protocol for use in spectrum sensing is demonstrated in [96]. In existing literature, narrowband spectrum sensing [97]–[99] and wideband spectrum sensing [100], [101] techniques have been extensively described for CR. Narrowband spectrum sensing is used to verify the presence of primary users and is further categorized into various techniques such as energy detection [102]–[105], matched filter detection [106]–[108], feature detection [109]–[112], and eigenvalue based detection [113], [114]. Similarly, wideband spectrum sensing is used to detect the available spectrum holes which is classified based on Nyquist and sub-Nyquist sampling [115], multiband sensing [116]–[119], wavelet-based sensing [120]–[122], filter-bank based sensing [123]–[127], compressed sensing [128]–[135], and multi-coset sensing [136]–[139].

Cooperative spectrum sensing [140], [141] enhances sensing performance by using the spatial diversity feature of wireless communications [142]. Fusion algorithms are proposed for centralized topology based cooperative spectrum sensing (CSS) using directional antennas in [143]. A reliability-based cooperative decision fusion [144], and integration of belief propagation with fast detection framework [145] for CSS has also been proposed in the literature. A reputation based CSS that is robust against attacks is discussed in [146]. Spectrum opportunities are found using clustering in heterogeneous CR networks in [147]. To suppress the malicious interference in CR networks, various frameworks are modelled in [148], [149]. Cluster based cooperative spectrum sensing has been studied by the authors in [150]–[152].

Green powered cognitive networks or green networks [153]–[159] have motivated research on energy efficiency and EH to capture and store ambient energy. In [160], the authors provide a summary of energy management techniques in IoT. In [161]–[163], scheduling for EH and spectrum sensing based heterogeneous CR sensor networks is discussed in the context of green communications. Physical layer security is also a primary concern in EH based CR, which is studied in [164]. Time scheduling for backscatter-aided RF powered CR networks is discussed in [165]. To overcome the shortcomings due to spectrum and battery resource allocation, EH-based cognitive M2M communication is proposed in [166]. Resource allocation in wideband sensing-based CR considering various constraints are provided in [167]–[169]. CR technology offers the ability to maximize spectrum usage as much as possible under the resource assignment and EH schemes. In [170], the authors present a technique where the CR does EH from RF signal. Resource allocation in wideband CR with SWIPT is studied in [171]. Optimal resource management and allocation for CR based sensor networks with EH are proposed in [172]. EH from the ambient environment is studied in [173], where slot mode based CR is proposed to increase throughput. A hybrid CR having sleep mode is considered in [174] to harvest energy from the primary users. In [175], a dynamic spectrum sensing mechanism with energy efficiency using a power assignment framework is proposed. A novel non-orthogonal multiple access (NOMA) assisted overlay spectrum sharing for multi-user CR networks for improved spectrum utilization with two scheduling schemes is proposed in [176].

Relay assisted CR for EH is proposed in [177], [178]. Interference-aided energy harvesting with decode-and-forward relaying (DF) in CR is studied in [179]. SWIPT based EH and DF relay-based cooperative spectrum sharing is proposed in [180]. In [181], [182], CR with EH is proposed. In [183], [184], the secondary and primary users cooperate for EH and to maximize the throughput. Cooperative spectrum sensing with RF energy harvesting employed for a multi-channel CR is proposed in [185]. A collaborative spectrum sensing with clustering of CR nodes is studied in [186], where spectrum sensing, EH, and information transmission is studied in a time slot. Relay based cooperative spectrum sensing is studied in [187]–[189] where RF and SWIPT-based EH schemes have been proposed. Cooperative sensing using clusters is proposed by the authors in [190], [191] for spectrum sensing and energy efficiency. In [192], cognitive wireless powered communication networks have been proposed for both underlay and overlay CR for wireless energy and information transfer.

II. ENERGY HARVESTING IN NEXT GENERATION WIRELESS NETWORKS

The interest in green communication has prompted a tremendous amount of research in related areas due to the significant rise in energy utilization by the communication and information sectors [39]. Green communication may be attained from two primary methods. The first one is consuming less energy with more information transmission, classified as energy efficiency [34], [35]. The second is by extracting and then transforming the energy from ambient environments, such as solar energy, wind energy, thermal power, etc., as shown in Figure 2, which is termed as energy harvesting [37], [2]. EH, also known as energy scavenging, focuses on obtaining clean energy from ambient renewable energy sources. Historically, researchers investigated harvesting energy from windmills, waterwheels etc. [42]. Figure 3 shows the 'power' waves of innovation [43]. In it, renewable energy is shown as the sixth power wave. Among its seventeen goals, climate action is one of the sustainable development goals (SDGs) listed by the United Nations (UN). The generation, transmission, and distribution of green and clean energy could alleviate the carbon footprint problem and contribute to achieving the critical SDG. Given its eco-friendly nature and other advantages such as improved network lifetime, researchers, industry, and academia worldwide are working on novel energy harvesting technologies and their integration with various systems and networks.

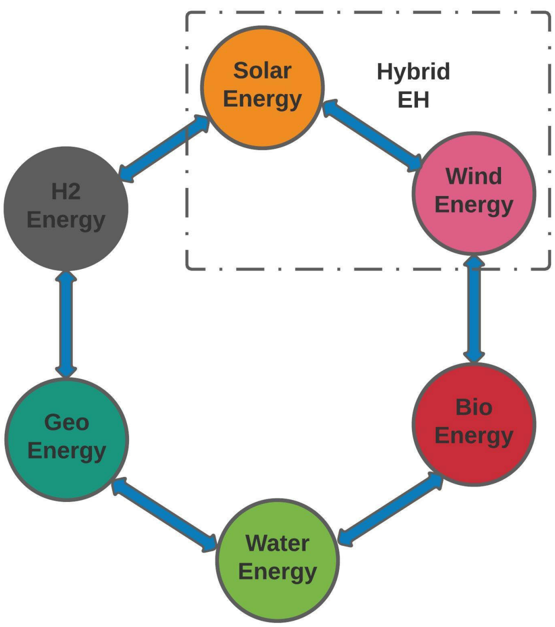

FIGURE 2. Popular renewable energy resources for scavenging clean and green energies.

For several decades, researchers and EH enthusiasts have explored EH methods, such as thermal and vibration. There are two motivating forces behind the quest for novel EH techniques: I) Desire to design autonomously powered sensor networks or mobile devices without batteries; II) Motivation to

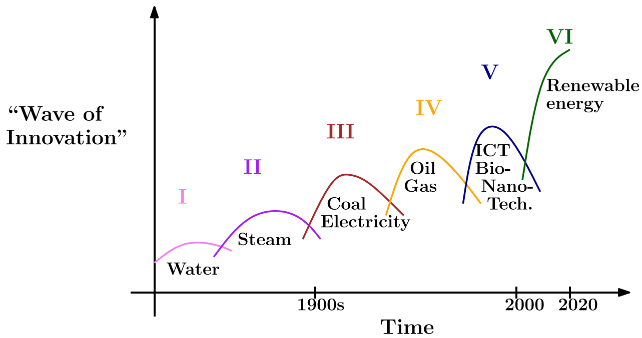

FIGURE 3. 'Power waves' of innovation [43].

address climate change or global warming issues due to CO_2 emissions. Figure 2 shows some popular renewable energy sources to scavenge energy via EH techniques. Each of these EH technologies has some merits and some limitations in terms of place and environment conditions. Furthermore, these EH technologies can find their place in big cellular communication network entities (e.g., green gNodeBs) and also in micro-scale low power nodes, for example, IoT sensors in cyber-physical systems.

It is possible to integrate two or more of these renewable energy resources to harvest more energy [40] at a larger scale, depending on the application and requirements. For instance, a cellular network could use a hybrid solar and wind base station (BS) [41], [53] to serve its subscribers or mobile users. If the energy harvested by a BS is below a certain threshold, the BS could switch to an alternate non-renewable energy source. Similarly, it is also possible to exploit other renewable energy sources for powering various physical objects or sensors in cyber-physical systems.

The research community has extensively published papers focusing on different techniques and applications of energy harvesting. Many recent green technology developments have attracted researchers to recognize a new change in the power supply framework due to fossil fuel usage in wireless network infrastructure. If the IoT sensors are deployed in a remote area for monitoring of the environment (e.g., forests), frequent replacement of batteries is infeasible. EH technologies are entirely appropriate for these applications. The low power sensors could harvest energy from ambient sources such as solar and wind. Some of these applications are shown in Figure 4. Not all EH technologies are appropriate for these heterogeneous systems and networks. For instance, wind-based EH is reasonable to power up a road-side vehicular infrastructure where air-flow is abundant. On the other hand, RF-based EH is suitable for low power IoT devices. Therefore, the green EH communication system designer should apply these EH techniques optimally.

A. AMBIENT ENERGY HARVESTING

Conventional communication systems that function using an abundant energy-efficient cell and those communication systems for which energy from environmental resources is

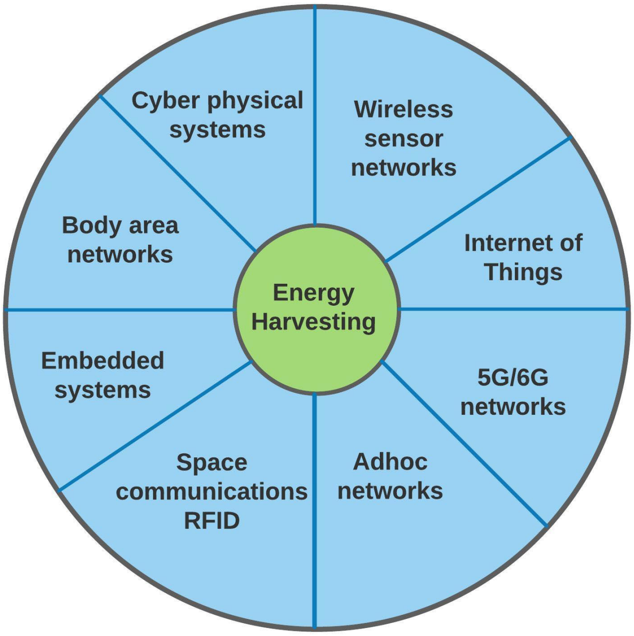

FIGURE 4. EH wheel consisting of various technologies and applications.

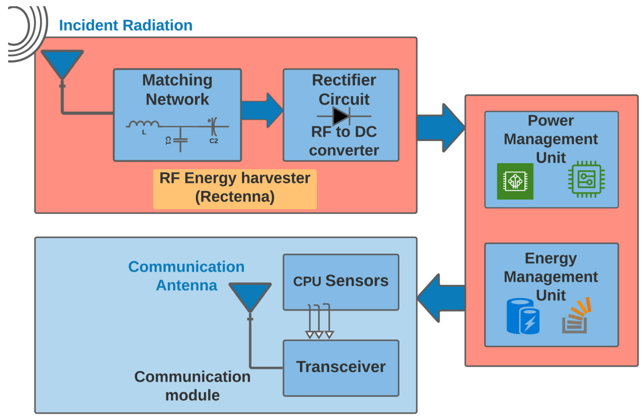

FIGURE 5. Block diagram of a typical power scavenging module powering a communication transceiver [65].

accessible to communication nodes for energy harvesting, are irregular and vary with time. Energy-efficient base stations in green cellular networks where energy is drawn from the grid is also considered in [3]. However, an unlimited quantity of energy is theoretically available, by using the wireless sensor system's energy-neutral operation, the node's energy consumption is always lower or equal to the energy obtained from the environment, so energy is stored in storage devices of limited capacity, leading to energy overflow or leakage. Figure 5 shows a wireless power scavenger consisting of a receiver antenna, a matching network, a radio frequency to direct current (RF to DC) converter or rectifier, a unit to manage power, and store energy. After complete charging of battery power is supplied to sensors. Generally, transmission power is a specific cause of energy usage; however, in some situations, alternative means of energy usage at the transmitter can influence radiated power. These design concerns, particularly energy considerations, are circuit processing power, battery leaks, and charging/discharging faulty batteries' ineffectiveness. In [54] for a base station, tolerable outage probability with constraints on photo-voltaic (PV) panel size and number of batteries is proposed. Similarly, in [55], necessary battery capacity, and PV panel sizing based on resource availability and detailed design of solar powered base stations [56] is formulated. Maximizing transmission rate and offline throughput using adaptable rate strategies with various energy impacts on costs such as currents due to battery leakage and storage shortfalls are considered in [49], [50]. The effect of the incompetence of battery charging / discharging upon the optimum transmission power strategy with throughput is examined in [51]. A framework for models on single-user and distribution channels is found to collect, extract, and use the battery's harvested energy. In [52], throughput efficient transmission mechanisms that consider non-ideal circuit power are considered for wireless energy harvesting with unlimited battery storage space for energy. A two-phase transmission framework is followed in offline strategies, where in the first step, the optimum transmission is on-off, the continuous transmission is best during the second step. Ultimately, a closed-loop online algorithm is suggested based on an offline solution.

In general, three protocols for ambient energy harvesting and usage have been suggested [44]–[47], namely: 1) Harvest-Use (HS): The correspondence node is driven directly by systems for extracting resources with no buffer for storage, 2) Harvest-Store-Use (HSU): Here, the harvested energy is used only after storage and 3)Harvest-Use-Store (HUS): It is instantly possible to use extracted energy which is briefly contained in a super-capacitor, and residual energy after processing is completed is stored; The HUS and HSU schemes are less efficient than the HU scheme. A harvest-then-cooperate (HTC) protocol is proposed in [48] where the downlink source and relay harvest energy from the access points, during collaborative work in the uplink for information transmission from the source. However, EH using naturally occurring sources gas not been as productive as they were anticipated since ambient sources are abnormal and unpredictable. There are however, specific environments and circumstances where they are relevant and appropriate.

B. RF ENERGY HARVESTING

Recently, some studies have suggested energy harvesting in wireless networks via RF signals. A distinct feature of RF energy harvesting is that RF signal carries both information and energy, which enables energy harvesting nodes to forage energy and receive information. RF energy harvesting is also suitable for long-distance and mobile environments. Among the various EH technologies, we mainly focus on RF-EH for IoT. The choice of RF-EH-IoT in this survey is because, for low-power IoT sensors, RF-EH seems more promising and feasible. A passive IoT device in a symbiotic radio system is referred to as the backscatter device (BSD). The most popular paradigm for the symbiotic radio is the ambient backscatter communication (AmBSC) system. AmBSC system uses ambient energy harvesting BSDs that harvest energy using ambient RF signals such as TV, Wi-Fi (ISM bands), FM, and RF radiated from other ambient sources. These BSDs backscatter the information signals by switching the impedance of the antenna. Two illustrations of AmBSC systems with single and multi-antenna tags are shown in Fig. 6, and Fig. 7, respectively.

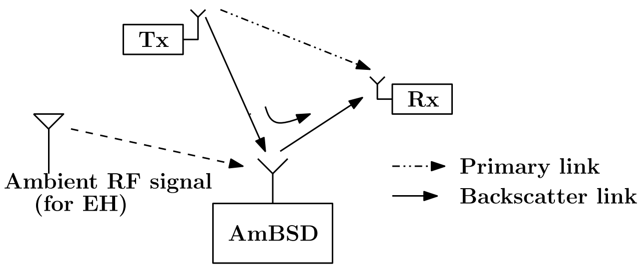

FIGURE 6. An illustration of the AmBSC system having a single antenna ambient EH tag, with Tx denoting the primary transmitter, and Rx representing the primary receiver with the backscatter link via tag.

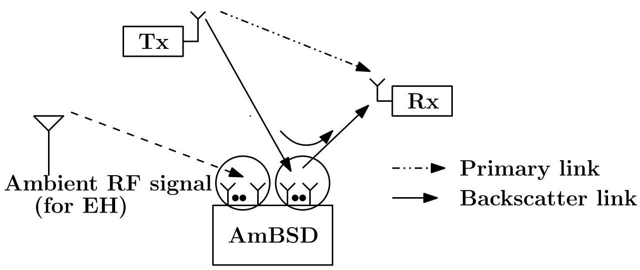

FIGURE 7. An illustration of the AmBSC system having a multi-antenna ambient EH tag, a subset of antennas is used for ambient RF-EH while the other subset of antennas participates in backscattered communication.

AmBSC system with multiple tags: In a large-scale passive IoT system, there could be many tags equipped with a single antenna or multiple antennas. Partial or best tag selection could be a practical solution that helps mitigate the problem of synchronization and RF chain complexity. However, the larger the number of tags, the higher the complexity of channel state information (CSI) and energy management. Specifically, acquiring accurate CSI is challenging because of limited pilot transmissions due to energy constraints. These issues lead to more technical challenges and open research problems in EH-SH passive IoT.

In [57], the authors proposed multi-antenna tag AmBSC where the backscatter system uses a $K > 2$ antenna-equipped tag; among these, $K - M$ antennas are used for RF energy harvesting and M antennas for backscatter communication and the difficulty due blind detection of ambient backscatter signals from a multi-antenna tag via generalized likelihood ratio test (GLRT) is also addressed. In [58], [60], the authors considered a single semi-passive BSD. These tags (i.e., the BSDs) have constraints on energy, which is a precious resource and should be utilized and managed efficiently where signal-to-interference-plus-noise ratio (SINR) constraint for successive interference cancellation (SIC) is also considered for effective backscatter transmission. In [59], the authors proposed a spectrum sharing AmBSC system. In the works mentioned above and the references therein, authors analyzed PHY performance measures such as channel capacity and bit error rate, and also addressed detection and resource allocation problems.

Table 1 shows a comparison of various studies on AmBSC systems in passive IoT. There exists a fair amount of literature on EH-tags assisted backscatter communication in passive (or semi-passive) IoT. The analytical results in the literature on AmBSC include detection, channel estimation, performance analysis, channel coding, EH, and transmission mechanisms (e.g., wireless power transfer) or protocols, to name a few. However, there are still several open problems in PHY, MAC and layers above. For instance, these include space-time block coding, non-orthogonal multiple access, joint spectrum and energy management, optimization, etc.

Remarks on AmBSC-enabled passive IoT: Single antenna versus multiple antenna tags: Unlike a single EH and transmitting antenna tag, a multi-antenna tag can simultaneously perform both EH and information transmission. However, this multi-antenna tag increases the AmBSC system complexity and cost. Furthermore, the issues of synchronization problems in multi-antenna tag-assisted AmBSC are higher. Antenna selection is a useful solution to address these timing issues. However, for the tag-antenna selection, partial or full CSI is essential. Thus, there is a tradeoff between AmBSC system complexity and performance.

C. SIMULTANEOUS WIRELESS INFORMATION AND POWER TRANSFER

Receivers can recover both information and energy at the same time from wireless RF signals, described as SWIPT [63], and this approach has been suggested to distribute RF energy in sensor networks. SWIPT offers the benefit of providing configurable and reliable energy and information upon request. Nevertheless, it is unrealistic to perceive simultaneous energy harvesting and data transmission as entropy rate accounts for the amount of data. At the same time, RF signal's average squared value determines its power. Consequently, information transmitted and the energy harvested cannot be maximized simultaneously, which triggers requirements to redesign wireless networks with relevant constraints [64]. In reality, most of the methods are based on *time switching* or *power splitting*. In *time switching* architecture, time for information processing and RF energy harvesting is harmonized while *power splitting* focuses on the optimal division of received power into two parts: EH and information filtering.

In [66], a relay distributed *power splitting* is done using game theory for information forwarding and EH. In [67],

TABLE 1. Comparison of various AmBSC models.

Model	Constraints	Performance measures	Remarks
The multi-antenna-tag ambient backscatter system [57]	Energy constraints on tags	Probability of detection using GLRT	An ambient system composed of an RF source, a single-antenna reader and a multi-antenna tag (K >= 2), K-M antennas for energy harvesting, M antennas for back scattering.
The symbiotic radio system with a cooperative receiver [58]	Peak transmit power constraint, average transmit power constraint	Ergodic weighted sum rate	A symbiotic radio system with cooperative receiver consists of an active primary transmitter, a semi-passive BSD, and a cooperative receiver that receives and decodes both the PT's signal and the BSD's signal.
Opportunistic Ambient Backscatter Communication in RF-Powered Cognitive Radio Networks [61]	Interference and energy harvesting constraints	Energy efficiency in the presence of sensing errors	1) AmBSC-harvest-then-transmit (HTT)-based cognitive radio network consists of a secondary user transceiver pair and a primary transceiver pair. 2) The CR network in the opportunistic spectrum access (OSA) paradigm, in which the PU channels are accessed opportunistically using SS to detect spectrum holes. 3) The secondary is equipped with an energy-based spectrum sensing unit, an RF energy harvesting unit, and an AmBSC unit.
A spectrum sharing AmBSC communication system [59]	Average transmit power constraint, primary transmission outage constraint	Ergodic capacity of secondary system	The primary communication pair is a conventional communication system. The secondary communication pair is an ambient backscatter communication system, which consists of a wireless-powered passive tag and a battery-powered reader.
Cooperative ambient backscatter system [60]	Primary transmitter's Average transmit power constraint, SINR constraint for SIC	Average achievable rates	Three practical symbiotic transmission schemes, i.e., commensal, parasitic, and competitive schemes, were proposed for the cooperative ambient backscatter system

a novel, SWIPT based cooperative NOMA is discussed. The user with a strong channel operates as an EH relay by implementing power splitting and optimizing the beamforming vectors while improving QoS for the user with weak channel conditions. Both time-switching (TS) and power-splitting (PS) are employed in [68], where cooperative DF relaying is used for EH and information processing. Energy-limited relays do EH from received and co-channel interference signals; after that, the harvested energy is used for forwarding the decoded signal accurately to the destination. At high SNR, PS performs better than TS for achieving throughput from ergodic or outage capacity, while at low SNR, TS is superior to PS.

The authors [69] have proposed a dynamic *time switching* protocol where the switch between EH and data transmission is done using AF and DF relaying by smartly tracking the level of harvested energy at the relay. It is appealing as CSI is not needed, and relays do opportunistic use of harvested energy by charging their battery for transmitting the information. In [70], the authors describe a mechanism to balance the time duration between wireless power transfer and data transfer by employing an optimization to satisfy energy, time duration, and QoS constraints. In contrast to the sum usable energy extracted from RF sources, the efficiency of communication of the EH method is defined using the harvested free energy at disposal effectively. In [71], the authors consider the non-linear features of EH circuits by employing a resource allocation algorithm for the SWIPT system to maximize total harvested power.

D. OFFLINE AND ONLINE ENERGY SCHEDULING AND OPTIMIZATION

The performance of an EH system also depends on how efficiently it utilizes the harvested energy available [158], [193]–[195]. Unlike conventional battery-powered systems, controlling power in EH systems has to be in synchronization with energy consumption and the recharging of the battery because of the dynamic nature of energy availability in nature. Energy outage and energy overflow create problems in harvested energy utilization. Energy scheduling techniques are of two types: *offline* and *online*, based on availability of knowledge of CSI and energy state information (ESI), causally and non-causally before transmission.

For *offline methods*, information about complete knowledge of CSI and ESI is known before transmission in the energy scheduling period. Reference [72] aims to minimize packet loss rate by jointly optimizing energy allocation and scheduling algorithms based on channel, battery, and queue state information in industrial wireless sensor networks. In [73], the authors investigate the optimum allocation of power to minimize a non-convex average outage probability over transmit power in a fading channel. It is shown that the ideal power profile is non-decreasing over time and has a conserve-then-transmit framework, and a forwarding search algorithm that finds the global optimal offline power assignment is proposed with non-causal energy state information (ESI). However, an online power assignment strategy also has been proposed for causal ESI by considering dynamic programming and inspecting the system of optimal offline solutions. In [74], a linear combination of outage probabilities is minimized over a limited time period with predefined transmission rates. A piece-wise power assignment framework is developed for both cells with limited and unlimited storage capacities. A divide-and-conquer algorithm is suggested to find the optimal power allocation iteratively. Authors of [75] investigate the concave utility maximization optimization problem for EH-wireless sensor networks (EH-WSNs) where sum-rate maximization and distributed estimation related to water filling algorithm is presented. In [76], performance limitations of sensor nodes with finite energy where harvesting occurs variably is studied. A concave non-decreasing utility function is analyzed while managing the energy locally, achieving performance near to that with unlimited energy while keeping the probability of complete battery discharge low and addressing the problem of energy management in energy-replenishing nodes with finite battery and data buffers. In [77], a reinforcement learning model is proposed to allocate resources and schedule users in heterogeneous networks (HetNets) with hybrid energy supply to power small base stations.

Online strategies account for causal ESI and CSI as in [78], where a feasible rate maximization task is modeled as a Markov decision process (MDP) with continuous battery states having an access control structure of the EH transmitter that has maximum power limitations and works in a time-slotted fashion. The proposed algorithms produce an optimal continuous power allocation and better performance than discrete state MDP. Offline algorithms typically outperform online algorithms owing to the presence of non-causal information of energy arrivals and channels. For two instances where the harvested energy and channel can be causal and non-causal, offline and online power distribution structures are devised in [79]. The authors propose an optimal energy scheduling algorithm with an objective of sum-rate maximization of energy examined over limited time slots for k-user multi-access channels which do ambient EH. Due to the convex nature of the optimization problem, an iterative dynamic water-filling algorithm is suggested with limitations on cell capacity and energy utilization by transmitters. The authors maximize the networks' performance with the availability of EH sources in [80] with two reinforcement learning algorithms Q-learning and speedy Q-learning are used to formulate transmission methods in real-time scenarios by using joint randomness in arrivals of data and energy produced due to sensors and energy sources.

Table 2 shows a comparison among different energy harvesting algorithms discussed in this survey paper. Several MAC layer protocols have been proposed due to the differences in energy between nodes, adjusting to dynamic EH, and maintaining network efficiencies such as low latency and high packet delivery probability. Cross-layer scheduling structures have been developed between three layers: regulation of the source rate at the transport layer, optimizing multipath routing and flowrate at the network layer, and optimizing the MAC layer's duty cycle. In [83], a hybrid time division multiple access (TDMA) based medium access protocol has been suggested that avoids collisions and effectively uses the energy of the nodes and dynamically schedules the sleep/wake-up modes according to variability at the nodes. This increase the energy conservation by 40-60% compared to the IEEE 802.15.4-based MAC protocol.

E. MERITS AND DEMERITS OF EH TECHNOLOGIES

In the following subsection, we present various EH techniques and their challenges, merits, and demerits. Clean energy derived from renewable sources is good for the environment as the energy generation process does not contribute to the carbon footprint. With reliable and sustainable EH technologies, it is possible to confront this century's most challenging global warming and climate change problems. While EH technologies exhibit several merits, they also have demerits such as cost and complexity. The expenses such as CAPEX, OPEX, and EH system complexity vary from one EH technology to the other. A discussion on the exhaustive list of these features individually on each EH technology is beyond this survey paper's scope. However, we present a brief summary of these merits and demerits.

Merits:

i) Renewable energy is good for the environment. Specifically, in wireless sensor networks, IoT, and cyber-physical systems, it is possible to significantly enhance network lifetime using these energy harvesting sensors or devices.
ii) EH technologies help in waste reduction and management. For instance, it is possible to eliminate heavy batteries in complex subsystems.
iii) Use of conventional non-renewable energy sources cause adverse effects on the environment. Furthermore, it is also difficult to power large numbers of IoT devices in the cyber cloud doing a wide range of sensing and communication tasks. For obvious reasons, EH technologies are an attractive option in these environments.
iv) EH technologies are mostly reliable and even cost-effective in some applications such as wireless sensor networks.

Demerits: EH technologies do have demerits. Some of these demerits are listed below.

TABLE 2. Comparison between different energy harvesting techniques.

Harvesting Model	Design objective	System model	Advantages
Throughput-optimal joint selection and rate adaptation for multi-EH nodes [50]	Minimizing energy consumption	Stationary and Ergodic EH with fading channel	Channel and cell capacity does not affect transmission
EH from an environment with offline and online optimization [52]	Optimum transmit power allocation to maximize throughput	On-off transmitter with non-ideal circuit power in AWGN channel	Deals with the incompetence of battery charging / discharging
Harvest-the-cooperate model [48]	Optimum relay selection	AF relay with WEH in DL and WIT in UL in Rayleigh fading channel	Impact of relay position, relay number, time allocation considered
RF-enabled SWIPT with power splitting and time-switching [63]	Optimum transmission tradeoffs between maximum information rate vs energy transfer	MIMO broadcast system with two receivers	*Energy modulation* for maximum energy efficiency
Cooperative SWIPT-NOMA protocol employing EH and power splitting [67]	Maximizing data rate for a strong user and QoS requirement for weak user	MISO in AWGN channel	Relays driven by harvested energy and does not absorb energy from its battery
Dynamic time-switching [69]	Intelligent EH and information transfer	Energy-limited AF and DF relaying in quasi-static channel	No requirement of CSI, relay transmission power fixed and storage of energy at relay
Non-linear EH and resource allocation in SWIPT [71]	Non-convex optimization for maximizing total harvested power at EH receivers	Flat slow fading channel with downlink multiuser with beamforming	Practical effects of non-linearity in transmitter is considered
Time-switching and power-splitting with interference aided EH for cooperative DF relaying [68]	Ergodic and outage capacity with impacts of interference power and achievable throughput is derived	Rayleigh fading with Block-fading model with CSI available at receiver	Considers CCI which occur in wireless channels
MDP and online stochastic algorithm with multi-level water-filling framework for distributed energy assignment [79]	Extending lifetime of sensor nodes and minimize packet loss rate	AWGN with flat fading	Energy allocation and scheduling done with considering CSI, QSI, and BSI
Offline and online power allocation algorithms with EH limitations and CDI at transmitter [73]	Minimizing of outage probability	Block-fading channel with transmission over N EH periods and M communication blocks	Both causal and non-causal ESI
Optimal offline and online power control policy [74]	Minimizing the weighted sum of the outage probabilities	Rayleigh fading channel with finite and infinite cell capacity	Robust to prediction errors of the harvested energy
Offline and online scheduling algorithm using stochastic optimization problem employing a continuous MDP [78]	Maximizing achievable rate and optimal continuous power allocation	Slow fading channel with causal CSI and ESI with EH in time-slotted fashion and access-controlled transmitter	Better performance than conventional discrete MDP having finite- and infinite-horizon cases

i) Several EH technologies are expensive; for example, in terms of initial deployment or infrastructure costs and materials cost.
ii) EH technologies (mostly) occupy a significant amount of space. However, this varies drastically from one EH technology to the other.
iii) Though most of the EH technologies are eco-friendly, some of them still cause some adverse effects on the environment, for example, biomass EH technology.
iv) EH technologies suffer from low or medium energy efficiencies. There are several open problems and technical challenges associated with this demerit of EH technologies.

F. ENERGY EFFICIENT WIRELESS NETWORK CHARACTERISTICS

Wireless networks maybe classified as energy-efficient, or not, dependent upon the performance of the network and the energy expenditure. In literature, studies on the energy efficiency of wireless networks can be classified based on the following definitions [32]:

- ***bits per Joule:*** Maximizing bits per Joule, or in other words,

$$\frac{\text{bits}}{\text{Joule}} = \frac{\text{capacity of the network}}{\text{throughput per unit of energy}}, \tag{1}$$

  covers both the performance of the network and the energy expenditure. The optimization of this parameter helps in classification into one of the categories under the energy-efficient wireless networks,
- ***Quality of service***: Minimization of energy with guaranteed performance needs to take care of the Quality of Service from the network point of view and Quality of Experience from the user point of view. The energy minimization with the fixed Quality of Service or Experience is one of the optimization parameters which helps

in classification into one of the categories under the energy-efficient wireless networks.

- ***Energy constraint***: In the cases with energy constraints such as battery-operated devices, networks with energy harvesting, and networks with limited energy, the energy-constrained optimization helps in classification into another category of energy-efficient wireless networks.

The next-generation networks are heterogeneous and need capabilities to process and acquire large amounts of data; this would pose major challenges for the network to remain energy efficient. Energy-efficient networks for handling data would need to take care of the aspects as described below [32]:

- ***Acquiring information***: Acquisition of information that is relevant out of the large volumes of information available is an important consideration. The commonly used devices from which data can be sensed are sensors and mobile devices. For instance, in wireless sensor networks, the sensor arrays are used to collect data and are deployed, taking into consideration factors like the coverage and the energy efficient data collection methods. Techniques like those based on compressive sensing have been deployed in sensor networks for data acquisition [32] and are found to be efficient in energy terms and accuracy.
- ***Communicating the acquired information***: The important consideration after data acquisition is the efficient communication of the information. In wireless devices, the primary source of energy consumption can be traced to power utilized during device operation, which is further dependent upon the time during which the device remains in the active state and resource allocation from the network. One possible solution for the offloading of the network traffic and making it spectrally efficient, as described in the literature, is the D2D communication technique. D2D communication has the advantage of providing spectral and energy-efficient communication as the users in proximity communicate directly with each other without the involvement of the network infrastructure.
- ***Storing the information efficiently***: The storage of data requires energy-efficient and cost-efficient techniques, since the storage costs of data are high and the repeat access of the stored data also involves challenges. In wireless devices, one source of network traffic is downloading of popular files by different users from the network, thus leading to the download of multiple copies of the same file and congestion in the network. A solution to this problem is given by D2D communication where the users can directly communicate and share the file instead of downloading again from the network, leading to reduced congestion in the network; mobile caching is also one of the solutions for this problem.
- ***Computation of the information***: To get analytical insights from the information which is acquired and stored, efficient computation of the information is an important step. The energy consumption of a typical data center is around the same as that consumed by 25, 000 households in [36], which shows massive energy consumption and points to the requirements for energy-efficient computations. In literature, it has been shown that computation offloading to cloud-based services is more efficient; by doing so, the computations are shifted from the mobile devices and save their power consumption and battery usage. In [17], the authors demonstrate the trade-offs between the costs involved in communication and computation while offloading to the cloud computing networks. It is shown that the energy that a node can save due to offloading can be expressed as

$$E_{save} = aA - \frac{b}{B} C \,, \tag{2}$$

where a depends on the nodes power consumption, b depends on the server, and both are constants. A denotes the computation instructions, C denotes the bytes of information sent by the mobile device for offloading, and B denotes the bandwidth for communication. We can see from (2) that whether the energy is saved or not by offloading will depend on both A and C values.

G. EH: INFORMATION THEORETIC SENSE

Consider the received symbol in an additive white Gaussian noise (AWGN) channel to be

$$y = s + n \,, \tag{3}$$

where s denotes the transmitted signal and n denotes AWGN with zero mean and unit variance. According to Shannon [81], the power constraint on the codewords for very large number of codewords m is given as

$$\frac{1}{m} \sum_{k=1}^{m} {s_k}^2 \leq P \,, \tag{4}$$

where P denotes the power. At every channel usage, the causality constraint [81] that needs to be satisfied is given as

$$\sum_{k=1}^{n} {s_k}^2 < \sum_{k=1}^{n} E_k, \, n = 1, \ldots, m \,, \tag{5}$$

where E_k denotes the stationary random ergodic process followed by the energy that is harvested at the transmitter such that $\mathbb{E}\,[E_k] = P$, with $\mathbb{E}[\cdot]$ being the expectation operator. This condition ensures that the codeword is transmitted without any outages in energy. Further, to save energy which is harvested for later applications, if battery is not available, then the constraint for the codewords is given as

$${s_k}^2 < E_k, \, k = 1, \ldots, m \,. \tag{6}$$

If the battery is available with a finite size, with a maximum size denoted by B_{max}, then we can say that

$$E_{B_{k+1}} = \min\left(E_{B_k} - s_k^2 + E_k,\ B_{max}\right) \tag{7}$$

which denotes that at first s_k^2 amount of energy is dissipated and then E_k amount of energy is harvested in the battery.

It has been shown in [81] that the capacity of the additive white Gaussian noise channel with the constraint as given by (5) is expressed as

$$C = \lim_{m\to\infty} \frac{1}{m} \max I(S^m; Y^m), \tag{8}$$

and further, the upper bound on the capacity can be expressed as

$$C \leq \frac{1}{2} \log(1+P) \ . \tag{9}$$

Energy capacity of the systems having nodes with buffer capability to store the energy harvested is larger, as shown in [16]. The channel capacity of an system under ideal conditions and having an infinite buffer is given as

$$C = \frac{1}{2} \log\left(\frac{\mathbb{E}[E_p]}{\sigma^2}\right) , \tag{10}$$

where E_p is stationary ergodic and denotes that the node is replenishing energy by E_p at time p and σ^2 denotes the noise variance.

III. SPECTRUM HARVESTING IN NEXT-GENERATION WIRELESS NETWORKS

The rising demand for wireless data is due to mobile devices unprecedented growth and Internet based applications. Due to the rapid increase in the number of IoT products, energy efficiency and spectrum efficiency are two critical concerns with IoT development. Machine-to-machine communications are perceived as one of the most likely innovations for IoT implementation in the 5G network. The 5G network [196]–[198] is flexible enough to allow a broad range of technologies and accommodate explosive traffic growth, thereby making headway for IoT development. Later on, 5G-based IoT can furnish a wide range of IoT systems with big data. As the evolution of the wireless communication systems continues, bandwidth requirements are also growing, and the increasing demand leaves wireless spectrum capacity even more inadequate. Cognitive radio has been recognized as a possible remedy for the scarcity of spectrum owing to its primary idea of dynamic spectrum access.

Figure 8 depicts the three phases of spectrum sensing, spectrum harvesting, and communicating tasks that a CR needs to accomplish for communicating opportunistically. Among these tasks, spectrum sensing is the unique signal processing task, which is essential for acquiring spectrum awareness for CRs in dynamic spectrum sharing networks. An overlay mode CR can acquire spectrum awareness via spectrum sensing (SS). SS is responsible for deciding on scanning spectrum spaces and is a unique characteristic of CR.

In the following subsections, we describe various spectrum sensing methods for next-generation wireless networks.

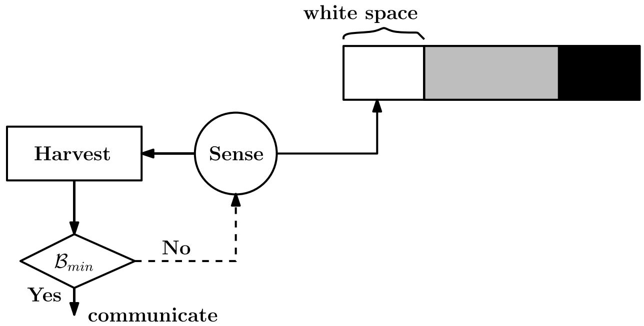

FIGURE 8. The phases of spectrum harvesting and communicating devices where the CR harvests minimum required bandwidth for communication.

A. SPECTRUM SENSING VIA CR

An intelligent wireless communication system, i.e., CR, could be a non-energy harvesting smart radio system or energy harvesting intelligent radio system. In the former, CR has to sense the unused EM spectrum and harvest bandwidth. On the other hand, in the latter, CR has to harvest both bandwidth and energy, which is more complex and highly limited in terms of its applications. For example, radio frequency (RF)-based EH-CR has to sense RF signals and harvest energy that can either be used on the fly or stored and then used for later tasks such as sensing and communication.

Figure 9 shows some of the applications and modes of CR. In the opportunistic mode, a CR, i.e., the secondary user (SU) or unlicensed user, could use the spectrum only when the primary or the licensed user is switched off. However, in underlay mode, both primary users (PU) and SU could co-exist. However, SU's transmissions should not cause interference at the primary receiver above certain thresholds. There are various technical and non-technical challenges in turning these applications and modes into reality. There do exist several tradeoffs among the operating modes of non-EH and EH CR and their performance. In the upcoming sections, we present various protocols developed in the literature on spectrum harvesting systems and networks. Later, we describe some exciting insights into EH and SH technologies from commercial and economic perspectives.

Figure 10 illustrates the motivation of spectrum sensing to find the spectral holes. A cluster-based wireless sensor networks (WSN) is also shown. Three clusters are present where sensor nodes send their information to the cluster head (CH), which is then sent to the sink node. In [86], the authors presented an overview of IoT-based cognitive radio systems and proposed that CR-based IoT systems are a feasible option for reliable and appropriate use of spectrum resources, including in the presence of primary users. They also provided a detailed survey on various architectures, frameworks, and spectrum-related functionalities of each layer in the CR-based IoT system. It is predicted that IoT without cognition can only be a strain on current infrastructure networks. The authors of [87] have reviewed a detailed

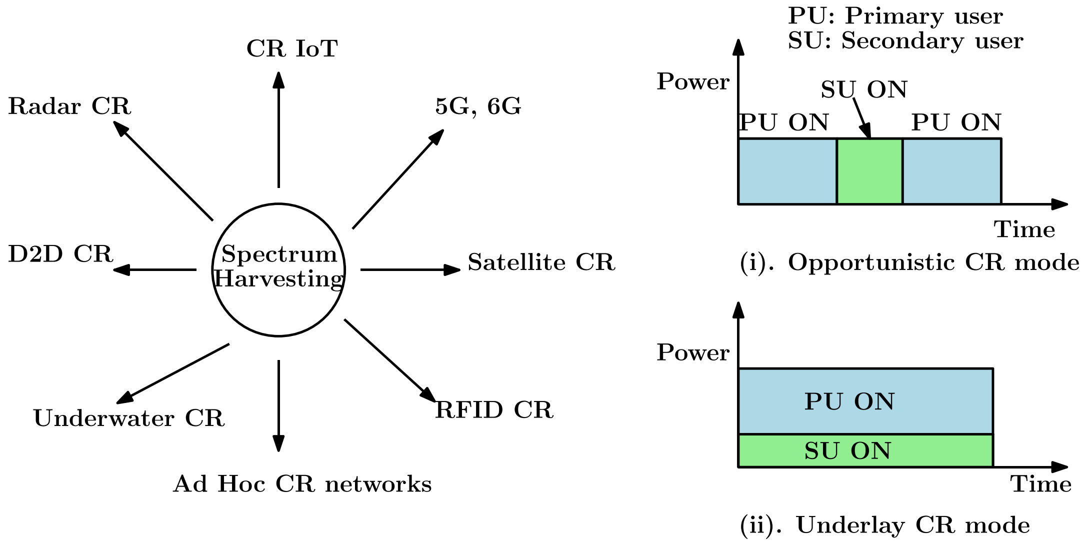

FIGURE 9. Applications (left) and modes (right) of CR.

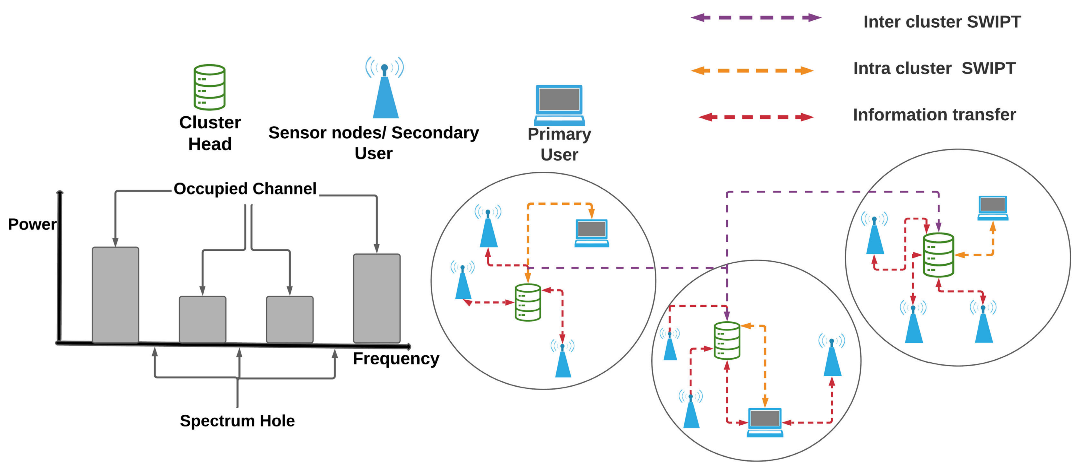

FIGURE 10. Illustration of spectrum sensing and cluster-based WSN [28].

study on the frameworks enabling sharing the spectrum in CR. Existing SS algorithms are also discussed, such as narrowband sensing, wideband sensing, and cooperative sensing, along with advances in various aspects of implementation such as power consumption, complexity, throughput, and performance. In [88], the optimum spectrum assignment concerning network throughput is examined, and the use of spectrum in IoT focused on CR. With mutual interference and resource allocation limitations under simultaneous transmission, a genetic algorithm optimization is proposed, with links acting as chromosomes, to achieve maximum spectrum utilization. Though the dynamic spectrum access mechanism helps the secondary users to access the wireless channels licensed to primary users due to high spectrum availability variations, it is difficult to establish an effective routing method for secondary users in cognitive sensor networks.

In [89], two cognitive sensor network (CSN) routing mechanisms are proposed, which account for spectrum channels' quantity and quality. One way to minimize rerouting is by re-transmission, considering the probability of successful delivery through all channels. In contrast, the other routing mechanism considers mean delay while transmission over all channels. Due to fading and shadowing, single secondary user performance is limited. For proper and effective wireless channel sensing, a collaborative spectrum sensing is proposed in [90], where the time slot is divided into two stages: spectrum sensing and reporting. The results reporting period depends on the number of collaborative sensing users, while the time invested in sensing the spectrum determines the number of sensing samples. Two scenarios with extra and shortfall of energy are considered, and a convex optimization problem is formulated for the overall probability of error with time and energy limitations. In [91], a full-duplex cognitive radio network (FD-CRN) is used where throughput maximization for SU is done. FD-CRN can sense the spectrum and transmit data in the whole time slot. Two algorithms based on brute-force search and particle swarm optimization (PSO) methods to help the SU achieve optimal detection thresholds and maximize throughput is proposed in SU spectrum sensing and cooperative sensing environments. In [92], SS for multi-antenna CR using support vector machine (SVM) algorithms is proposed. The SS problem for multiple PUs is modeled as a multiple detection problem with a beamformer-aided feature realization method to boost the capacity of the SVM. Sensing of PUs spectrum occupancy state by SUs reduces the throughput for SUs. In [93], a simultaneous spectrum sensing and information transfer framework with imperfect signal cancellation and energy detection technique to detect PU is proposed. An opportunistic spectrum access (OSA) model is developed in [94], where SU performs OSA with a dynamic PU having a two-state random process modeled using Markov chains. The probabilities of detection and false alarm are established using chi-squared distributions and acts as test statistics for the energy detector.

A colony-based energy-efficient-sensor scheduling algorithm is proposed in [95] for a collaborative CR with constrained energy source using heterogeneous sensors, where optimal scheduling of sensors is performed in order to ensure the necessary output by sensing and increase the throughput of the secondary system. For effectively sensing of PUs, synchronization of secondary and primary networks is desired to decrease the probability of failure while transmission of PUs, but is challenging to achieve. In [96], a full-duplex MAC protocol SS framework for a multiple channel non-time slotted CR networks (CRNs) is proposed where SUs can sense PUs reactivation time in a timely manner while transmitting. The proposed protocol provides high throughput for PUs with efficient use of the channel by SUs.

As mentioned earlier, depending on the size of the band of concern, spectrum sensing approaches can be graded into two categories. Narrowband sensing [97] addresses the issue of determining whether a specific slice of spectrum is the hole. On the other hand, wideband spectrum sensing [100] is focused on categorizing individual wideband slices to be either occupied or empty. In reality, we require both the sensing technologies in the cognitive cycle. Usually, there exist two separate stages of PU detection in interweave CR. During the preliminary sensing process, in order to detect the accessible spectrum holes wideband spectrum sensing is used [101]. In compliance with specific requirements, the finest possible spectrum band is selected after identifying and examining spectrum holes. Nevertheless, due to high variations in mobile scenarios, the chosen narrowband may be occupied by the primary user once the communications begin. To overcome such difficulties, narrowband sensing by SU is done to verify whether PU is present or not prior to communication. Figure 11 shows various techniques as available in the literature that have been proposed to overcome the challenges in spectrum sensing.

B. NARROWBAND SPECTRUM SENSING

In interweave CR, before communication, SU must sense and verify whether spectrum is available or not, which is carried out by narrowband spectrum sensing. The authors of [98] suggest two architectures to perform narrowband spectrum sensing: single-radio and dual-radio. Merits of single-radio architecture are low power consumption, low cost, and simplicity, but it has less spectral efficiency [99]. Sensing by dual-radio architecture has demerits like increased power consumption and hardware cost. SU must be efficient in detecting the weak signals of PU so that it can rapidly evacuate the occupied spectrum.

We present below the various narrowband spectrum sensing techniques and recent developments as available in the literature. Further, techniques related to narrowband sensing are summarized with its classifications, its limitations, and associated references in Table 3.

Energy detection (ED) is a non-coherent detection technique where there is no requirement of prior information of PU signals and has less complexity. In [103], a kernelized ED scheme is proposed for various Gaussian and non-Gaussian impulsive noises, accounting for practical human-made noise conditions which comprise of higher-order and fractional lower-order moments using non-linear kernel functions for optimal sensing. As the ED method for spectrum sensing needs to be aware of noise power, it therefore has performance degradation due to noise uncertainty. To overcome this noise uncertainty and achieve reliable computing performance with low complexity, a blind ED for spatial spectrum sensing using maximum-minimum energy is proposed in [102], where an electronically steerable parasitic antenna receptor (ESPAR) is used, which can split the space into multiple sectors and switch the receive beam pattern to individual sectors in a time splitting approach. *Matched Filter Detector* (MF) uses coherent detection and maximizes the received signal-to-noise ratio (SNR) by applying cross-correlation between already known primary user signal and the received signal. Due to coherent detection, the SU needs to be completely aware of the characteristics of the PU signal, such as bandwidth, frequency of operation, the shape of the pulse, order, and format of modulation, etc. Due to its robust performance in low SNR conditions, MF detection is employed to detect weak signals. It has been shown that the efficiency and sensitivity of the MF detector decline quickly as mean noise power fluctuation increases and gets even poorer at low SNR conditions. This occurs due to a specified threshold; however, the performance can be enhanced by modifying this threshold. In [106], a dynamic sensing threshold is estimated to increase the efficiency of sensing detection. In [107], an MF detector is employed to recognize the presence of the primary user and its power level. This framework provides great flexibility to PU to vary its transmit power according to the situation of the environment. Even SU can modify its transmit

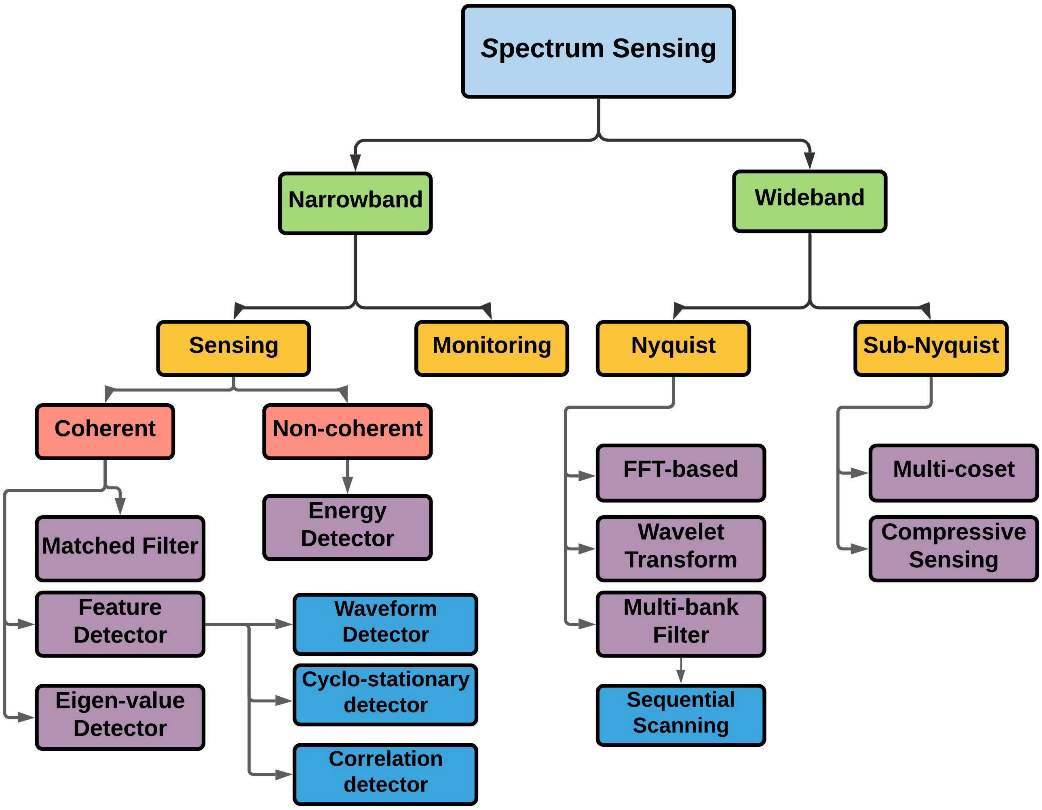

FIGURE 11. Classification of spectrum sensing techniques based on bandwidth.

power to fulfill the interference conditions for various power levels of PU. Authors of [108] have implemented a framework where SU has multiple antennas, and PU has a single antenna and the primary user's training signal set is known apriori by secondary users by cooperation. Even though MF detection has better performance, it requires knowledge about fading of the channel, frequency offset, or proper timing, or else the correlation becomes weak, which degrades the performance.

Feature detection comprises of a comprehensive class of spectrum sensing techniques. A subset of feature detectors, referred to as waveform detectors, is based on prior awareness of the construction of the PU signal. Waveform detection is coherent in nature, so it performs a correlation between the real known signal and the received signal. A comparison is then made between the output and the threshold for detecting the presence or absence of PU. In [109], first, a range decision test is proposed to set the threshold for comparison, which does not vary due to the variations in the SNR based on new decision criteria. In the second approach, SU senses the availability of channel while it is transmitting by using waveform detection so that SU's rate rises. Since PU signal undergoes modulation due to second-order periodicity, PUs have cyclostationary feature. These features are used for detecting the presence of primary users by PU signals as cyclostationary features are absent in stationary noise or interference signal [97]. In [110], using the cyclostationary features of the modulated signal, optimized recovery of generalized frequency division multiplexing (GFDM) signal is presented. By exploring the sparse property, the spectral correlation function (SCF) of the GFDM signal and the covariance function of its compressive samples are constructed. Further, a generalized likelihood ratio test (GLRT) is employed to find out the occupied spectrum. Numerical results prove that the proposed method has good performance at low SNR conditions. Detection of the GFDM signal has significantly better performance than detecting OFDM signals, so GFDM is a better technique that can be used in 5G and CR. Cyclostationary property is used in [111] to avoid the intercell interference in femtocell heterogeneous Long-Term Evolution Advanced (LTE-A) networks. It is shown that employing cyclostationary detection has better performance, particularly in the case of noise uncertainty, in terms of false alarms, detection probability, and deflection coefficient.

Eigenvalue based detection: due to constraints of coherent detection and implementation of a practical system, various other methods have been proposed, one of them being eigenvalue based detection. In [113], [114] to reduce false alarm probabilities under noise uncertainty, a Max-Min eigenvalue detection is proposed where the ratio between maximum to minimum eigenvalues of the covariance matrix is set as a test statistic. This removes the need for PU and the transmission

TABLE 3. Summary of various narrowband sensing techniques in cognitive radio networks.

Technique	Design model and References	Advantages	Remarks
Energy Detector (ED)	• Blind spatial SS [102]. • Kernel ED in Gaussian and non-Gaussian impulsive noises [103]. • Adaptive algorithm for SS [104]. • Four-level hypothesis blind detector for SS [105].	• Less complexity and operating cost with easy implementation. • Non-coherent detection with no requirement of preliminary knowledge of primary network.	• Performance degradation at low SNR conditions. • Highly vulnerable to uncertainty in noise. • Cannot differentiate between primary signal and noise. • Unsuitable for spread spectrum methods.
Matched filter (MF)	• MF with dynamic threshold [106]. • MF based SS and power level recognition using multiple antennas [108].	• Lesser sensing time and maximize the received SNR. • Robustness against interference and stationary Gaussian noise. • Better performance at low SNR.	• Requires prior knowledge of PU. • Dedicated synchronization sensing receiver for each SU. • Large complexity and power consumption.
Feature detection (FD)	• Waveform detection by threshold comparison [109]. • Quasi-cyclostationary feature (QCF) detector [112].	• Reliable sensing with detection at low SNR. • Robust against uncertainty in noise. • Distinction among types of transmission and primary systems.	• Slow sensing than ED and requires high cost and complexity. • Prior knowledge of PU required. • To achieve high accuracy a longer length of known sequence is needed thereby reducing efficiency of spectrum.
Eigenvalue-based detection (EVD)	• Throughput maximization of SU by eigenvalue-based SS [113]. • Effect of noise correlation on eigenvalue SS [114].	• Robust against fluctuations in noise and detects signals with low SNR. • Non-coherent detection and reliable sensing.	• High computational complexity and time required for sensing.

channel's prior information and overcomes noise uncertainty at the receiver.

C. WIDEBAND SPECTRUM SENSING

Sensing of bandwidth exceeding the channel's coherence bandwidth is done by wideband spectrum sensing, for example, ultra-high frequency (UHF) TV band (between 300 MHz and 3 GHz). With respect to the sampling frequency, two primary wideband spectrum sensing schemes have been proposed. The first approach is to sample the required spectrum using simple Nyquist frequency [115]. The second approach advocates the division of the sampling problem into multiple narrowband spectrum detection scenarios, or the edge between the occupied and vacant band is detected. These methods have large computational complexity and require high sampling rates, large sensing time, and processing delay. Algorithms related to wideband spectrum sensing with its classification, its brief description, and limitations are tabulated in Table 4.

Multiband Sensing or FFT-Based Sensing is proposed in [116], where sampling of a wideband signal is done by an analog to digital converter (ADC) at a high sampling rate. After dividing the samples into multiple segments, a Fast Fourier transform (FFT) is applied to estimate the power of each segment. Each segment is further divided into multiple narrowbands, and spectral occupancy is found out using binary hypotheses tests. Hardware implementation of FFT-based spectral correlation and pilot sensing SS framework is implemented in [117] on FPGA as per IEEE 802.22 standard. An adaptive multiband SS is derived in [118], where the framework incorporates two phases, the exploration phase and the detection phase, where several spectral holes are recognized among the surviving channels. A multiband SS technique and cross-layer reconfiguration resource allocation, i.e., the channel for IoT in cognitive 5G networks, is proposed in [119].

Wavelet-Based

Sensing is proposed in [120] for 60 GHz Millimetre-wave (mmWave) 5G small cell heterogeneous networks. The suggested framework can mitigate leakage in the spectrum and interference caused due to other prevailing networks in identical frequency bands by modifying the sub-carriers in accordance with cognitive information supplied by wavelet packet-based spectrum sensing (WPSS) and by utilizing a wavelet-based filter bank multicarrier (FBMC) modulation for reduction of sidelobes. Implementation of wavelet-based spectrum sensing is carried out in [121] for low SNR conditions. Wavelet transform (WT) is utilized as a tool that

TABLE 4. Summary of various wideband sensing techniques in cognitive radio networks.

Technique	Design model and References	Advantages	Remarks
FFT-based Detector	• FFT algorithm used to identify multiple spectral holes [116]–[118].	• Nyquist sampling and Non-coherent detection. • Medium complexity and upgrades acquisition performance. • Removes the effects of phase rotation.	• Requires high sampling rate and high power consumption.
Filter-bank Detector	• Prototype filters used with low sampling rate [125]–[127].	• Provides high performance and detects the dynamic nature WBSS.	• High complexity due wide number of RF front-ends devices.
Wavelet-based Detector	• PSD of wideband spectrum used for exact location of spectral densities [120], [122].	• Non-coherent and edge detection with Nyquist sampling.	• High computational complexity.
Compressive Sensing	• Extract and detect the wideband signal directly to attain effective wideband sensing with a much lower sampling rate than the Nyquist scenario [129]–[135].	• Less power and sampling rate. • Quick and precise detection of spectrum with sub-Nyquist sampling, non-coherent detection.	• High dynamic range, more sensitivity to noise and sparse nature.
Multi-coset Sensing	• Adaptive blind non-uniform Multi-coset samplers [136]. • Discrete MC sampling [137]. • Reconstruction of spectrum [138], [139].	• Blind sensing, sub-Nyquist sampling, non-uniform quantizer.	• Need of synchronization circuits.

produces information about the details on the precise frequency transition locations and spectral densities. Consequently, the wavelet transform is used to find out singularities in wideband power spectral density (PSD), where identification of the anomalies is considered an edge detection problem. In [122] an improved WT algorithm is derived in which non-linear logarithmic scaling of WT coefficients is carried out after normalization of the wideband PSD. In this framework, by carrying out such a process, WT-based edge detection achieves better accuracy and is more effective than conventional WT-based edge detection.

Filter-bank sensing: Fast convolution filter banks are studied in [123] for flexible and optimized processing of waveforms and sub-band energy detection in professional mobile radio (PMR) used for broadband data communication. The designed system shows better robustness to noise uncertainty and interference. A dual-stage SS algorithm for CR is designed in [124] using cosine modulated filter banks (CMFB), which have a simple design and real coefficients for the filter.

Compressed sensing is based on the presumption that the sparsity of the wideband spectrum is known, but due to the dynamic spectrum environment and dynamic nature of PU, the sparsity is unknown. In [128], an adaptive compressed spectrum sensing scheme is proposed to find the optimal sampling rate and detect the spectral holes when the sparsity of the wideband signal is unknown or varying. The authors in [129] use a hybrid model by merging compressive spectrum sensing with geolocations to determine spectral holes in a decentralized CR. A dynamic compressive wideband SS is proposed in [130], which is based on recovering the channel energy of the spectral components, which show varying occupancy status in successive time slots. Bayesian compressive sensing with L_1-norm minimization and with circulant matrix is proposed in [131] to improve the speed and efficiency of the recovery stage in compressive sensing.

Multi-coset sensing (MC) is a periodic non-uniform sub-Nyquist sampling method for obtaining sparse multiband signals. In [136], an adaptive blind wideband spectrum sensing for CR is proposed where the wideband SS is based on non-uniform multi-coset samplers, and the system adapts to variations in the number of active bands and input signals. The main advantage of multi-coset sensing is that each channel's sampling rate is much lower than the Nyquist rate. In [137] the problem of unknown band position is handled through discrete multi-coset sampling. A joint optimization

TABLE 5. Classification of cooperative sensing models.

Topology	Design model and References	Advantages	Disadvantages
Centralized	• A central node or fusion center chooses a frequency band, merges the collected local sensing data from all CR users, evaluates the existence of PU, and the decision is disseminated back to cooperating CR users [143], [144], [140].	• Efficient decision made by FC after complete local data acquisition. • Can achieve multiple optimization objectives. • Fewer message transmission.	• Vulnerable to FC failure. • More energy requirement for transmission if distance and number of nodes are high. • If more nodes, the data collection phase is large. • High-quality channel required due to CCC.
Cluster-based	• Division of the network into multiple clusters with each cluster comprising of a CH and several members.Nodes report their local decisions to CH which forwards the data to FC or makes a decision at cluster level, and reports it to FC [147], [150]–[152].	• Reduction in the time needed for delivering data by a factor of the number of CH. • Mean data transmission distance lower than centralized topology, so less transmit power required.	• More consumption of energy at CH for processing of data.
Distributed	• No requirement of central node. • Nodes exchange data in a determined order, then take global decisions based on data obtained from neighbouring nodes.	• Data collected from surrounding nodes. • Reduced number of links.	• Not efficient as only local data used to make decisions. • At risk due to malicious activities and inaccurate data. • Inefficient in terms of power consumption.
Relay-assisted	• Relaying the reported sensing messages by another node to the FC or a selected node where local sensing information depends upon the channel quality experienced by a node [68], [176], [177], [178].	• Message exchange time depends on the longest route of network but it is shorter than centralized topology. • Distance among neighboring nodes is shorter than the average distance in a centralized case.	• High energy consumption at relays due to data processing. • Fast and efficient route selection mechanism required for less consume less energy and time.

algorithm is developed using an adaptive least coset number to recognize various features and choose an appropriate algorithm for signal reconstruction.

When the primary user's usage information is unknown to the CR, wideband spectrum sensing makes greater use of the frequency spectrum. However, the execution of WBSS is quite complicated as it has extensive usage of energy. The spectrum sharing stage aims to assign vacant bands to secondary users efficiently, without any collisions.

D. COOPERATIVE SPECTRUM SENSING

Single-node spectrum sensing provides us with unreliable performance due to deep fading and shadowing, which increases the rate of missed detection. CR receivers require high sensitivity, which in turn increases the implementation cost and complexity. Moreover, if primary users' SNR is below a certain threshold, increasing the sensitivity would not help in improving the detection performance [141]. To overcome these issues, cooperative sensing is used wherein the spatial diversity advantages are exploited to strengthen sensing performance. It is possible to distinguish cooperative sensing models into four categories: centralized, distributed, relay-assisted, and clustered [142]. Table 5 classifies various models in cooperative spectrum sensing with a brief description, their advantages, and disadvantages.

Centralized cooperative sensing consists of a fusion center (FC) which controls the stages of cooperative sensing. Omnidirectional antennas are used in most of the cooperative sensing techniques. In [143], to achieve fine-grained sensing and broader sensing range of PU, a directional antenna is used. The fusion center gathers the sensing information from SU and optimizes the sensing power, sensing period, and sensing beams for each SU with reduced energy consumption and maximized probability of detection. A reliability-based decision fusion scheme for cooperative spectrum sensing is proposed in [144], where the reliability of each SU decision is considered as a weight factor while deciding upon the ultimate decision at the FC. Probabilistic estimation is carried out by comparison with the past data about local and global decisions. In [145], integration of belief propagation (BP) algorithm with a fast detection technique is used

TABLE 6. Comparison between different spectrum sensing techniques.

Harvesting Model	Design objective	System model	Advantages
Wavelet-based spectrum sensing [120]	Mitigate spectrum leakage and interference using WPSS, and reduction of sidelobes using FBMC	60 GHz mmWave cognitive 5G heterogeneous small cell networks with interference from WiGig system	Improved performance compared to conventional OFDM
Centralized cooperative directional sensing [143]	Optimized sensing parameters for each SU and maximize detection probability	FC forms multiple clusters and is equipped with directional antennas	Reduced energy consumption and better performance than non-optimized schemes
Multi-objective optimization using genetic algorithm for spectrum allocation [88]	Maximizing both network throughput and spectrum utilization	Multi-hop concurrent data flow CR for IoT	Constraints of mutual interference and resource competition in link concurrent transmissions is considered
Bayesian data clustering for dynamic SS [147]	Find spectrum opportunities in temporal, spectral, and spatial domains with faulty sensing data and correlation among SU measurements	N stationary SUs and M frequency channels with CCC with SUs and BS	No requirement of prior knowledge of network topology, location of the sensors, or the number of clusters
FD-CRN with brute-force search and PSO algorithms [91]	Acheive optimal detection thresholds for SU spectrum sensing with throughput maximization	PU and the SU operate in a time-slotted manner with SU having self interference cancellation capacity	Higher throughput in conditions of low SNR or high transmission power for PU
Transferring reputation mechanism and dynamic game model based secure collaborative spectrum sensing strategy [149]	Decreases malicious attacks, resolves the reputation loss problem, and helps SUs to provide honest data	SU have CR with omnidirectional antenna in a CRN-CPS with energy sensing	Increases spectrum sensing accuracy and protects against the internal attacks
Multiband SS and cross-layer reconfiguration for dynamic resource allocation [119]	Optimization problem to find optimal number of channels to be assigned to each IoT node for SS	IoT applications in cognitive 5G networks	Fulfil QoS requirement by opportunistic spectrum access

for cooperative spectrum sensing in order to attain a better detection performance in terms of delay and false alarm rate, where PU actions are heterogeneous in space and dynamic in the time. After considering the practical and imperfect common control channel (CCC), the authors of [146] suggested a robust reputation based cooperative spectrum sensing technique where the impact of imperfect CCC on detection of malicious SU is studied and is verified to be resilient against attacks. In [147], a Bayesian data mining framework is proposed for clustering SU based on their observations in a spectrum heterogeneous CR network. Each SU's reliability and spectrum occupancy are inferred, and a multi-label graph cuts method is proposed to find out spectrum opportunities. Cooperative spectrum sensing performance gets deteriorated due to the existence of malicious interference in CRNs. In [148], to tackle malicious interference, a new cooperative spectrum sensing detector is proposed to estimate the local signal-to-interference-plus-noise-power ratios (SINRs) at secondary users and then transmit it to a fusion center for making the decision. To counter the potential security risks from internal nodes, in [149], a location-aware transferring reputation mechanism and dynamic game model-based secure collaborative spectrum sensing strategy is presented. This helps to solve the reputation loss by user mobility, motivate SUs to provide honest information, and increases the precision of spectrum sensing in CR network-based cyber-physical systems (CRN-CPS). Table 6 compares various spectrum sensing protocols discussed in literature.

E. MERITS AND DEMERITS OF SH AND CR

CR in opportunistic mode senses the unused or underutilized EM spectrum to harvesting bandwidth. These licensed frequency bands are allocated to primary users, which include TV, satellite, and beyond. While the SH technologies are critical, bandwidth resources are limited, whereas communication networks are many. With reliable and efficient SH technologies, it is possible to mitigate the spectrum scarcity problem. While SH technologies do possess several merits, they also have demerits, for example, implementation issues. Below, we present a brief summary of these merits and demerits that may vary from one SH approach to another.

Demerits: SH technologies have certain demerits, mainly in terms of implementation issues. Some of these are listed below. In opportunistic CRs, accurate spectrum sensing is the most challenging task. The false negatives during detection would result in simultaneous communication by primary and secondary users, thus interfering with licensed users.

i) SH-enabled CR improves the complexity and cost of intelligent systems. This cost and implementation issues vary drastically from one cognitive network to another, such as terrestrial and satellite cognitive networks and ad-hoc cognitive networks.

ii) The complexity of energy harvesting and bandwidth conserving CR is even more. For example, the harvested energy has to be utilized for spectrum sensing as well as data communication.

IV. HYBRID SYSTEMS: PERSPECTIVES AND REMARKS

This section provides a brief overview of some of the hybrid systems that employ the energy and/or spectrum harvesting techniques.

Next generation EH wireless systems and EH-IoT: We can broadly classify next-generation EH communication [38], [159] systems into three categories: non-EH wireless systems, EH, or fully autonomous wireless systems, and hybrid or partially autonomous wireless systems, including IoT and cyber-physical systems. The first category of wireless systems, non-EH systems, needs dedicated and reliable power sources. In the second category, EH wireless systems, there is no need for a dedicated power source such as a battery. These wireless systems are fully autonomous because they can harvest energy from ambient sources and perform sensing and communication tasks. However, intermittent communication is a potential risk if the ambient energy sources are not available or sufficient to harvest the required energy. Therefore, these wireless systems are not useful for some critical applications such as broadcasting.

It is more practical to design and develop hybrid wireless systems and EH-IoT that consists of some fraction of EH nodes. The protocol stack should work in such a way that each layer's protocol(s) is(are) aware of the node or terminal's energy consumption and delivers optimal performance by utilizing power adaptively. Modifying the existing protocols such as artificial intelligence (AI)-enabled protocol stack can provide superior performance in complex, hybrid, next-generation wireless systems. The AI-enabled stack should also include a dedicated environment layer (or its equivalent) in addition to layers such as infrastructure, perception, computation, storage, and application. The environment layer may consist of protocols that could process and communicate data related to the carbon footprint by the AI-enabled hybrid cyber-physical system (CPS) or hybrid cyber-biophysical system (CBPS) or network. It could also be responsible for communicating useful data (environmental conditions, machine health, etc.) to the remote server during emergencies (like natural disasters). Furthermore, this layer could improve the AI-enabled CPS or CBPS' protection and security in which the AI stack is mounted. Since AI is being applied (and would be applied) in several complex systems in various fields of science, engineering, business, and health, the AI stack needs to be greener and eco-friendly.

Next-generation SS/SH wireless systems and SS/SH-IoT: We can broadly classify next-generation communication systems into three categories: non-spectrum sharing wireless systems, SS/SH wireless systems, and hybrid or partially spectrum sharing wireless systems, including IoT or CPS. The first category of wireless systems, non-spectrum sharing systems, needs dedicated bandwidth resources always—for example, security and surveillance satellite links. In the second category, SS/SH wireless systems, there is no need for dedicated bandwidth. The nodes are intelligent and harvest bandwidth opportunistically from the unused EM spectrum of primary users. These secondary SS/SH wireless systems also have limited applications in which continuous transmission of information is not needed.

It seems more practical to design and develop hybrid SS/SH wireless systems and cognitive IoT that consists of some fraction of primary nodes with dedicated bandwidth allocation and others being secondary. The protocol stack of such hybrid cognitive networks should work in such a way that each layer's protocol(s) is(are) aware of the node or terminal's bandwidth consumption and delivers optimal performance by utilizing limited harvested bandwidth in the best possible manner.

Next-generation EH-SS/SH wireless systems and EH-SS/SH-IoT: It is quite challenging to develop a protocol stack for such complex wireless systems. With the advent of AI tools and algorithms, it is possible to build a protocol stack in which each layer is aware of energy consumption and bandwidth utilization. As mentioned before, it is a good idea to first design hybrid next-generation EH-SS/SH wireless systems and IoT before making them autonomous. Depending entirely on EH nodes whose performance depends on ambient energy sources, makes it hard to achieve better reliability, quality of service (QoS), and quality of experience (QoE). However, using multi-energy harvesting systems and efficient combining of these EH modules could enable the complex EH-SS/SH-IoT to utilize more green and clean energy than non-renewable energy. Thus, the hybrid and optimal designs would provide a balance while reducing the carbon footprint significantly over time.

Figure 12 illustrates a CR network with energy harvesting. A fading channel with additive Gaussian noise is assumed and data and energy queues are present with the transmitters in which data packets and harvested energy or arriving energy are stored, respectively. SUs do both information transmission in the unused spectrum and RF energy harvesting in the spectrum occupied by PUs. Integration of energy harvesting technologies and bandwidth conserving CRs could provide even more benefits to the next generation of communication systems, networks, cyber-physical systems, etc. For instance, in EH-CR-IoT, the IoT-sensors could leverage ambient renewable resources (e.g., RF energy resource) for energy harvesting and the harvested bandwidth for communication. However, there are various implementation challenges and open problems such as design and development of efficient spectrum, and energy-aware, and optimal protocols for dynamic EM spectrum access and harvested spectrum management. Furthermore, the cost and complexity of the EH-SH CR system are other significant challenges that need to be addressed by researchers and industries.

Numerous technologies such as cooperative communication and CRs are suggested to resolve the constraints of two valuable assets, energy and spectrum, and lack of

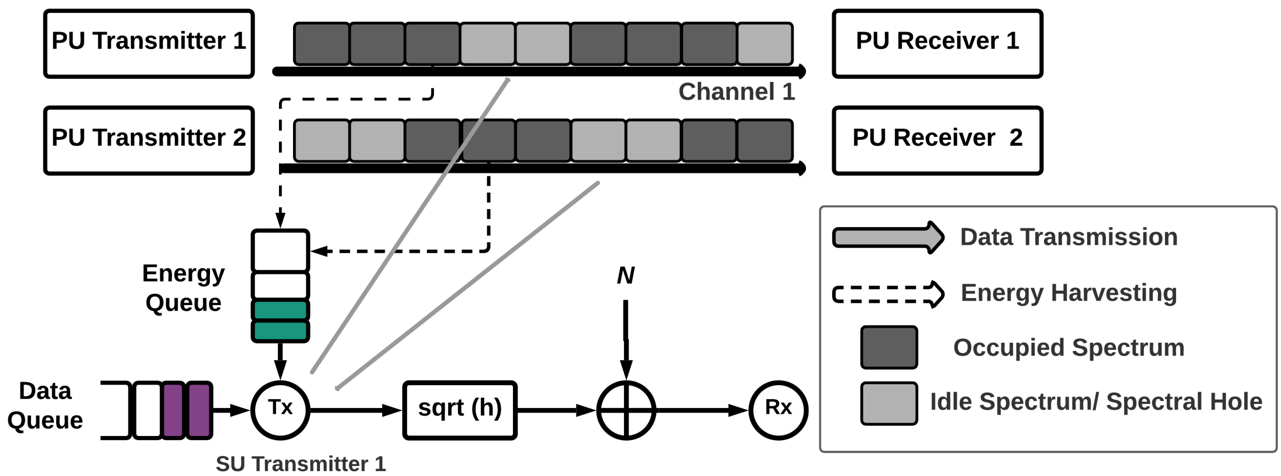

FIGURE 12. The model of CR network with energy harvesting [20].

performance due to wireless fading channels. Communication with cooperation has generated a great deal of interest because of its ability to minimize the fading due to wireless channel and enhance wireless links' performance by leveraging the spatial diversity benefits inherent in multi-user scenarios [120]. As nodes communicate with one another to transmit the information, they form an invisible multi-input multi-output (MIMO) system. Nevertheless, as we know that wireless nodes are mostly constrained in terms of size, these nodes require batteries with longevity and large storage capacity, so EH methods have been introduced to enhance the throughput without the need for replacement of batteries periodically.

Medium access control in cooperative and cognitive wireless systems plays a crucial role in sensing the channel, mobility of spectrum, allocating the resources, and sharing of spectrum. MAC design is affected by sensing duration and precision with an extra burden of optimizing the energy consumption for better system performance and QoS. In [156], a cooperative MAC protocol or cooperative cognitive TDMA is proposed for cognitive networks that does opportunistic EH in SUs. It uses both standard and spectrum leasing methods to achieve QoS for PUs and increases throughput.

A. ENERGY EFFICIENT RESOURCE MANAGEMENT

Energy consumption in wireless CRN is also affected by the radio resource management techniques. A summary of the energy management and related IoT problems is provided in [160], two types of IoT management are classified. Energy-efficient remedies include optimum sleep and idle state scheduling. Repeated scanning of the spectrum for efficient protection of PU results in wastage of energy. In [161], EH-SS based cognitive radio sensor networks (HCRNs) are proposed to deal with the problem of allocating the resources in HCSRNs. Scheduling is done for spectrum sensors to maximize the mean accessible time of channels and resource allocation, i.e., power, channel, and time for data sensors for minimizing its energy consumption. For example, in [162] an energy-efficient spectrum sensing heterogeneous cognitive radio sensor network (EH-CSRN) is considered. The proposed technique focuses on reducing the implementation cost, ensuring the sensing performance, and detection of usable channel time for the transmitting data by using a SS algorithm. It is based on cross-entropy to identify channel assignment scheme which reduces the deployment cost of network equipment, thereby promoting green communication.

In [164], physical-layer security for EH-aided CR is proposed. Two scheduling algorithms that are advantageous for the users are described as channel-aware user scheduling (CaUS) and energy-aware user scheduling (EaUS). In CaUS, a user with maximal channel gain is selected for cooperative transmission users. In [165], time scheduling for a backscatter-aided RF-powered CR network is proposed, where multiple SUs transmit information to the same secondary gateway, which then allocates the time-resources in the backscatter mode and the harvest-then-transmit mode. For conducting time resource management, two auction-based time scheduling methods have been suggested. In [163], a heterogeneous cognitive radio network (CRN) that minimizes energy consumption due to sensing, reporting, and channel switching per unit by a joint objective function for spectrum sensing and energy efficiency is proposed. An energy-efficient resource allocation method is proposed in [166] for energy harvesting-based cognitive machine-to-machine (EH-CM2M) communication to control the limitations due to spectrum and battery capacity. The joint optimization of channel selection, peer discovery, power control, and allocation of time is done to maximize M2M transmitters' energy efficiency. Resource allocation in wireless powered wideband CR under a practical non-linear EH model is considered in [167] to jointly optimize EH time, transmit power, channel allocation, and maximizing sum throughput of SUs.

An optimal resource allocation is proposed in [168] to maximize the sum energy harvested and max-min fairness harvested energy in a wideband sensing-based CR network with SWIPT, subject to limitations on transmit power, rate, sub-channel assignment, and interference. A resource allocation in multi-carrier CR is proposed in [169], where PUs are powered by SUs in a cooperative manner. In this scheme, SU can concurrently transmit both its own data as well as transfer data to PU where harvest-then-transmit for synchronizing WPT and WIT. First wireless power transfer is done to PU, then two methods, subcarrier sharing and subcarrier exclusivity, are used for data transfer and resource allocation algorithms are used to maximize the rate of SU under limitations to achieve minimum PU rate and SU transmit power.

B. ENERGY EFFICIENCY VIA CR

In wireless communications, energy availability is often a significant problem, and SUs have to expend extra energy to identify several channels and continuouly switch between various channels. Thus, energy efficiency and spectrum efficiency are key aspects in CR. Currently, the battery is the primary energy source. However, limitations of battery life, periodic replacement, and environmental pollution have led researchers to look into sustainable, environmentally friendly power supply.

In [170], the authors propose a CR system that harvests energy from the RF signal of PU during sensing time and detection time. An optimal sensing time is estimated, which maximizes the harvested energy and average throughput of the system. In [171], a wideband CR with SWIPT based EH is proposed, where max-min fairness in the allocation of resources between users is studied. Further, opportunistic accessing of the spectrum with imperfect CSI with maximization of throughput of the worst-case SU by performing a joint optimization of the sensing time is studied. In [172], a utility-optimal resource management and assignment scheme for cognitive radio based sensor networks (CRSNs) with EH is proposed with continuous supply energy for facilitating the power-constrained sensors. An online framework for managing the energy and spectrum resources and distribution of resources is proposed by Lyapunov optimization. Three stochastic processes are handled by this approach: dynamics of energy harvesting, channel utilization inaccuracy, and channel fading. The algorithm fulfills two significant objectives: first, regulating the harvest and use of energy by sensors while maintaining the queues for energy and data, and second, optimization of the use of spectrum which is licensed while preserving a bearable collision rate among the unlicensed and licensed users. A slotted mode CR system is presented in [173], in which SU is powered by EH from an ambient environment. The mechanism considers EH and SS in three non-overlapping time-slots using data fusion and decision fusion and focus on the ''harvesting-sensing-throughput'' by considering multi-slot spectrum sensing paradigm and maximizing SU's throughput and finding out optimal sensing duration and threshold. Based on the sensing effects, in [174], the SU can work in both overlay or underlay mode while transmitting to maximize throughput, and continue in sleep mode to preserve energy, or extract energy from PUs. A partially observable Markov decision process method is suggested to evaluate the mode of transmission with a threshold on energy, and choose between SS or sleep mode depending upon actions of PU. With the increase of throughput, there is also an increase in SU's computational complexity, latency, and the system's energy demand. A two-way information exchange dynamic SS framework is proposed in [175] to enhance energy efficiency for transmitting data in licensed channels. Also, an energy-efficient optimal transmit power allocation scheme is derived to improve dynamic SS and data throughput. A novel non-orthogonal multiple access (NOMA) assisted overlay spectrum sharing for multi-user CRNs for improved spectrum utilization is proposed in [176]. Scheduling of a SU, which acts as a relay, is done to transmit both its own and PU signals using NOMA based cooperative spectrum sharing. Two scheduling schemes: reliability oriented secondary user scheduling (R-SUS), which helps in minimizing PU and SU outage probabilities, and fairness oriented secondary user scheduling (F-SUS) achieves superior user fairness are used, which achieves full diversity order.

Outage performance analysis is studied in [177], [178] for wireless EH underlay Relay-Assisted CR networks with node position taken into consideration. Based on stochastic geometry, outage probability with and without relay-assisted transmission is derived, and selection of the optimum relay based on the comparisons of above-derived probabilities is made. In dominant interference and noise environments, a spectrum sharing scenario is considered in [179], where the SUs communicate via an interference-aided EH DF relaying with multiple primary transmissions and outage limitations. Relays use time-switching to shift between EH and data transfer. In the EH scenario, the advantage due to harvesting energy from primary interference, which acts as an energy source, suppresses the negative effects of primary interference and helps to maximize the secondary throughput. Also, using multiple antennas at the secondary relay aides in EH. In [180], an overlay spectrum sharing is considered for SWIPT based EH. By employing decode-and-forward relays for assistance during PU transmission under Nakagami-m fading channel, outage probability expressions for PU and IoT devices are derived. EH is done by IoT devices with RF signals from PU with maximizing system throughput and energy efficiency. In [181], joint optimization of EH and SS is done with limitations on energy causality, collision, and temporal correlation of channel sensing probability and mean channel capacity as the realizable throughput. Maximized throughput and optimum detection threshold is obtained, where the primary channel state is a discrete Markov process. In [182], a green CR that operates in a harvesting-transmitting fashion within each time slot is proposed where CR nodes harvest energy first then transmit data using the harvested energy.

C. EH USING COOPERATIVE COMMUNICATION

CR implementation with cooperative communication makes it possible for the SUs to get more chances for transmission by acting as a relay for PUs. In [183], the authors consider SU with ambient EH and infinite cell capacity that can possibly cooperate with PU for EH duration and relaying power to maximize throughput. The authors in [184] considered a CR system where SU creates a limited capacity energy and unlimited capacity data queues to store its own and PU's data packets which are not delivered successfully. SU uses the Alamouti coding scheme for cooperation with PU, which has queuing delay limitations; after that, throughput maximization of SU is carried out subject to constraint of all data queues' stability.

In [185], a multichannel CR is suggested to improve the performance. At the same time, the transmitting SU divides the subchannel into two slots, the first one for sensing the PU by cooperative SS and the other for harvesting PU's RF energy by multichannel EH. By jointly optimizing the subchannel set, the time required for sensing and power used for transmission, throughput, harvested energy, and effective energy utilization by SU is maximized. A collaborative scheme for sensing the spectrum (CSS) in EH-CWCPN is proposed in [186]. The clustering of CR nodes is done based on the received signal's power levels for increasing the utilization of the spectrum. The time slot is shared between the harvesting of energy, sensing the spectrum, and information transmission. The optimization problem aims to maximize the throughput with energy and collision limitations under a detection threshold, which is obtained by formulating a fictitious cognitive node and number of clusters of cognitive nodes. Cooperative sharing model for CWPCNs with both amplify-and-forward (AF) and decode-and-forward (DF) protocols to maximize its uplink energy efficiency by using an optimization problem and then dividing it into two parts, uplink scheduling and cooperative power control, has been proposed in [187]. In [153], the cognitive sensors sense licensed channels and find out PU's availability by computation over multiple-access channel (CoMAC) soft-decision cooperative spectrum sensing method. Energy-efficiency maximization is done for CSNs by using the time required for sensing, the detection threshold, and the length of symbol sequence as variables. In [188], a SWIPT-enabled cooperative network is proposed where a relay helps in PU's transmission. Here, SUs acting as relays superimpose their data on PU's information. SWIPT relay uses an energy-assisted decode-and-forward (EDF) protocol. A relay-based spectrum sharing protocol in CR is proposed in [189]. SU does RF-energy harvesting from PU in exchange for helping out in data transmission. Alamouti coding is used for primary data relaying. Superposition coding techniques are adopted for secondary data transmission in a continuous manner with joint decoding and interference cancellation methods employed at receiver. Finally, optimal power assignment is done to maximize SU throughput and guaranteed PU QoS.

A dynamic way of accessing the channel has been suggested in [190] for clustered CR nodes where maximizing the resource distribution by finding out conditions for both inter and intra clusters is proposed, and sensing and switching to a licensed spectrum by a sensor is performed to increase energy efficiency and maximum utilization. Due to limited spectrum and increasing wireless devices and cognitive radio, a new cognitive wireless powered communication network (WPCN) is proposed in [192]. In the proposed WPCN, devices are powered via wireless energy transfer (WET) by a hybrid access point in the downlink and does wireless information transmission (WIT) in the uplink. Sum-throughput maximization is done for cognitive WPCN by jointly optimizing the time assignment for the harvest-then-transmit protocol and the WET/WIT transmit power. Both underlay and overlay-CR are used to maximize the sum throughput for wireless energy and information transfer by optimizing different transmission limitations. Figure 13 shows a WPCN network where W amount of time in each block is for WET, and the remaining time (T-W) is for WIT. In [191], a double-deck cluster cooperative relay assistance model in hybrid spectrum sharing CR networks is proposed where energy efficiency is achieved by optimizing SUs for the upcoming 5G networks.

D. APPLICATIONS IN DIVERSE FIELDS

With the advent of 5G, IoT, and its variants such as IoMT, IoBNT so on, there are promising potential applications of EH and SH in various cyber-physical systems and nanoscale networks. Some of these applications are listed below. First, we mention EH applications followed by SH and EH-SH applications.

SWIPT-enabled wireless networks: EH radios can harvest energy from ambient renewable sources such as RF signals and also simultaneously transmit information. The harvested energy can be used instantaneously or stored in a supercapacitor for future communication, depending on the application. For example, low power sensors-equipped body area network (BAN), and wearable devices for smart health could exploit techniques like SWIPT. With proper energy management, these networks could be more energy efficient or greener.

Ambient backscatter communication systems: AmBSC comes under passive IoT. The ambient backscatter devices (AmBSD) such as EH tags can harvest energy from ambient RF signals such as TV, Wi-Fi, etc. The number of EH rectennas varies from one type of AmBSC to another. Intuitively, it is expected that more number of EH rectennas can scavenge more ambient energy. However, as the number of rectennas increases, the size and complexity of the AmBSC would also increase.

Cooperative D2D communications: EH relays are useful and can deliver superior performance when compared to D2D communication without relays if designed optimally. The performance benefits include increased data rates, network throughput, network lifetime. selection of the type of relay. Its optimal design depends on various aspects such as power

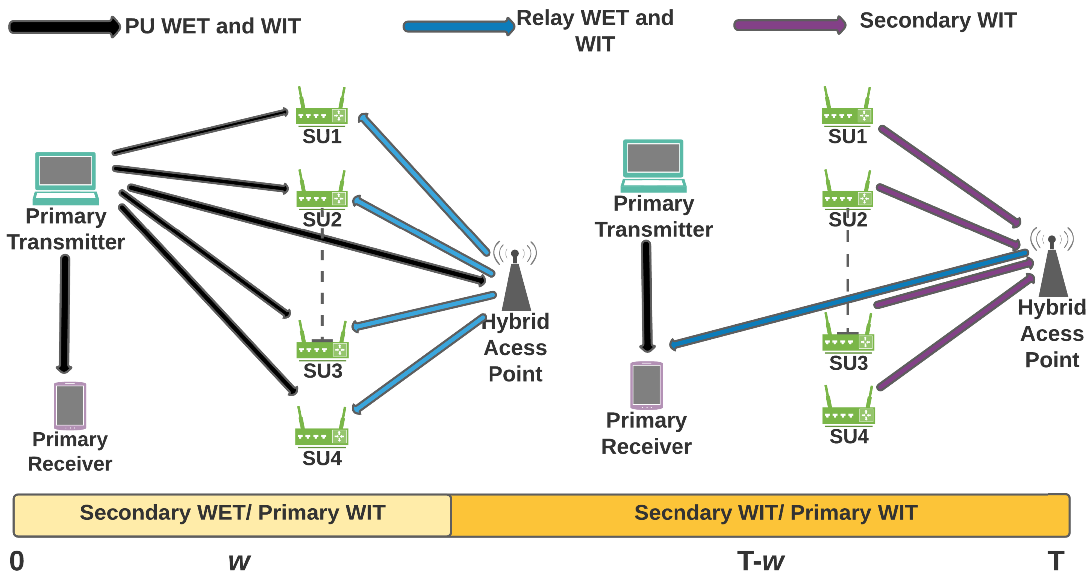

FIGURE 13. A cognitive WPCN with cooperation between primary and secondary systems with the harvest-then-transmit protocol for WPCN [192].

and bandwidth constraints, acceptable complexity, to name a few.

Wireless sensor networks (WSNs)/IoT: IoT focuses on making the Internet universal and omnipresent and can impact many aspects that affect the standard of living of consumers. Technologies intended for IoT cover a broad range of areas comprising cyber-physical systems, automation at home, smart healthcare, smart cities, monitoring, intelligent ecosystems, smart transportation, and many more. The implementation of IoT devices, therefore, will provide substantial savings and revenues through the provision of control and management services. This acceleration has forced organizations to implement various methods to address this rapid growth and development and the problems connected with them. These include: allocation of sufficient spectrum bands in IoT, improving transmission efficiency, scarcity of spectrum, sharing of spectrum, interference among devices, etc. For example, a wireless sensor network (WSN) usually comprises of many affordable sensor nodes. Such nodes have restricted battery power capacity. When the node's battery drains, it should be restored as the network may not function correctly if adequate nodes are not properly working. A feasible approach for extending the lifespan of wireless energy-limited networks is the energy harvesting methodology that has lately gained tremendous attention. It allows wireless nodes to scavenge energy from the local environment. In scenarios where the frequent replacement of batteries is infeasible, EH technologies are a suitable alternative. However, if deploying EH sensors is not feasible, hybrid sensors could be useful, which harvest energy whenever available and as a backup, depend on battery energy. These hybrid sensors could enhance battery life as well as the WSN life period.

In wireless sensor networks, nodes typically transmit whenever an event of interest occurs. Since the continuous transmission is not required, the cognitive radio-enabled nodes can occasionally harvest spectrum and transmit data. This way, no dedicated bandwidth is necessary for these networks. Similarly, CR-enabled IoT communications over the harvested spectrum will improve spectrum utilization. However, various technical challenges and open problems such as spectrum sensing, spectrum allocation, dynamic spectrum access and management, modeling, and simulation of complex cognitive IoT environments need to be addressed.

5G and beyond: Next-generation 5G/6G mobile networks could use EH technologies in some of their network components. For instance, the hybrid base station of eNodeB/gNodeB partially depends on harvested energy. The inclusion of hybrid EH network entities could make the 5G/6G networks greener and reduce their carbon footprint.

Applications of spectrum harvesting/sharing systems: Though there exist some unlicensed frequency bands (ISM bands), a majority of the frequency bands are licensed. As the spectrum is precious, it cannot be underutilized. As mentioned before, spectrum sharing/harvesting systems are useful in addressing these issues. Below, we present some of the applications of spectrum sharing or cognitive radio systems.

a. ***Collaborative or cooperative spectrum sharing systems:*** The application of cooperative relaying techniques enhances secondary user performance for devices that opportunistically sense the primary user's spectrum and harvest it. However, a secondary underlay user can only transmit while satisfying the constraints imposed on transmissions. These are interference constraints which the limit secondary's performance. Cooperative relays adaptively adjust the parameters (e.g., gain) to optimize the end-to-end secondary performance in terms of error probability, spectral efficiency, and energy efficiency.

b. ***Passive IoT of AmBSC:*** In addition to backscatter tags, in non-reliable links, adaptive relays can be exploited to improve the AmBSC system performance. Incorporating both battery-less tags and efficient relays could enhance the reliability and data rates of AmBSC. The optimal placement of these tags and relays is an open problem and can be explored by researchers.

c. ***Emergency communications:*** Professional mobile cognitive radios could sense and exploit the unused EM spectrum for emergency communications and public safety communications. These radios are useful for emergency services and could be used by ambulance, fire-station staff, and police, to name a few. Limited efforts in industry and research have been conducted to use small cell base stations installed on drones for emergency communications [199]. It is possible to use such flying base stations in disaster zones, emergencies, or in rural areas. Data security [200] is the primary obstacle in implementing such flying base stations. It is difficult to deploy complex security mechanisms with drones as there are resource-constrained devices. Furthermore, in implementing such networks, the aspects of user affiliation, drone operation, and bandwidth allocation are major bottlenecks. Thus, in such cases, energy harvesting and spectrum harvesting can be a very useful tool.

The applications mentioned above are also valid for EH-SH systems. However, the performance of these systems is highly limited due to harvested energy and bandwidth limitations. These systems are more suitable for low power IoT applications in which nodes have minimal harvested energy and transmit at low data rates. Energy-aware optimal PHY and routing protocols need to be implemented to optimize their performance.

V. FUTURE RESEARCH TRENDS

In this comprehensive survey, we reviewed EH and SH from different perspectives. We now summarize the key themes and the lessons. The rapid growth of feasible and implementable ESH techniques would lead to their application in various systems and networks from an economic perspective. Further, the standardization of these technologies in next-generation IoT and cyber-physical systems would enable rapid manufacturing and production. Thus, these technologies will eventually appear in the market as commercial products for various life needs, such as infotainment, smart health, smart transport services, etc. However, several obstacles exist in making this a reality due to several critical issues like security, privacy, and other technical challenges like poor or low efficiencies. For instance, most green energy harvesting approaches can only deliver limited power, limiting their applications. Similarly, spectrum harvesting methods' success is also limited due to the highly random and dynamic nature of the primary users, causing dynamic spectrum access and management exceptionally challenging. Incorporating automation with artificial intelligence, machine learning, or deep learning wherever feasible and applicable would address this problem in more complex IoT or cyber-physical systems. Furthermore, the performance of EH and SH techniques and protocols implemented in secondary users or terminals will drastically vary depending on the mode of the operation and type of communication system or network. In addition to this, there are compatibility, interoperability, and scalability issues that need to be addressed in more complex systems that exploit EH and SH techniques.

Some of the EH related challenges and issues may find their solutions in the form of smartly controlled energy harvesting, integrated storage, and efficient transmission approaches. Similarly, some of the SH related challenges could be resolved using hybrid and flexible modes of operation of spectrum sensing and sharing systems and networks. Various proprietary technologies (e.g., ZigBee and Bluetooth) should come forward and work together to alleviate issues such as interoperability, compatibility, and scalability. This paper presented various EH and SH-enabled network architectures, techniques, protocols, and EH and SH standards. The optimization and practical implementation of these green systems and networks under various power and energy constraints form the lion's share of further research in EH, SH, and ESH communication technologies.

This paper also discussed various recent investigations in order to highlight technical challenges and open problems in areas such as green cognitive IoT and its variants such as energy-efficient xG, and M2M communications. Especially for EH and SH enabled IoT, there are issues such as privacy and security. Novel algorithms with moderate complexity to improve end-to-end performance in energy efficiency, spectral efficiency, reliability, and security for various IoT applications are very much needed. Smart and hybrid computing and communications techniques and algorithms would improve the ESH-enabled IoT and other systems and network performance. However, these techniques or algorithms should be feasible and practically implementable.

Future technologies need to be green as much as possible. Eco-friendly communication technologies and IoT systems and its variants should replace power-hungry low energy-efficient, and low spectral-efficient systems and networks. Overall, despite the growth of EH and SH technologies in research for green communication and networking, their visibility in various commercial wireless networks and IoT is not significant. There exists a significant gap between analytical EH and SH techniques and protocols, and their implementation in practice. This gap needs to be minimized as much as possible. This bridging of theory and practice seems possible with out-of-the-box thinking and developing next-generation miniaturized electronics, as well as robust and secure algorithms based on intra-disciplinary and inter-disciplinary approaches wherever possible.

A. COMMERCIAL AND ECONOMIC PERSPECTIVES

With the advent of feasible EH and SH techniques and technologies, manufacturing industries could find ample growth opportunities to develop new heterogeneous sensors and cognitive devices. These EH and SH enabled sensors and CRs would bring more revenue for various sectors related to IoT, 5G, defense, aviation, consumer electronics, etc., Figure 14 depicts the predicted EH electronic devices market scenario [33]. The growth of the EH and SH components or devices market will lead to the economic development of various autonomous cyber-physical systems and next-generation wireless systems and networks. Figure 15 shows the projected SH or cognitive radios market. From the bar chart, we can see that there is approximately an increase of 164% in the CR market. The CR market may be viewed in two segments, namely, component and application. While the former segment includes antennas, RF, or millimeter wave (mmWave) electronics, the latter segment includes cognitive radio networks, CR-IoT, ad hoc networks, to name a few. Based on [24], the CR market is expected to be worth 7.44 billion USD by 2022. In it, the CR market mainly comprises of components such as software tools and hardware; the application consists of spectrum sensing, spectrum access, cognitive routing, etc. The statistics depicted pictorially in Figure 14 and Figure 15 reveal that significant and rapid growth in SH and EH devices and systems can be expected in various CPS and communication networks.

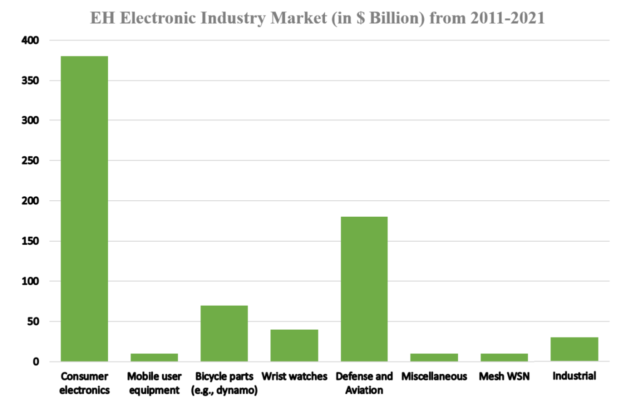

FIGURE 14. EH market scenario (2011-2021).

B. TECHNOLOGY READINESS LEVEL

For the energy and spectrum efficiency research, in this section, we present a technology readiness level (TRL) diagram, as shown in Fig. 16, which maps the output levels of the research across different levels of maturity. The TRL is divided into three stages with TRLs level 1-2 denoting the fundamental research in the area, level 3-5 denoting the technology development, and level 5-6 denoting the technology demonstration in practical networks. The research in EH and SH technology has matured significantly with the greater push and awareness on the green communication networks and further, due to the focus on energy optimization. Many of the present communication networks and the future

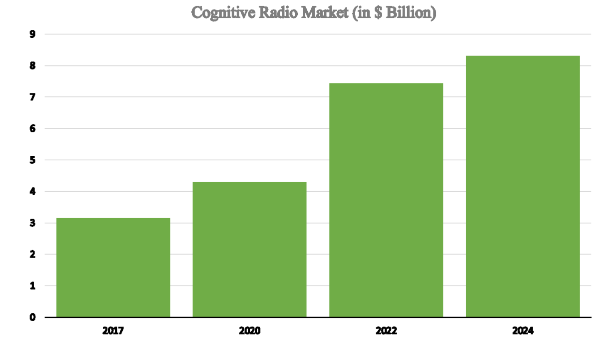

FIGURE 15. CR market scenario (2017 to 2024) [19].

wireless networks are envisaged to be green networks with energy efficiency as one of the desired characteristics. On the other hand, due to spectrum scarcity and an increase in the number of users and diverse fields of applications, spectrum efficiency is a desirable feature. The TRL diagram gives a pictorial representation of the development of the EH and SH technology from the fundamental research level to the present and future aspects of implementation.

C. TRADEOFFS FOR GREEN NETWORKS

Future wireless communication networks, specifically 5G and beyond 5G networks, have a greater push towards efficient green communication, which is seen in both academic and industrial research. For an AWGN channel, the tradeoff between the spectrum and energy efficiency can be expressed as [157],

$$T_{ES} = \frac{T_S}{\left(2^{T_S} - 1\right) N_o}, \tag{11}$$

with

$$T_S = \log_2 \left(1 + \frac{P}{B N_o}\right), \tag{12}$$

where P denotes the total transmit power, W denotes the total bandwidth, and N_o denotes the noise power density.

The present communication networks have orthogonal-frequency-division multiplexing (OFDM) as the key enabling technology, which forms the basis for 4G systems: For future communication networks, which include 5G and beyond 5G, new technologies which are more efficient than OFDM are being explored. The non-orthogonal access technologies studied in the literature that are considered as prime candidates for future network deployments are D2D and non-orthogonal multiple access (NOMA) [23], with both the techniques focusing on inter-user interference. The capacity of non-orthogonal access technologies, as described above, can be expressed considering all the transmitter-receiver pairs as [154],

$$C = B\,\mathbb{E}_{h_p, h_p^m} \times \left[\sum_{p=1}^{N_t} \log_2 \left(1 + \frac{P_p ||h_p||^2}{B N_o + \beta \sum_{m=1, m\neq p}^{N_t} P_m ||h_p^m||^2}\right)\right], \tag{13}$$

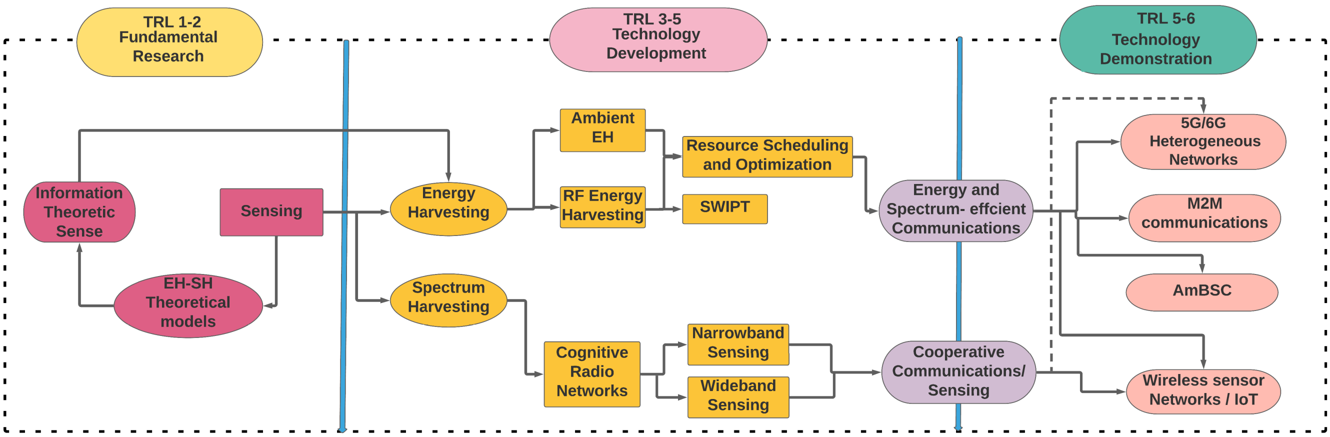

FIGURE 16. TRL diagram for EH and SH technologies for the next generation wireless communication networks.

where N_t is the total number of transmitter-receiver pairs, h denotes the channel gain, and β denotes the equivalent capability of interference cancellation. In comparison to the orthogonal schemes, the non-orthogonal schemes are able to achieve better spectral efficiency values. Further, the non-orthogonal schemes do not require additional costs as they do not need any significant hardware improvements over the existing infrastructure [49].

The implementation of energy-efficient techniques for future wireless communication networks needs to address several challenges, like whether the schemes be applied in a centralized or decentralized fashion. The answer to this lies in the way the infrastructure is utilized, and how the protocols are implemented. Future networks need to follow an approach in terms of maximum infrastructure utilization so that there is less strain on the resources For instance, the processing at the baseband level may be centralized, and the radio resource functionality may be divided across the whole network.

VI. CONCLUSION

The recent past has witnessed the rapid growth of heterogeneous sensors in IoT and proposals for architectures for their integration with the fifth-generation (5G) networks and beyond. Energy harvesting and spectrum harvesting technologies are essential to meet the requirements of two precious resources: energy and bandwidth for reliable and efficient communication. This survey paper provided a comprehensive overview of the EH and SH techniques for the next generation of wireless systems and networks. We presented an overview of the present trends of the EH and SH technologies, the implementation challenges, and open research areas. Specifically, we covered the techniques like the ambient RF-EH techniques and presented the spectrum harvesting techniques like those based on CR and cooperative sensing. Further, we introduced the TRL of the harvesting technologies and gave an overview of the future trends and challenges in the context of next-generation wireless networks. The EH and SH technologies have become an integral part of the next-generation wireless communication networks' design and planning. This comprehensive survey provided various themes, perspectives, methods, and protocols that would serve as a useful resource for researchers in the field of advanced green and energy-efficient cognitive wireless systems and networks.

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